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The Use of Occupation and Education Factors in Automobile Insurance

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INTRODUCTION

Background

Occupation and educational attainment are two of more than one dozen commonly used factors for determining the price of auto insurance in most states, but the use of these factors has become a source of debate in New Jersey and some other jurisdictions, leading to a variety of analyses, public hearings and legislative initiatives.

In New Jersey and elsewhere, the practice of considering an insurance applicant's occupation or level of education is decades old; some insurers will only cover drivers who hold specified occupations, and in several states insurers charge less to applicants who have achieved certain educational goals.[1]

Not until 2004, however, had a company used occupation and education factors both simultaneously and on a wide scale in New Jersey. GEICO's national business model is based in part on the use of these factors, and the company, now the nation's fourth largest, extended that model to New Jersey when it re-entered the state in August 2004 after a 28 year absence. GEICO grew extraordinarily quickly in New Jersey while using this model, becoming the state's third largest auto insurer by the end of 2006.

GEICO's rapid growth and its use of these factors garnered public attention that year, and legislative concern about the company's use of the factors came to the forefront with a Senate Commerce Committee hearing on June 12. Witnesses

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[1] "Membership" companies such as New Jersey Manufacturers Insurance Co., the state's largest auto insurer, require applicants to belong to specified occupations or trade organizations. Premium reductions for specified educational achievements are provided in New Jersey under the "Good Student Discount." California has some of the most restrictive rules on auto rating factors in the United States but nonetheless recognizes "academic standing" as a rating characteristic. See California Insurance Code, 10 CCR 2632.5(d). The California Insurance Department advises that it also permits separate rating systems for "affinity groups" that may be related to occupation.

included New Jersey Citizen Action (NJCA), a citizen watchdog organization; New Jersey Citizens United Reciprocal Exchange (NJ CURE), a New Jersey-based auto insurer that objects to the use of these factors; GEICO; a variety of insurance trade organizations; and Department of Banking and Insurance Commissioner Steven Goldman.[2]

In general, those who supported the ability to use these factors testified that a wide range of New Jersey consumers were benefiting from a 2003 package of auto insurance reforms that attracted new insurers to the State and thus prompted the growing use of the factors; that the ongoing use of the factors appeared to be contributing to increasing price competition and availability of coverage; that a regulatory change of course might jeopardize the market's substantial progress since 2003; that the factors appeared actuarially justified; and that the Department had no statutory or regulatory grounds upon which to deny their use.

Opponents of the use of these factors generally questioned the extent of the success of the 2003 auto reforms; questioned the role of these factors in implementing the reforms; questioned the actuarial basis for the factors; asserted that the factors were proxies for race and income or, at minimum, had a differential and negative effect on protected classes; asserted that the Department violated its own regulations by allowing their use; and asserted that, regulations aside, as a matter of policy the State should prohibit their use because of their impact on low-income and minority drivers.

Attention to the use of these factors was further heightened on February 28, 2007, when NJCA issued a report titled, ***Risky and Wrong: New Jersey Auto Insurance Rates for Lower Income and Minority Drivers, An Analysis of the Impact of GEICO's Use of Education and Occupation on the Price of Auto Insurance.***[3]

[2] Written testimonies are found in Attachment 1.
[3] See Attachment 2. Note that this attachment is the report as revised by NJCA on March 2.

The NJCA report expounded on the assertions that NJCA and other concerned parties had made in the preceding months, and sought to quantify the impact of education and occupation factors through an analysis of U.S. Census data and actual rates charged by GEICO. NJCA reported that GEICO charged dramatically higher rates to drivers with blue-collar occupations and less than a college degree, and that census data demonstrated that this practice was a proxy for race and class and had a differential effect on racial minorities and low-income drivers.

On March 5, following the release of the NJCA report but before the Department had an opportunity to analyze it, Department staff testified before the Commerce Committee on S-1714 (Gill/Vitale), a bill to prohibit insurers from considering an applicant's occupation or education.[4] The Department stated its specific concerns about the scope and potential unintended consequences of the proposed bill and reiterated its general concerns about changing course during a period of extensive progress in the auto insurance market.

The bill was not released by the Committee. However, the Department subsequently pledged to meet with NJCA and other groups to better understand their concerns, and to conduct an analysis of both the NJCA report and the issues raised by the sponsors and supporters of S-1714. The Department has done so. This document reports the Department's findings.

<u>Process</u>

As part of its analysis the Department examined:

- Statutes and regulations governing rating and acceptance decisions in New Jersey.
- Relevant statutes, regulations and practices of other jurisdictions.
- The data and methodology of NJCA's report.

[4] S-1714 is Attachment 3; the Department's testimony is Attachment 4.

- GEICO and other insurer rate filings with the Department.
- The findings of the Maryland and Florida insurance departments, two insurance regulators that have issued reports on this issue since the return of GEICO to New Jersey.
- Census data correlating race with occupation and education.
- Academic and government studies related to the potential differential effect of various insurer practices.
- Court filings in a pertinent class action lawsuit against GEICO in Minnesota.

In addition, the Department met with plaintiffs' counsel in the Minnesota case and conducted an independent, anonymous survey of GEICO's rates via the company's website.

In each instance, the goal was to establish facts about the use of these factors in New Jersey and across the country, to attempt to independently validate NJCA's findings (and where they could not be validated, to understand the methodological or other issues responsible for the difference) and to better understand various viewpoints on the issue of the possible differential effect of the use of education and occupation as factors in auto insurance.

RATE REGULATION AND THE USE OF OCCUPATION AND EDUCATION FACTORS IN NEW JERSEY AND OTHER STATES

New Jersey's statutory standard for the approval of automobile and other personal lines rating systems is set forth in N.J.S.A. 17:29A-7. That statute directs that:

> "If the Commissioner shall find that such rating-systems provide for, result in or produce rates that are not unreasonably high, and are not inadequate for the safeness and soundness of the insurer, and are not unfairly discriminatory between risks in this State involving the same hazards and expense elements, he shall approve such rates . . ."

This standard was originally adopted in New Jersey in 1944 and has continued in effect to date. It is similar to the general standard applicable in most United States jurisdictions since the 1940s.[5]

Since that time, New Jersey and many other states have amended their insurance rating laws in various fashions while maintaining the "not excessive, not inadequate, not unfairly discriminatory" standard as the fundamental criteria for insurance rates.

In New Jersey, the statutory criteria have been amended to include the following:

1. N.J.S.A. 17:29A-15.1 requires premium credits for various optional policy provisions required to be offered by New Jersey law;
2. N.J.S.A. 17:29A-36 requires uniform Statewide rating classifications; a 250% cap on the variation of base rates by class; a cap on the base class in any territory (since repealed but with the limitation that the resulting territorial rating differentials not be significantly disproportionate to those

[5] Enactment of insurance rating laws in all states were precipitated by the enactment of the McCarran-Ferguson Act, 15 USC 1101 et seq. which authorized the states broadly to regulate the business of insurance.

preexisting); and restrictions on the rating of automobiles with principal operators age sixty-five and over.

3. N.J.S.A. 17:29A-37, which requires flattening of taxes, licenses, fees and other expenses per insured automobile statewide; and
4. Various statutes enacted at different times that directed across-the board rate reductions upon enactment of changes in other laws.

While other states have modified their insurance rating laws in similar ways, either for general purposes or for automobile coverage in particular, few have directly addressed the use of occupation or education level as auto rating criteria. The absence of proactive statutory measures regarding such factors has therefore meant wide acceptance of their use under the bedrock “not excessive, not inadequate, not unfairly discriminatory” standard. [6]

Thus, at the time of its approval of the GEICO rating system in 2004, the Department understood that both occupation and education level were permitted as rating factors in most other jurisdictions, with only a small number of states having statutes or regulations that specifically addressed the issue in order to set forth conditions under which such factors could be used. [7] This group included Colorado and Pennsylvania.

The Department’s understanding in 2004 is consistent with a finding by counsel for plaintiffs in a current, pertinent lawsuit against GEICO in Minnesota (discussed later in this report) that, in actual practice, GEICO uses occupation and education factors in essentially the same manner in forty-four jurisdictions.

In order to better understand how variations in state laws might affect the determination to permit the use of these rating criteria, or to regulate the manner in which they are used, the Department reviewed the auto insurance rating

[6] Under this standard, “unfairly discriminatory” means that the factors are not actuarially measurable and credible, and not sufficiently related to actual or expected loss and expense experience of the group.

[7] New Jersey is among the minority of states that impose specific statutory restrictions on the use of occupation as an acceptance criteria (as opposed to a rating criteria). These are discussed later in this report.

statutes of several other jurisdictions, starting with Colorado and Pennsylvania. The Department's findings are set forth below.

Colorado

Colorado's statute addressing insurance rates is set forth in the Colorado Revised Statutes at C.R.S. 10-1-101, a single paragraph that includes the standard:

> ". . . insurance rates shall not be excessive, inadequate or unfairly discriminatory."

Regulations promulgated by the Colorado Division of Insurance, found at 3 CCR 702-5, Section 5B limit insurers' action to refuse to write, cancel, nonrenew, increase premium, surcharge or reduce coverage. Section 5B.1 provides: "Basis for refusal to write a policy of automobile insurance (i.e., acceptance criteria):

a) Colorado law prohibits discrimination solely based on age, color, sex, national origin, residence, marital status or lawful occupation including military service". (emphasis added)

Section 5B.5.a provides a similar prohibition against refusing to renew.

On their face, these provisions appear to preclude the use of occupation in insurance acceptance decisions, though not in rating decisions. Personnel from the Colorado Division of Insurance confirmed that while these provisions prohibit the use of occupation as a reason to refuse an application or to nonrenew a policy, they do not prohibit the use of occupation in a rating system to reflect price differentials, so long as the differential is supported by adequate actuarial justification. Additionally, the Colorado Department advised that they have similarly required clear actuarial justification for any rating differences based upon education. Therefore, it appears that Colorado's use and application of its law and rules regarding these rating factors are similar to the New Jersey practice.

Pennsylvania

Pennsylvania statutes addressing this issue are set forth in its code at 40 P.S. 1171.5. Paragraph (a) of that statute defines "Unfair Methods of Competition" and "Unfair or Deceptive Acts or Practices" in the business of insurance to include:

> ". . . (7) unfairly discriminating by means of: . . . (iii) making or permitting any unfair discrimination between individuals of the same class and essentially the same hazard with regard to underwriting standards and practices or eligibility requirements by reason of race, religion, nationality or ethnic group, age, sex, family size, occupation, place of residence or marital status. The terms "underwriting standards and practices" or "eligibility rules" do not include the promulgation of rates if made or promulgated in accordance with the appropriate rate regulatory act of this commonwealth and regulations promulgated by the commissioner pursuant to such act." (emphasis added)

This statute appears to set a standard similar to the New Jersey practice which distinguishes acceptance criteria (whether coverage is provided) from rating criteria that determine price. According to the Pennsylvania Insurance Department, this reading is correct and neither this statute nor any other current provision of Pennsylvania insurance law would prohibit varying rates based on occupation if the insurer provided sufficient actuarial evidence supporting the differential.

Minnesota

Minnesota's statute at section 70A.04 sets forth the standard language that rates shall not be "excessive, inadequate or unfairly discriminatory," adding that an insurer shall not use rates to engage in unfair price competition. With respect to unfairly discriminatory rates, Subdivision 4 of the statute states that:

> "One rate is unfairly discriminatory in relation to another if it clearly fails to reflect equitably the difference in expected losses, expenses and the degree of risk. Rates are not unfairly discriminatory because different premiums result for policyholders with like loss exposures but different expense factors, or like expense factors but different loss exposures, so long as the rates reflect the differences with reasonable accuracy. Rates are not unfairly discriminatory if they attempt to spread risk broadly among persons insured under a group, franchise or blanket policy."

As noted in the Minnesota litigation referenced above, it appears that GEICO's use of occupation and level of education is permitted by this standard.

<u>Florida</u>

Florida statutes addressing automobile insurance rates are set forth in the Florida Statutes at section 627.0651. That statute contains the widely accepted standard to prohibit rates that are "excessive, inadequate, or unfairly discriminatory." Subparagraph (6) states: "one rate shall be deemed unfairly discriminatory in relation to another in the same class if it clearly fails to reflect equitably the difference in expected losses and expenses." Paragraph (7) states: "rates are not unfairly discriminatory because different premiums result for policyholders with like loss exposures but different expense factors, or like expense factors but different loss exposures, so long as rates reflect the differences with reasonable accuracy." Paragraph (8) states: "rates are not unfairly discriminatory if averaged broadly among members of a group; nor are rates unfairly discriminatory even though they are lower than rates for non-members of the group. However, such rates are unfairly discriminatory if they are not actuarially measurable and credible and sufficiently related to actual or expected loss and expense experience of the group so as to assure that non-members of the group are not unfairly discriminated against."

Based upon this statute, it appears that occupation and education factors are to be approved when loss experience is advanced to actuarially justify the rating differential, and legislative action would be required to implement a policy prohibiting the use of such factors. [8]

Michigan

Michigan's statute addressing rates for automobile and homeowners' insurance is set forth at Michigan Compiled Laws, section 500.2109 through 500.2111. That section includes the standard criteria that rates "shall not be excessive, inadequate or unfairly discriminatory" and defines unfairly discriminatory in paragraph (c) as follows:

> "A rate for coverages is unfairly discriminatory in relation to another rate for the same coverage if the differential between the rates is not reasonably justified by differences in losses, expenses, or both, or by differences in the uncertainty of loss, for the individuals or risks to which the rates apply."

Section 2111, however, sets forth with specificity a limited number of factors that may be used in automobile insurance rating. These factors do not include occupation or education level and thus these criteria are, on their face, prohibited. According to the Michigan Insurance Department, however, section 2110 of the Michigan statutes, enacted in 1997, permits auto insurers to establish and maintain premium discount plans utilizing factors in addition to those permitted by section 2111 "if the plan is consistent with the purposes of this act and reflects reasonably anticipated reductions in losses or expenses." The Michigan Insurance Department acknowledges that some insurers have used occupation and/or education level as the basis for discounts as permitted by that statute.

[8] Indeed, this was a conclusion of a March 2007 Florida Office of Insurance Regulation report on this issue, which report is discussed later in this document.

California

California's statutes concerning automobile insurance rating are set forth in the California Insurance Code, section 1861.02 which provides as follows:

> "(a) Rates and premiums for an automobile insurance policy, as described in subdivision (a) of Section 660, shall be determined by application of the following factors in decreasing order of importance:
>
> (1) The insured's driving safety record.
>
> (2) The number of miles he or she drives annually.
>
> (3) The number of years of driving experience the insured has had.
>
> (4) Those other factors that the commissioner may adopt by regulation and that have a substantial relationship to the risk of loss. The regulations shall set forth the respective weight to be given each factor in determining automobile rates and premiums. Notwithstanding any other provision of law, the use of any criterion without approval shall constitute unfair discrimination."

This California statute was adopted on initiative by voters as Proposition 103, Section 3, effective November 9, 1988. The California Commissioner's regulation setting forth rating factors is codified at 10 CCR 2632.5(d); these rating factors do not include occupation or education level. Subsection (d) 13 and (e), however, recognizes "academic standing" as a secondary driver characteristic and as a factor that may be combined with the three mandatory factors in order to rate an automobile insurance policy.

The California Insurance Department confirmed that based on the Proposition 103 law, occupation and education level are not currently used to rate auto insurance policies in that state. The reference to "academic standing" in the regulation is intended to permit the use of "good student discounts."

However, California also permits the use of "affinity groups" that provide separately rated auto insurance coverage to members of particular groups, which may be related to profession or occupation. The California Department advised that they review such programs to assure they are not being created simply to evade the prohibition in the law. As applied, rating of these affinity groups appears to be similar to the programs provided under New Jersey's rules. [9]

<u>Massachusetts</u>

Massachusetts statutes regulating insurance rating are set forth in the Annotated Laws of Massachusetts, Part 1, Title XXII, chapter 175E. Section 4 sets forth the standards for rates, directing that rates "not be excessive or inadequate . . . nor shall they be unfairly discriminatory." Although the balance of that section also includes other generally accepted insurance rating standards, section 5 of the statute authorizes the Massachusetts Commissioner to set rates required to be used by insurers upon a finding that competition is either insufficient or destructive. This finding has been made for the personal auto insurance market every year since 1977, and as a result all auto insurers in that state have used the same regulator-directed rating system for 30 years. The presently approved system uses a limited number of rating factors which do not include occupation or education level.

On October 5, 2007, the Massachusetts Commissioner proposed new rules (211 CMR 79.00) intended to bring competition and new entrants into the market, which currently consists of only nineteen companies. Most of the large national auto insurers do not write there and the major participants are "Massachusetts-only" companies. The new rules promulgate standards for insurers to file their own distinct rating systems. In section 79.05(11) the proposal sets forth a list of prohibited rating factors that include occupation and education. The prohibitions also include a number of factors that are used in most jurisdictions for auto

[9] NJAC 11:2-12 permits a discount from the insurer's standard rate to employees of particular employers or members of particular associations or organizations.

insurance rating such as sex, marital status and age (prohibited, but with an exception to allow special discounts for seniors).

According to the Massachusetts Department, action on the proposed rules is expected in the first quarter of 2008, after receipt and review of public comment, with an effective date later in the year.

In summary, the Department's review of rating laws and regulations around the country confirms the Department's original understanding that occupation and education factors are widely permitted. They tend to be permitted because, as the Florida statute puts it, the factors are "actuarially measurable and credible and sufficiently related to actual or expected loss and expense experience of the group so as to assure that non-members of the group are not unfairly discriminated against." California and Massachusetts are much more restrictive. However, in the few other cases where states proactively address the use of such factors, the general effect is to permit them under conditions not dissimilar to those already imposed in New Jersey.

ANALYSIS OF THE NEW JERSEY CITIZEN ACTION REPORT

New Jersey Citizen Action undertook a comprehensive review of the issue of occupation and education factors in automobile insurance, with a particular focus on the use of these factors by GEICO and an extensive investigation designed to determine the price impact of GEICO's rating system on applicants with varying levels of occupational and educational attainment.

However, the NJCA report contains several key assertions that, upon examination, appear to be unsupported. A foundational issue involves the assertion that the Department lacked the authority to permit the use of occupation and education factors. The Department also finds to be inadequately supported NJCA's claims that the factors are not actuarially justified;[10] that their use results in dramatically higher prices for certain classes of New Jersey drivers; that they are used by GEICO for marketing reasons not disclosed by the company; that they are used as proxies for race and income; and that the Department has exaggerated the positive impact of auto reforms and the linkage of these factors to improvements in the marketplace. Each of these NJCA assertions and the Department's responses are outlined below.

[10] As noted elsewhere in this document, insurance regulators in multiple other states have also found these factors to be actuarially justified.

<u>NJCA Report: Department Lacked Authority to Approve GEICO Rating System</u>

The use of occupation and education as rating or underwriting factors is prohibited by <u>N.J.A.C.</u> 11:3-19A, which states in part that "The placement of applicants and insureds at or within a tier and the movement of insureds between tiers shall be based on underwriting rules that…are mutually exclusive per tier, objective and not applied so as to violate any statute or regulation of the United States or the State of New Jersey." NJCA asserts that this rule is violated because "GEICO is using education and occupation in a manner that is not objective and in a manner that violates regulations of the United States and the state of New Jersey." (pp. 10-11)

While not part of its original report, NJCA made a related argument in a letter to the Commissioner dated June 6, 2007, so the letter is treated here as an addendum to the report.[11] In that letter, NJCA asserted that the Department's approval of the GEICO rating system also violated N.J.A.C. 11:3-35, which lists prohibited underwriting rules including occupation.

<u>Department Finding</u>

The regulations and the practical distinction between a set of acceptance criteria in a company's underwriting rules and a company's rating criteria appear to be the subject of general misunderstanding.

N.J.A.C. 11:3-35, by its own terms, does not apply to filings made after March 1, 1998. N.J.A.C. 11:3-35.1(c) states that "No private passenger automobile insurer shall make any filing pursuant to this subchapter after March 1, 1998." GEICO filed its rating system in August, 2004.

As applied by the Department to post–1998 rating systems, the acceptance criteria in a set of underwriting rules determine whether coverage will be provided

[11] See Attachment 5

at all. An insurer's rating system, in contrast, determines the price of coverage. The Department has consistently prohibited the use of occupation as an acceptance criteria (i.e., the offer of coverage or the refusal to offer coverage), except in the case of "membership" companies. But neither this nor any other regulation prohibits its use or the use of educational level in rating.

N.J.A.C. 11:3-35 was adopted as part of the implementation of the Fair Automobile Insurance Reform Act of 1990 (FAIRA). FAIRA established a legal requirement that insurers write business for all "eligible persons" (the "take-all-comers" law). The context for the requirement actually pre-dated FAIRA; prior rules prohibited use of occupation as a basis for canceling or non-renewing an auto insurance policy. The previous prohibition was unrelated to issues of race, creed or ethnicity, but instead arose from concerns about the availability of coverage for applicants in certain occupations that were perceived to generate more claims. These occupations included bartenders, entertainers and persons employed by race tracks. Other high profile occupations such as actors/actresses, professional athletes and politicians were perceived to represent "target defendants" more likely to be sued. Auto insurers in some other jurisdictions simply refused to write persons in these occupations, and so the rule was adopted to assure availability and continuity of coverage for such consumers in New Jersey.

FAIRA also restricted premium differentials to eligibility point surcharges in "standard/non-standard" rating systems. N.J.A.C. 11:3-35 was adopted to implement and enforce these provisions of FAIRA by requiring insurers to file acceptance criteria assuring that all "eligible persons" would be offered coverage.

In 1997 the Legislature significantly amended the automobile insurance laws, including repealing FAIRA's provisions establishing "standard/non-standard" rating systems, and substituted in their place "tier rating," which allowed insurers greater flexibility in the factors permitted to affect individual rates. The

Department implemented this new statute by adopting N.J.A.C. 11:3-19A, the regulation that NJCA cites in its report.

N.J.A.C. 11:3-19A established rules for the new tier rating systems. Occupation as a prohibited criteria was never transferred from N.J.A.C. 11:3-35 into this rule because tier rating involves pricing, not the ability to offer or deny coverage or a renewal of coverage (i.e., acceptance decisions). The applicability of N.J.A.C. 11:3-35 was thus limited to rating systems filed on or before March 1, 1998, because those were the only rating systems to which the provisions applied.

The 2003 automobile insurance reform laws began to phase out the "take-all-comers" requirement by permitting the use of underwriting rules with alternate acceptance criteria in order to exempt insurers that met specific growth targets from the obligation to cover all eligible persons. The Department's rules implementing those laws are set forth at N.J.A.C. 11:3-35A. Since these rules establish acceptance criteria standards (i.e., whether an applicant is able to obtain or retain coverage), the standards include a continued prohibition on the use of occupation or profession as an acceptance criteria.

As this background demonstrates, while the use of occupation or profession as an acceptance criteria has consistently been prohibited by the Department for non- "membership" insurers, the use of occupation or profession in rating (i.e., as part of the determination of the premium charged for coverage) has never been prohibited by any rule. In fact, the Department's "mass marketing" rules at N.J.A.C. 11:2-12 specifically permit the application of special price discounts for employees of particular employers, or for members of associations or organizations that may be based upon occupation, profession or education groups.

Since the enactment of FAIRA in 1990, many auto insurers have utilized a system of several separate companies in order to meet the requirement to write all eligible persons. The use of multiple companies to provide coverage to all eligible persons has been consistently recognized by the Department as an acceptable rating system to satisfy the "take-all-comers" requirement within the group. The Department has prohibited certain acceptance criteria only when individual risks are being excluded from coverage, either initially or upon renewal; these standards have not been applied to rating systems that merely vary the price of coverage.

Since the approval of GEICO's rating system in 2004 was consistent with the statutes and rules then and currently in effect, the Department concludes that ordering its modification to exclude use of these factors would have been arbitrary and unable to withstand challenge.

With respect to NJCA's assertion that the use of the factors should be prohibited because it is "not objective" and violates U.S. law, the Department is unable to find support in the NJCA report or elsewhere for this conclusion. The footnote accompanying the assertion instead refers back to the Department regulation being quoted.

Perhaps more importantly, the Department has determined that the factors are, in fact, being applied by insurers in an objective, mathematical manner, with no knowledge of, or reference to, an individual applicant's race or income. Neither race nor income data is collected by New Jersey insurers (or, to the best of the Department's knowledge, by any other auto insurer in the country). Nor does GEICO in particular, as a predominately direct writer utilizing internet and telephone systems for its sales, come "face to face" with its applicants. All applicants with the same risk characteristics are treated in the same manner within each insurance company.

The impartial and consistent application of data that correlates losses to certain occupations and educational levels would seem clearly to constitute an "objective" use of that data, particularly since the data has been vetted by the Department, other regulators and the workings of the marketplace.

Additional support for the idea that the practice is well within insurance regulatory norms comes from the fact that it has been accepted in most other jurisdictions, as discussed previously in this report.

By way of confirmation, the Department also contacted the Maryland Insurance Administration (GEICO is domiciled in Maryland) to confirm usage of the model by GEICO in particular, and found that it generated no significant complaints.

<u>NJCA Report: GEICO's Use of these Factors Results in the Exclusion of Certain Occupations and Levels of Education from GEICO's Best Company and Rating Tiers</u>

*"Contrary to GEICO's public representation, both a driver's education and occupation **alone** can determine eligibility for one of GEICO's preferred companies, regardless of driving record." (p. 4)* (emphasis added)

"…GEICO fails to mention that drivers with lower education and nonprofessional jobs are denied access to the preferred company without notice and hence denied the lowest available rates." (p. 4)

<u>Department Finding</u>

This NJCA assertion appears to result from a methodological flaw that the Department found when attempting to replicate NJCA's findings on rate differentials. [12]

The Department conducted its own review of GEICO's acceptance criteria to determine if any risks were automatically excluded from GEICO's lowest-rated company (i.e., "preferred" company) and rating tier. DOBI determined that risks with a High School Diploma and Group 5 Occupation Class (the "least preferred" class) could in fact be eligible for the preferred company and rating tier.

With respect to the overall impact of GEICO's system on actual consumers in the market, the Department found that, for the 12-week period ending June 9, 2007, the preferred GEICO company wrote 4,417 policies (42.4%) where the named insured did not have a college degree, and 5,935 policies (56.9%) where the named insured was not placed in Occupation Classes 1 or 2 (the "most preferred" classes).

[12] This methodological flaw is discussed in more detail in the section on GEICO's rates.

For all companies combined, GEICO wrote 16,526 policies (63.2%) where the named insured did not have a college degree, and 19,481 policies (74.5%) where the named insured was not placed in Occupation Classes 1 or 2.

NJCA Report: The Factors Do Not Correlate to Risk

“There is no evidence that education or occupation – characteristic traits being used by GEICO to class drivers – correlate to risk.” (p. 10)

“…demonstrating a correlation between education and occupation and corresponding loss ratios…does not constitute sound “actuarial loss data’.” (p. 10)

“The industry fails to mention that the reason for this correlation is that education and occupation are simply proxies for income.” (p. 10)

Department Finding

The Department finds NJCA’s discussion of this issue to be contradictory and unclear. Department actuaries reviewed GEICO loss experience data and determined that the use of occupation and education was actuarially valid. The loss ratios are as follows: [13]

Occupation Group 1	0.849	High School or less	1.131
Occupation Group 2	0.837	Associate’s Degree	1.027
Occupation Group 3	0.967	Bachelor’s Degree	0.901
Occupation Group 4	1.047	Master’s Degree	0.822
Occupation Group 5	1.257	Unknown	1.069
Student	1.084		
Military	1.040		

[13] This data was originally submitted to the Department in 2004 as proprietary and confidential. In September of 2006 GEICO authorized the Department to release the data in response to a legislative request for information about the issue. It has since been filed as an exhibit in a pending legal matter. Since it is directly relevant to the subject of this report and is no longer confidential, it is being reproduced here. Its reference should not be construed to indicate in any manner that the confidentiality of other proprietary information submitted to the Department by GEICO or any other insurer is deemed waived or otherwise compromised.

This information demonstrates that Occupation Groups 1 and 2 have better loss experience than the others, and that drivers with a Bachelor's or Master's degree are similarly less risky than the population generally. The differences are statistically significant and thus sufficient under current insurance statutes to be reflected in the rates charged to these driver groupings.

Based on this data, for example, individuals in Occupation Group 1 generate about 15% less claims than average drivers, while individuals in Occupation Group 5 generate greater than 25% more claims than average drivers. Similar results are documented in the loss ratios for groups with various levels of education.

It is unclear to the Department how the NJCA report concluded that this kind of data "does not constitute sound 'actuarial loss data'."

By way of confirmation, a Maryland Insurance Administration Market Conduct Examination report states: [14]

- GEICO has demonstrated that education and occupation are predictors of loss;
- GEICO's use of education and occupation as risk characteristics meets actuarial standards of practice and principles related to risk classification; and
- From an actuarial perspective, GEICO's use of education and occupation is reasonable.

Based on its review of testimony before the Senate Commerce Committee, and subsequent discussions with NJCA and others, the Department believes that the core issue here may be a desire that insurer rating systems be based on proven *causal* relationships between the factors used and losses incurred, instead of on statistical correlations.

[14] See Attachment 6.

While this may be appealing on an intuitive level, causation is ultimately not a meaningful or workable concept for insurance companies or regulators. This is because no currently used factors are proven to have causal relationships to losses, and seemingly commonsensical assumptions about causes are sometimes disproved mathematically. Having an accident this year does not *cause* a given driver to have another accident, yet it is typically reflected in the driver's rates based upon data that demonstrates a higher likelihood of future claims by insureds who have incurred past claims. Likewise with age, gender, marital status and other commonly accepted rating factors: none cause losses; they are simply statistically predictive of greater or lesser losses compared to all drivers combined.

Thus, as a predominately mathematical exercise, the assigning and pricing of risks is based on statistical correlations instead of on assumptions about causation, however logical they may seem. The more predictive those correlations are in practice, the more powerful and useful they are for the insurer.

Interestingly, some factors that intuitively seem most predictive are in practice less than ideal because of the infrequency of occurrence. For example, in New Jersey collision claims are made on average only once every 16 years. For comprehensive claims the period is 27 years. This is one of the reasons that insurers have searched for other correlations upon which to base their rates. Relying too heavily on accidents in the calculation of rates risks overcharging a customer who, statistically, is unlikely to have another accident for several years. Likewise, such over-reliance risks undercharging a customer who has not had an accident in several years but may have one soon. [15]

NJCA appears to believe that a "real" or "hidden" reason for the use of occupation and education factors is that they correlate with race and / or income,

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[15] Indeed, the "standard/non-standard" rating systems created by FAIRA in 1990, which differentiated price primarily by surcharging those with accidents and motor vehicle violations, were criticized as unfairly penalizing minor transgressions. The statute was repealed in 1997.

and that race and / or income are what are in fact being measured here, but by proxy. The Department is aware of no evidence of an interest by any auto insurer to measure race, income or any other characteristic by proxy. But the argument does illustrate the fact that any given characteristic is part of a complex web of statistical correlations. One thing correlates with another which correlates with yet another, and so on. This reality and the thorny problems it raises are discussed later in this report with respect to the issue of differential effect.

NJCA Report: GEICO’s Use of these Factors Results in Dramatically Higher Prices for Applicants with Certain Occupations or Levels of Education

A specific example based on a 51 yr-old female in Camden shows a rate difference from GEICO of 61% when education and occupation are varied. (p. 7)

GEICO’s average rate quote for consumers without a Bachelor’s Degree is 19% higher than for consumers with a Bachelor’s Degree. (p. 8)

GEICO’s average rate quote for consumers with a nonprofessional job is 27% higher than for consumers with a professional job. (p. 8)

GEICO’s average rate quote for consumers with a Bachelor’s Degree and a professional job is 38% lower than for all other consumers. (p. 8)

GEICO’s average rate quote for consumers without a Bachelor’s Degree and with a nonprofessional job is 22% higher than for all other consumers. (p. 8)

Department Finding

NJCA’s findings are the result of a methodological flaw that results in an exaggeration of the differences in rates being quoted. NJCA used fictitious applicants without actual Social Security numbers and credit histories when requesting quotes from the GEICO website. The lack of actual credit information from a real applicant resulted in a large overweighting by GEICO’s automated rating system of remaining factors such as occupation and education. This type of problem would arise in any case where insufficient or inaccurate information was provided to an insurance company by an applicant, regardless of whether or not the company used occupation or education factors. All auto insurers set prices based on a combination of factors; the removal of any one of the factors from the insurer’s calculation would necessarily result in the remaining factors having an unexpectedly higher impact on the final price.

In addition, NJCA assumed that its drivers had no prior insurance (i.e., had been uninsured). That is an unlikely scenario for someone such as the 51 year old driver for whom NJCA got its most dramatic results.

DOBI compiled quotes based on a 51 yr-old female in Camden with the same characteristics as those selected for the NJCA study, except that DOBI varied the risk's prior insurance and credit histories. The results are as follows:

- For a driver with both prior insurance and a valid credit history, the impact of education and occupation combined was 8% ($524 v. $486 - both risks in GEICO);

- For a driver with a valid credit history but no prior insurance, the impact of education and occupation combined was 0% ($770 - both risks in GEICO Indemnity);

While the use of the factors clearly can result in more significant price differences than those above using this specific, fictional applicant, 19% was the largest difference that the Department found in its experiments with GEICO's online quote system using real drivers and varying both occupation and education level from the lowest to the highest categories.

With respect to the implications of GEICO's rating system for actual consumers shopping for insurance in New Jersey, it is worthwhile to note that prices also vary substantially between companies in the marketplace.

For example, a comparison of GEICO to six additional insurer groups for the risk discussed above, with prior insurance and a valid credit history, shows that four of the six insurers are significantly more expensive than GEICO despite GEICO's use of education and occupation as rating factors:

	GEICO	Insurer "A"	Insurer "B"	Insurer "C"	Insurer "D"	Insurer "E"	Insurer "F"
Prof. w/ Degree	$973	$1,792	$1,437	$1,541	$1,412	$1,000	$870
Non-Prof w/o Degree	$1,048	$1,792	$1,437	$1,541	$1,412	$1,000	$870

Thus, for actual consumers, GEICO's use of occupation and education rating factors results neither in dramatic rate differentials within GEICO nor in rates that make the insurance marketplace as a whole less affordable. On the contrary, as the following section describes, rates have generally fallen across the marketplace since the re-entry of GEICO in 2004 and the increase in competitive pressures to which that re-entry contributed.

<u>NJCA Report: The 2003 Auto Reforms Have Failed to Create the Market Improvements Claimed by the Department and Others, and the Use of Occupation and Education was Not Part of Those Reforms</u>

"…despite countless press releases, (the Department) and lawmakers have curiously failed to mention several key facts to the public regarding the condition of New Jersey's auto insurance market post (reform). First…the actual number of insurers writing auto insurance has decreased since 2003…Second, New Jersey continues to maintain the title for having the highest auto insurance rates in the country as of 2004. Third, the country-wide private passenger auto insurance marketplace has reported record profit levels since 2003, discrediting claims that (auto reform) was primarily responsible for the improved profits by auto insurers in New Jersey. Most importantly, the concerted effort to lure national auto insurers into New Jersey went beyond the scope of (the) original reforms and ultimately resulted in accommodations to the auto insurance industry at the price of consumer protections, in particular, protection for lower income individuals and racial minorities in New Jersey." (p. 5)

<u>Department Finding</u>

The NJCA report contains the following numbers of insurers: 2003 – 82; 2004 – 79; 2005 – 73; 2006 – 82; 2007 – 82.

DOBI has reviewed its records to determine that of the 82 insurers authorized for private passenger auto insurance in 2003, only 63 actually wrote private passenger automobiles; others wrote miscellaneous/specialty vehicles or motorcycles. Between 2003 and 2006, the number of insurers actually writing automobiles had increased to 69, a gain of six.

Since 2003, 13 new companies were licensed to write, and have begun writing private passenger automobiles. They are:

Company	**Effective Date**	**Exposures as of 12/31/2006**
Mercury Indemnity Company of America	8/14/2003	121,332
Government Employees Insurance Company	8/16/2004	387,121
GEICO Casualty Company	8/16/2004	36,689
GEICO Indemnity Company	8/16/2004	183,806
Esurance Insurance Company	3/29/2005	16,858
AMEX Assurance Company (transferred to IDS PC Ins Co)	7/1/2005	10,270
Progressive Garden State Insurance Company	9/30/2005	16,520
Progressive Freedom Insurance Company	9/30/2005	20,387
Drive New Jersey Insurance Company	9/30/2005	44,876
AIG Premier Insurance Company	3/1/2006	2,086
Unitrin Direct Insurance Company	4/18/2006	3,550
21st Century Insurance Company	10/8/2006	14,403
Personal Service Insurance Company	11/9/2006	1,111
13 Companies		859,009

NJCA is correct that New Jersey has consistently ranked first in national surveys of the average premium paid per vehicle. The Department does not share the conclusion, however, that the 2003 reforms have therefore failed to accomplish their goals.

First, the reforms were crafted in response to a crisis of availability, not affordability.[16] While the Department hoped for and expected downward pressure on premiums as a result of competition generated by the entrance of new insurance companies, the primary goal was to increase capital investment by insurers and thus the capacity and appetite to cover drivers who were then having difficulty finding coverage regardless of price.[17]

That the availability of coverage has risen dramatically since the reforms is beyond dispute. It is demonstrated by the more than 75% reduction since 2004 in the number of vehicles in the state's insurer of last resort, the Personal Automobile Insurance Plan (PAIP). PAIP insured 143,516 exposures in 2004. That number had dropped by more than 50% by the end of 2006, to 61,016 exposures. By the end of 2007, the figure had fallen by more than 50% again, to 29,285 exposures. Vastly improved market conditions are also reflected in the more than 50% reduction in auto related consumer complaints to the Department since 2004.

Second, premium reductions resulting from the competition spurred by new entrants and capital investment have, in fact, been substantial, and have resulted in a decline in the annual average premium paid in New Jersey.[18] In total, more than $1.2 billion has been returned to consumers in the form of dividends or rate reductions filed with the Department. That figure does not include savings consumers have presumably realized by switching to new entrants or other companies because of lower rates.

It is also an error to conclude that the relatively high premiums paid by New Jerseyans are, per se, an indication of a failure of the marketplace or reform. While the cost of insurance can certainly be problematic, particularly for lower income drivers, New Jersey's average premium figures are primarily reflective of two main circumstances that are largely beyond the control of insurers,

[16] See Attachment 7.
[17] See Attachment 8.
[18] See Attachment 9.

regulators and policymakers: 1) the high population and motor-vehicle density of New Jersey; and 2) the amount of coverage most New Jerseyans choose to buy.

Average premium figures measure both *rates charged by insurers* and the *coverage-level choices made by consumers*. In New Jersey, 87.5% of drivers choose at least $250,000 in Personal Injury Protection (i.e. medical benefits). This is the second highest level of medical coverage in the nation. And 82% choose at least $100,000/$300,000 split limits in bodily injury liability protection, roughly ten times the amount required by law.

New Jersey is consistently ranked as one of the nation's most affluent states. [19] It should be expected that residents with high levels of assets would choose to purchase high levels of insurance protection, and to drive vehicles that are more expensive to repair and replace, and thus more expensive to insure. Naturally, those choices would be reflected in the premiums that New Jersey drivers pay.

The Department is unsure how to respond to NJCA's assertion regarding the connection between reforms and insurer profitability in New Jersey, as the Department's interest in reform has always focused first on its role in expanding access to coverage and secondly on the ability of competition to put downward pressure on rates, thereby enhancing affordability. The Department notes, however, that after auto reform New Jersey fell sharply in national rankings of the most profitable states for auto insurers, to a mid point amongst the states. And National Association of Insurance Commissioners data shows that rates have dropped along with profits, suggesting that auto reform has been successful on more than one front. [20]

The Department agrees with NJCA that the 2003 statutory reforms are silent on the issue of occupation and education factors in auto insurance rating. But the

[19] U.S. Economic Census spreadsheet, Attachment 10
[20] See Attachment 11

Department does not share NJCA's inference that this silence should be construed to mean that such factors are prohibited.

As has already been demonstrated, these factors have long been utilized by insurers in New Jersey and most other jurisdictions. The 2003 reforms amended no statutory or regulatory provisions relevant to this matter. What the reforms did do -- primarily through a rationalization of rules regarding withdrawal from the market, excess profit, "Take-all-Comers" and rate filing process -- was make New Jersey more attractive to national carriers. When such carriers applied to enter the State, they did so with the business models that they were accustomed to using in other parts of the country. To the extent those models conformed with New Jersey statutes and regulations, they were approved by the Department. This is the connection of these factors to auto reform that the Department has cited.

The assertion that these market changes resulted in worsening conditions for consumers appears to the Department to be contrary to the evidence. The availability of coverage clearly increased. The price of coverage clearly decreased. And consumer complaints dropped precipitously.

NJCA Report: The Real Reason for Using the Factors is to Insure More Affluent Drivers to Whom the Insurer Can Sell More Profitable Products

"Higher income consumers have more profit potential for multi-line insurance companies. Private passenger automobile insurance typically yields small profit margins in comparison to homeowners', boat, life and umbrella insurance. With higher income households, a multi-line insurance company has the opportunity to reap larger profits because higher income households possess more assets to insure. Auto insurance in this fashion is being used simply as a "foot in the door" to sell other types of insurance." (p. 9)

Department Finding

GEICO does not write homeowners, boat or life insurance in New Jersey.

<u>NJCA Report: the Factors are Proxies for Race and Income</u>

"GEICO's use of education and occupation as rate-making factors results in discrimination against lower income people and minorities, because education and occupation are serving as proxies for race and class." (p. 11)

<u>Department Finding</u>

In this context the term "proxy" suggests a proactive decision to use one rating characteristic in place of another characteristic of similar predictive power in an effort to circumvent obstacles to using the "original" factor. The Department found no evidence that GEICO or other companies are using occupation and education factors in this manner.

The actuality that a "Factor X" used by an insurer correlates with losses, and that a "Factor Y" not used by an insurer may also correlates with losses, does not make "X" a proxy for "Y." In practice, a multitude of correlations exist, some known to the insurer and some not, some measurable by the insurer and some not, and some stronger than others. The insurer is interested in strong correlations that it can measure. The Department believes that is what is happening when insurers choose to use factors such as occupation and education.

A better understanding of the interplay of various correlations in a complex web of correlations – whether or not they are considered, known to, or measured by an insurer – may be worthwhile and could be the subject of academic analysis by scholars who specialize in this area. Such an analysis would be interesting, especially were it to provide more statistical detail of the impact of actual rating factors on actual customers.

While the Census data and analysis in this specific Department Finding is limited to correlations between racial categories and occupation and education levels, it would be helpful for public policy deliberations on insurance rating factors in general to learn more about correlations involving rating factors other than occupation and education.

As it stands, the Census data points seen by the Department are not always specifically matched to the insurer criteria at issue in the present discussion, limiting the understanding of exact impacts. Thus, while general inferences about the impact of these factors on certain populations can be drawn with some confidence, the details are difficult to pin down.

To better understand what can currently be inferred, however, the Department conducted a review of New Jersey census data for the year 2000 on occupation and education levels, and on census data for the year 2002 on income in the United States by racial category. [21]

The occupation and education data indicates that most adults in New Jersey, regardless of race, have less than a Bachelors degree and work in non-professional occupations. However, with certain exceptions, non-Hispanic Whites are generally more likely than non-Whites to have Bachelors degrees or higher, or to work in professional occupations.

[21] For extensive relevant income data and analysis, see the Census report, *Income in the United States: 2002* in Attachment 12.

New Jersey
2000 US Census Data - % Bachelor's Degree or Higher by Race Category
Ages 20 Years and Over

	Bachelors or Higher	%	Less than Bachelors	%	Variance
White non-Hispanic	1,055,365	**38.4%**	1,693,380	**61.6%**	---
Hispanic	67,155	14.1%	408,480	85.9%	24.3%
Black non-Hispanic	92,965	19.9%	375,220	80.1%	18.5%
Asian non-Hispanic	159,470	66.2%	81,260	33.8%	-27.8%
NHOPI non-Hispanic	322	34.1%	623	65.9%	4.3%
AIAN non-Hispanic	1,294	23.9%	4,115	76.1%	14.5%
Black & White non-Hispanic	1,138	24.3%	3,550	75.7%	14.1%
Asian & White non-Hispanic	2,995	42.3%	4,085	57.7%	-3.9%
AIAN & White non-Hispanic	1,205	20.3%	4,735	79.7%	18.1%
AIAN & Black non-Hispanic	882	24.7%	2,690	75.3%	13.7%
Balance 2+ Races, non-Hispanic	13,670	28.4%	34,495	71.6%	10.0%
Sub-total All except White non-Hispanic	341,096	**27.1%**	919,253	**72.9%**	11.3%
New Jersey Total	1,396,461	34.8%	2,612,633	65.2%	

As shown above, 65.2% of all adults have less than a Bachelors Degree, compared with 61.6% of non-Hispanic Whites, 80.1% of non-Hispanic Blacks and 85.9% of Hispanics.

The largest discrepancy from the overall average is seen for non-Hispanic Asians, where only 33.8% have less than a Bachelors Degree. Asian is the only racial category in which a majority of members have attained a Bachelors degree or higher.

In summary, Asians are dramatically more likely than average to have attained a Bachelors Degree, Whites are slightly more likely than average, and Blacks and Hispanics are moderately less likely than average.

A similar pattern is found in the Census data on occupation:

New Jersey
2000 US Census Data - % Professional Occupation by Race Category

	Prof	%	Non-Prof	%	Variance
White non-Hispanic	1,074,825	**37.5%**	1,787,735	**62.5%**	---
Hispanic	77,600	15.2%	431,360	84.8%	22.3%
Black non-Hispanic	113,150	22.9%	380,305	77.1%	14.6%
Asian non-Hispanic	127,675	51.6%	119,835	48.4%	-14.0%
NHOPI non-Hispanic	325	32.7%	670	67.3%	4.9%
AIAN non-Hispanic	1,430	25.2%	4,255	74.8%	12.4%
Black & White non-Hispanic	1,184	22.1%	4,170	77.9%	15.4%
Asian & White non-Hispanic	2,665	34.3%	5,094	65.7%	3.2%
AIAN & White non-Hispanic	1,555	24.5%	4,795	75.5%	13.1%
AIAN & Black non-Hispanic	1,120	29.9%	2,620	70.1%	7.6%
Balance 2+ Races, non-Hispanic	11,490	22.6%	39,250	77.4%	14.9%
Sub-total All except White non-Hispanic	338,194	**25.4%**	992,354	**74.6%**	12.1%
New Jersey Total	1,413,025	33.7%	2,780,120	66.3%	

As shown above, 74.6% of all adults work in non-professional occupations, compared with 62.5% for non-Hispanic Whites, 77.1% of non-Hispanic Blacks and 84.8% for Hispanics.

Again, the largest discrepancy from the overall average is seen for non-Hispanic Asians, where only 48.4% work in non-professional occupations. Asian is the only racial category with a majority of members working in professional occupations.

In summary, Asians are much more likely than others to be working in a professional occupation, Whites are moderately more likely than average, and Blacks and Hispanics are moderately less likely than average.

From the results combined, it is reasonable to conclude that Asians are far more likely than the general populace to benefit from auto insurance rates that reward high educational and occupational attainments, Whites are slightly to moderately more likely than the general populace to benefit from such rates, and Blacks and Hispanics are moderately less likely than the general populace to benefit from such rates.

This also means, however, that each racial category includes a sizeable percentage of people who benefit from such rates, and a sizeable percentage who do not. It is because of this that NJCA appears to overstate its case that educational and occupational factors single out minorities as a group. The impact of these factors is by no means limited to any given racial category. In fact, the members of one minority group (Asian) are more likely than not to experience a positive impact from these factors. And the members of all other racial categories (*including Whites*) are *less likely* than not to experience a positive impact.

That NJCA appears to the Department to overstate the impact of these factors on minorities and non-professional workers does not, however, mean that NJCA's concern is without foundation.

The fact that drivers who belong to a minority racial group or have non-professional occupations are, on average, less likely than others to receive the best rates from an insurer that uses occupation and education rating factors means that these factors do indeed have a differential effect on racial minority and lower income drivers.

The Department looked to a variety of sources to try to better understand this issue. One source was the ongoing litigation, Amos, et al. v. GEICO, et al., a Minnesota case specifically challenging GEICO's use of occupation and education factors in auto insurance.

<u>Amos, et al. v. GEICO, et al.</u>

By Amended Complaint dated May 12, 2006 filed in the United Stated District Court in Minnesota (Civ. No. 06-1281), six African American GEICO policyholders sought declaratory, equitable and monetary relief to remedy the asserted racially discriminatory conduct of GEICO and its affiliate companies for using education level and occupation as auto insurance rating factors. Plaintiffs, for themselves and others similarly situated, allege that use of occupation and education level in auto insurance rating violates 42 U.S.C.1981, the federal civil rights statute which prohibits the use of race in the making and enforcing of contracts.

Plaintiffs' Amended Complaint identifies themselves as four GEICO policyholders from Minnesota, one from Georgia and one from East Orange, New Jersey. Plaintiffs allege that GEICO's use of occupation and/or level of education to set auto policy rates discriminates against African American/black policyholders because of race.

In response to the complaint, GEICO filed a Motion to Dismiss on grounds that Plaintiffs' Amended Complaint does not allege intentional discrimination, as is required under the federal civil rights statute, but rather only alleges disparate impact, which it asserted is not actionable under that statute.

A hearing on the motion was held August 24, 2006 and a Magistrate Judge's written decision denying GEICO's motion was issued October 27, 2006 and later confirmed by court order. While not reaching the merits of plaintiffs' claims, the Magistrate Judge found that plaintiffs had adequately alleged a case of intentional discrimination under the federal civil rights law.

Besides reviewing various court documents filed in this case, Department personnel communicated by telephone with Plaintiffs' counsel and, on October 1, 2007, met with them.

Counsel stressed that the Minnesota litigation is an action brought under the Federal Civil Rights Law, which they believe GEICO's practice violates, and not under the insurance laws of any jurisdiction. They stated that the practice of using occupation and education level in auto insurance rating is not inconsistent with nor prohibited by the insurance laws in the approximately forty-four jurisdictions where GEICO utilizes the same method of evaluating education and occupation in auto insurance rating. Plaintiffs' counsel further noted that they accepted insurance regulators' duty to administer the insurance laws as they exist in each jurisdiction, but believed that the practice is actionable as a violation of the federal Civil Rights Law.

The Minnesota litigation is currently in the discovery phase. Through discovery and continuing research, plaintiffs' counsel are developing their case for ultimate presentation to the Court. The Department will continue to monitor future developments in this case to evaluate the impact of the issues being litigated on public policy regarding auto insurance regulation.

Florida Office of Insurance Regulation Report

Another source of information on the impact on minorities of the use of education and occupation in rating is a Florida Office of Insurance Regulation (OIR) report issued in March, 2007, after a public hearing on February 9.

The hearing investigated the following eight questions:

I. Is there a correlation between Education/Occupation and Race/Income?
II. Is the insurance industry aware of such correlations between Education/Occupation and Race/Income?
III. Does the insurance industry believe its corporate responsibility extends to ensuring its policies do not negatively impact people due to race/income?
IV. Has the insurance industry researched the impact of its practices on Floridians as it relates to minority or low-income individuals?
V. Is there a correlation between education/occupation and loss ratios and or accident statistics?
VI. If it is determined that the use of education and occupation negatively impacts protected classes, what is the magnitude of the impact?
VII. If the FL Legislature does not change the laws, what will be the potential impact on the auto insurance industry?
VIII. If education and occupation were not allowed for underwriting factors, would the insurance industry still be competitive?

The OIR determined that there is a strong correlation between the factors in question, and that use of education and occupation would “negatively impact minorities.” This conclusion is based on a review of US Census data revealing that higher percentages of White individuals are employed in management/professional occupations and have bachelors degrees. Data also shows that those employed in management/professional occupations have higher median incomes, and also that those with more education also have higher median incomes.

The industry denied knowing of any statistical correlations between education/occupation and race/income. All of the industry representatives (except for Eric Poe from NJ CURE) said that they did not review Census data, nor were they aware of anyone in their respective companies who did. The General Counsel for the OIR asserted that this was “willful blindness” by the industry.

OIR noted that much of the industry loss data is proprietary to individual insurers and could not be reviewed in the hearing process; most industry representatives alleged that supporting data is on file with OIR from past filings, and could be reviewed privately going forward. Some discussion occurred regarding a study conducted by Quality Planning Corporation (QP) demonstrating differences in accident frequency across various occupations. The QP study showed that students have by far the worst frequency, followed by doctors, lawyers, architects, and real estate brokers; farmers had the lowest frequency.

The QP study led to questioning of GEICO as to why doctors and lawyers are in GEICO’s more preferred occupation classes, in apparent contradiction to the QP data. The main conclusion was that insurers review claim data, while the QP data simply measured accident involvement.

Industry representatives also stated that it is inappropriate to analyze occupation/education (or any rating variables) by themselves without analyzing the interaction between all rating characteristics via multivariate analysis.

OIR asserted that rate impacts varied up to 200% based on changes in occupation or education in some of the quotes obtained from the GEICO website. Liberty Mutual testified that occupation would not result in more than a 30% change (LM does not use education).

OIR acknowledged the assertion by various companies that the elimination of predictive variables adds risk to each policy written, and that increased risk is generally associated with higher prices. The level to which prices might rise due solely to the elimination of occupation and education was not quantified.

OIR also commented, however, that “all regulation implicitly limits freedom of insurance companies in exchange for a perceived societal benefit.” Examples cited were standardized forms, prohibition of misleading advertising, and solvency requirements. OIR also noted that the life insurance market in Florida is “robust” despite the prohibition of race-based rating.

Maryland Insurance Administration Market Conduct Report on GEICO

The Maryland Insurance Administration (MIA) conducted a target market conduct examination of the GEICO Companies, focusing on whether the Companies' practice of using education and occupation as acceptance criteria is prohibited by Section 27-501(a) of the Insurance Article in Maryland statutes.

Section 25-501(a) provides:

> (a) In general. – (1) an insurer or insurance producer may not cancel or refuse to underwrite or renew a particular insurance risk or class of risk for a reason based wholly or partly on race, color, creed, sex, or blindness of an applicant or policyholder or for any arbitrary, capricious, or unfairly discriminatory reason; (2) Except as provided in this section, an insurer or insurance producer may not cancel or refuse to underwrite or renew a particular insurance risk or class of risk except by application of standards that are reasonably related to the insurer's economic and business purposes.

The Executive Summary states: "In general, the MIA found:

- GEICO's use of education and occupation as underwriting factors is reasonably objective;
- GEICO has demonstrated that education and occupation are predictors of loss;
- GEICO's use of education and occupation as risk characteristics meets actuarial standards of practice and principles related to risk classification;
- From an actuarial perspective, GEICO's use of education and occupation is reasonable;
- GEICO noted to the Administration that it does not use education or occupation to solely underwrite a risk, but the examiners identified a certain sub-class within an occupational group that was not eligible at initial application for the most preferred company based solely on

occupation This occupation sub-class, however, was eligible for the preferred company at renewal. GEICO has corrected this rule to ensure that no applicant is denied access to the preferred company based solely on occupation at the time of initial application.

- The Companies' use of education and occupation as underwriting factors is not in violation of Section 27-501(a) of the Insurance Article."

MIA contracted with an actuarial consultant, Merlino & Associates (M&A), who reviewed GEICO's use of education and occupation as they relate to actuarial principles and standards of practice. Based on a review of some of GEICO's confidential multi-variate analysis, M&A concluded that GEICO's use of these variables complies with actuarial principles and standards of practice. No study was conducted that included any data regarding race or income.

Federal Trade Commission Report on Credit-Based Insurance Scores

Another source of information regarding the issue of the effect by race or income on the basis of a rating factor is a July 2007 Federal Trade Commission (FTC) report to Congress, *Credit-Based Insurance Scores.* [22]

While not addressing the issue of occupation and education factors, the FTC report nonetheless delves into the use of a risk characteristic – credit history information – that the FTC found appears correlated to income and race.

The FTC first concluded that credit-based insurance scores are effective predictors of risk:

> "Using scores is likely to make the price of insurance conform more closely to the risk of loss that consumers pose, resulting, on average, in higher-risk consumers paying higher premiums and lower-risk consumers paying lower premiums. It has not been clearly established why scores are predictive of risk." (p. 82)

The FTC also concluded that the use of credit-based insurance scores appears to benefit consumers in general, though data in support of this conclusion was lacking in specificity:

> "Scores may permit insurance companies to evaluate risk with greater accuracy, which may make them more willing to offer insurance to higher-risk consumers. Scores also may make the process of granting and pricing insurance quicker and cheaper, cost savings that may be passed on to consumers in the form of lower premiums. However, little hard data was submitted or available to the FTC to quantify the magnitude of these potential benefits to consumers." (p. 82)

Importantly for the subject of the Department's analysis, the FTC also determined that credit-based insurance scores are distributed differently among racial and

[22] See Attachment 13.

ethnic groups, though the FTC report found that this fact does not necessarily make insurance scores a significant proxy for race or income:

> "The FTC's analysis revealed that the use of scores for consumers whose information was included in the FTC's database caused the average predicted risk for African Americans and Hispanics to increase by 10% and 4.2%, respectively. The Commission's analysis also showed that using the effects of scores on predicted risk that come from models that include controls for race, ethnicity, and income caused scores to increase the average predicted risk for African Americans and Hispanics by 8.9% and 3.5%, respectively. The difference between these two predictions for these two groups (1.1% and 0.7%, respectively) shows that a relatively small portion of the impact of scores on these groups comes from scores acting as a proxy for race, ethnicity, and income." (p. 82)

Of particular interest to the Department is the FTC's understanding of the concept of "proxy," as the FTC used that concept in coming to the conclusion above.

> "…the Commission analyzed whether scores predict risk within racial, ethnic, and income groups. <u>If scores do not predict risk within any group defined by race, ethnicity, and income, then the sole reason that scores predict risk in the general population would be because they act as a proxy for membership in different groups."</u> (p. 62) (Emphasis added).

In other words, for credit history to be a workable proxy for race or income under the FTC's standard, it would have to fail to be predictive of loss *within* a given racial or income group. The FTC, although focusing on credit history instead of occupation and education factors, finds that such data is predictive of loss whether or not the group being studied is one race, one income bracket or all races and income brackets combined. [23]

[23] It should be noted that the FTC report was not unanimous. A dissent (see Attachment 14) asserted that the report suffered from methodological problems and inadequate data, and that the proxy effect, while statistically small, should be a source of concern. On the other hand, the dissent supported the underlying conclusion that credit-history based insurance scores appear predictive of losses.

Whether the use of this type of data is desirable from a public policy point of view, however, remains an open question.

THE BROADER PROBLEM OF EFFECT BY RACE OR INCOME LEVEL

Analyzing the FTC report and the Census data that indicates correlations between occupation, education, income, and race sparked interest at the Department in understanding what other commonly used rating factors might have similar correlations.

In considering this question it became clear that many rating factors used here and nationwide can be assumed to have a differential effect.

For example, accidents are more common in urban centers (a fact presumably related to traffic density) and many New Jersey urban centers have higher-than-average populations of racial minorities and low-income citizens. Thus, higher-than-average accident rates are correlated with higher-than-average minority populations and lower-than-average incomes. Auto policies priced in part on accident history would, on average, charge more to minority and low-income customers because those customers would be more likely to have experienced an accident.

Likewise with rates based in part on claims under auto comprehensive (or "other than collision") coverages Urban centers have higher-than-average incidents of auto or contents theft, so residents in such areas are more likely than average to have had a car stolen and perhaps to file a claim that contributes to higher premiums. [24]

Related to the above is the premium savings that are typically offered to drivers who have garages in which to shelter their vehicles when not in use. Naturally, garages are far more common in suburbs than in urban centers.

[24] Insurers generally refer to these kinds of not-at-fault events as "occurrences" or "incidents" and have varying rules on how they are reflected in rates. Often, more than one such incident in a given period of time would have to occur before rates are affected.

Not surprisingly, rates based in part on the zip code in which a vehicle is kept (i.e. “territorial rating”) would have a similar impact, even for drivers who have yet to file a claim.

Moving violations might be another rating factor that correlates with race and income. It appears plausible that lower income drivers would be less likely to expend the resources – such as hiring an attorney or taking a day off from work to attend a trial – to contest a ticket and seek a lessening of the violation that is recorded and ultimately seen by insurers. Thus, even a factor that intuitively appears highly correlated with driving behavior – and therefore seems particularly “fair” – may in fact disadvantage minority and low income drivers.

In summary, long-accepted rating factors such as accidents, comprehensive claims, territory and perhaps moving violations all may appear to correlate with higher-than-average minority populations and lower-than-average income levels. This would seem to complicate public-policy considerations involving potential responses to the problem of differential effect by race and income.

CONCLUSION

While occupation and education factors – and, indeed, several other factors with apparent differential effect – are permitted under current insurance statutes, public policy concerns about resulting socio-economic impacts may warrant a comprehensive analysis of potential different approaches to insurance company rating systems.

Because of its complexity, a full consideration of the issue, including by the Legislature, Administration, interested parties and the academic community, would be necessary to fully understand the impact of any proposed new approach on consumers, the insurance industry and by extension the State's economy.

The consequences of any regulatory change in New Jersey for the progress of the auto reforms of 2003, which continue to favorably unfold, is an important consideration. The Department hopes to continue to attract new companies – and thus new capital investment – to the State, further expanding the availability of coverage and improving price, service and product offerings. The predictability and stability of the regulatory system is of concern to potential new entrants to any marketplace.

The Department further notes the various indications, outlined in this report, that low-income and minority consumers are in fact benefiting from the marketplace improvements spurred by the current regulatory system. The potential for unintended, negative consequences from regulatory changes on these consumers must likewise be considered.

To briefly summarize the conclusions of this report:

- The Department's various approvals of automobile insurance rating systems employing occupation and education factors, including the 2004 approval of GEICO's rating system, are consistent with New Jersey statutes and regulations then and currently in effect. The Department has had no legal basis on which to disapprove such filings, and disapprovals would have been unlikely to withstand legal challenge.

- GEICO's rating system expanded but by no means introduced the use of occupation and education factors in automobile insurance in New Jersey. The occupation and educational attainment of applicants has had an impact on premium and company placement in this State for decades, both through the existence of membership companies with special acceptance criteria and rates for eligible groups (typically members of a specific profession or trade association); and through the long standing practice of providing "Good Student Discounts."
- The use of such factors is likewise common throughout the United States. The large majority of states approve such factors (so long as they are actuarially supported) under the ubiquitous, half-century-old regulatory standard that rates be neither excessive, inadequate nor unfairly discriminatory between risks involving the same hazards. In practice, this has meant approval of these factors in general (and GEICO's use of them in particular) in at least 44 jurisdictions.
- Few states proactively address the use of occupation or education in their insurance statutes or regulations. In practice, those states that do have such provisions nonetheless generally approve the use of occupation and education factors in one form or another.
- Across the country and in New Jersey, where insurance regulators have examined the issue they have found that such factors are predictive of losses and are thus actuarially justified to support pricing differences.
- The re-entry of GEICO into New Jersey after a 28 year absence, as well as the entry of other new insurers and the resulting increase in competition for New Jersey consumers, was made possible by a package of regulatory reforms in 2003 that resolved an insurance availability crisis, prompted widespread rate reductions and greatly increased consumers' satisfaction with auto insurers.

- The use of these factors naturally results in lower premiums for some customers than for others. However, the difference is not as large as that portrayed in a February, 2007 report issued by citizen watchdog group New Jersey Citizen Action (NJCA). That report contained methodological flaws that exaggerated occupation and education rating differentials and led to the incorrect conclusion that drivers with blue-collar jobs and low educational attainment were ineligible for the best rating tiers and placement in preferred companies. In actuality, these factors are just two of many, and other characteristics are also important for determining rate and company placement.
- An analysis of the rates of multiple insurers demonstrates that the use of these factors has not created higher overall premiums for drivers with lesser occupational and educational attainment. Indeed, GEICO's New Jersey rates for these consumers are often lower than the rates of competing companies where such factors are not used.
- Allowing insurers to use a wider variety of rating factors has contributed to overall improvement in the marketplace for many kinds of drivers and in all regions of the State.
- The Department found no evidence that such factors are used as a proxy for race or income. U.S. Census data and common sense indicate that, on average, these factors have a differential effect on low-income and minority drivers, in that such drivers are less likely than average to have professional jobs and college degrees. However, such groups are not singled out, as the range of education and occupation is great in every category. For example, most Whites would fail to qualify for the best possible rates. Still, on average, minority and low-income drivers are less likely than White drivers and drivers with professional occupations to benefit from the lowest rates available from a company that uses occupation and education factors.
- It is problematical, from an insurance regulatory perspective, to "pick and choose" between all of the factors with the potential for differential effect on the basis of race or income. This is especially the case because all of

> these factors are equally permitted by current insurance statutes. Because there is no actuarial basis or regulatory theory under which an insurance regulator could reasonably discern between “acceptable” factors with a differential effect and “unacceptable” factors with a differential effect, the question is ill-suited for resolution by the Department.

Further examination of the impact of the use of a variety of rating factors on the affordability of auto insurance may be appropriate. If that determination is made the Department will be a willing and active participant in that evaluation.

ATTACHMENT 1

Senate Commerce Committee Public Hearing
Regarding underwriting factors and rating systems used by private passenger automobile insurers
June 12, 2006

Public Hearing

before

SENATE COMMERCE COMMITTEE

"Testimony to examine the underwriting factors and rating systems used by private passenger automobile insurers to determine driver eligibility and premiums for insurance coverage. This examination will include, but not be limited to, information concerning the use of occupation and education to determine driver eligibility and premiums"

LOCATION: Committee Room 1
State House Annex
Trenton, New Jersey

DATE: June 12, 2006
1:00 p.m.

MEMBERS OF COMMITTEE PRESENT:

Senator Nia H. Gill, Chair
Senator Nicholas P. Scutari, Vice Chair
Senator Raymond J. Lesniak
Senator Gerald Cardinale
Senator Robert W. Singer

ALSO PRESENT:

David J. Lorette
Office of Legislative Services
Committee Aide

Linda Schwimmer
Senate Majority
Committee Aide

Laurine Purola
Senate Republican
Committee Aide

Hearing Recorded and Transcribed by
The Office of Legislative Services, Public Information Office,
Hearing Unit, State House Annex, PO 068, Trenton, New Jersey

NIA H. GILL
Chair

NICHOLAS SCUTARI
Vice-Chair

RAYMOND J. LESNIAK
GERALD CARDINALE
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New Jersey State Legislature

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PUBLIC HEARING NOTICE

The Senate Commerce Committee will hold a public hearing on Monday, June 12, 2006 at 1:00 PM in Committee Room 1, First Floor, State House Annex, Trenton, New Jersey.

The public hearing will examine the underwriting factors and rating systems used by private passenger automobile insurers to determine driver eligibility and premiums for insurance coverage. This examination will include, but not be limited to, information concerning the use of occupation and education to determine driver eligibility and premiums.

At this public hearing, **the committee will receive testimony from invited presenters only.** Invited presenters, as well as other members of the public, who wish to submit written comments or other documents for consideration by the committee should submit **15 copies** of all materials to David Lorette, Committee Aide, **no later than Wednesday, June 7, 2006.**

The public may address comments and questions to David J. Lorette, Committee Aide, or make scheduling inquiries to Cristi J. Cameron, Secretary, at (609)984-0445, fax (609)777-2998, or e-mail: OLSAideSCM@njleg.org. Written and electronic comments, questions and testimony submitted to the committee by the public, as well as recordings and transcripts, if any, of oral testimony, are government records and will be available to the public upon request.

Issued 6/5/2006

For reasonable accommodation of a disability call the telephone number or fax number above, or TTY for persons with hearing loss (609)777-2744/toll free in NJ (800)257-7490. The provision of assistive listening devices requires 24 hours' notice. Real time reporter or sign language interpretation requires 5 days' notice.

For changes in schedule due to snow or other emergencies, call 800-792-8630 (toll-free in NJ) or 609-292-4840.

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rs: 1-101

SENATOR NIA H. GILL (Chair): Good afternoon.

The Senate Commerce Committee will come to order.

May we please have a roll call?

MR. LORETTE (Committee Aide): Senate Commerce Committee roll call: Senator Singer.

SENATOR SINGER: From the Minority, Senator Singer is here.

MR. LORETTE: Present.

Senator Cardinale.

SENATOR CARDINALE: Here.

MR. LORETTE: Senator Lesniak is not present at this time.

Senator Scutari is not present at this time.

Senator Singer. (laughter)

Senator Gill.

SENATOR GILL: From the Minority. (laughter)

MR. LORETTE: Senator Gill is here.

SENATOR GILL: My understanding is that Senator Scutari and Senator Lesniak are on their way.

MR. LORETTE: Madam Chair, you have a quorum.

SENATOR GILL: Thank you.

Today we're going to consider the bill that deals with using the use of education and occupation as part of underwriting factors. And we know that in order to further enhance the competition and maximize consumer choice in the automobile insurance marketplace, the Department of Banking and Insurance determined that permitting the use of insurance scoring by insurers would further this objective, provided that appropriate protections of consumers' interests were established. In protecting consumers, there are two areas that are extremely important: transparency in the process of review by the Department of Banking and Insurance, and the statutory prohibitions against auto insurance companies from using scoring models that consider, among other things, race and income.

Consumer protection is the centerpiece of today's hearing. The issue before us is whether the use of education and occupation, as factors in underwriting insurance, circumvents the prohibition of using race and income in determining automobile insurance rates.

It has been asserted that the use of education and occupation has resulted in a discriminatory impact upon less educated, blue and gray collar workers, and a disparate racial impact against minorities. Statistically, we understand that, based on the 2000 census, 70.2 percent of our state's residents do not have a college degree. When we examine our individual districts, the percentages of our constituents without college degrees are as follows: District 20, Senator Lesniak--

SENATOR LESNIAK: No, I have my college degree.

SENATOR GILL: --83.1 percent of the people in his district do not have college degrees; District 22, Senator Scutari, 75.1 percent of the constituents in his district do not have college degrees; District 30, Senator Singer, 75 percent of the constituents in his district do not have college degrees--

SENATOR SINGER: I'm with the majority in that.

SENATOR GILL: Including the distinguished Senator.

District 34, Senator Gill, 71 percent of the constituents in my district do not have college degrees; District 39, Senator Cardinale, 53.9

percent of the constituents in his district do not have college degrees. The statistics for minorities in New Jersey are even higher. Eighty-two point nine percent of African-Americans and 87 percent of Latinos are without college degrees.

Given the state of today's economy, and the fact that New Jersey has one of the highest automobile insurance rates in the nation, the use of education and occupation as factors in underwriting poses a serious economic consequence to working families of New Jersey.

In response to this concern, I introduced legislation, Senate Bill 1714, which would prohibit any underwriting rule from operating in such a manner as to assign a risk to a rating plan on the basis of: one, an insured's educational background; or, two, his or her employment, trade, business, occupation, or profession.

Likewise, as to any application or selection of coverage for an automobile insurance policy issued or renewed in this state, under this bill an insurer would be prohibited from using those factors.

Today, we will hear testimony from insurers, pro and con; from the Department of Banking and Insurance; consumer protection advocates; and the industry trade associations. The purpose of this hearing is to make an objective inquiry into the use of these criteria in a fair and impartial public forum that allows all interested parties to express their concerns. This hearing will result with the presentation of adequate information that allows us, as a legislative body, to determine the best course of action that protects the consumer from discrimination, while still fostering a competitive marketplace for affordable insurance.

Thank you.

Are there any other Senators that have any preliminary comments before we start with the testimony? (no response)

Seeing no hands, we will start with the first witness, please.

MR. LORETTE: The first presenter today before the Senate Commerce Committee will be a consumer protection advocacy panel consisting of Phyllis Salowe-Kay, the Executive Director with New Jersey Citizen Action; and Abigail Caplovitz, with the New Jersey Public Interest Research Group.

SENATOR GILL: Good afternoon, and thank you for taking your time to come.

You can decide who would like to go first.

And identify yourself for the record, please.

P H Y L L I S S A L O W E - K A Y E: My name is Phyllis Salowe-Kaye. I'm the Executive Director of New Jersey Citizen Action.

I'm going to begin by saying that we have nothing against doctors, dentists, and lawyers, especially those on the Committee. However, we don't think that you're any better drivers than welders, wait staff, and water filter salespeople.

So I will begin with that, and then also say that Senator Gill's testimony sort of took a lot of the information that is in my prepared testimony -- spoke to a lot of it. So I'm going to eliminate some of it.

Citizen Action is very concerned about the fact that insurance companies -- and in this case, particularly GEICO -- is using rating methods and underwriting guidelines that have a serious adverse affect on minority consumers and lower-income residents in the State of New Jersey. These practices may actually be discriminatory under Federal or State civil rights laws. And we know that in several parts of the state, the Consumer Federation of America and other civil rights groups are actually moving forward with lawsuits concerning that.

We believe that the State-- We believe that, first of all, that State legislation is absolutely needed to rectify the harm that has been done by the regulation that was promulgated by the Department of Banking and Insurance. We realize that this was done in an effort to urge insurance companies to do business in New Jersey. And we want to see companies come to New Jersey. We think New Jersey is a good place to do business. But we don't think that it should be -- that the -- that it should be done at the expense of low-income and minority New Jersey residents.

We're here today to ask you to ban the use of rate-making methods that directly base eligibility and premiums upon educational background and occupation. The use of this information results in unjustified increases in insurance rates for many lower-income minority residents of New Jersey. We all know that, currently, insurance companies are not permitted to use race or income in the setting of rates.

GEICO, the nation's fourth largest insurer, has adopted rating methods and underwriting guidelines that directly base rates and eligibility on education and occupation in 44 of the 50 states. New Jersey is one of the states. GEICO's underwriting guidelines not only directly harm lower income Americans, but they also have an indirect effect on minority consumers.

Using the-- Under the criteria used by GEICO, a factory worker without a four-year college degree in New Orleans -- and I'm using New Orleans -- I will use New Jersey in a second -- and New Orleans is probably the extreme -- would pay more than 90 percent more than an attorney with a graduate degree in the same place. Nationally, the average surcharge being applied by GEICO for being poor is over 40 percent. In Princeton, New Jersey, a blue collar worker would be paying 32 percent more than a white collar worker for the same exact coverage.

Now, GEICO would say that education and occupation are only two of the things that they -- of many factors that they use when setting rates. What we believe is that these two have a very high impact upon a class of people, that actually ends up being discriminatory.

We also keep hearing about actuarial data and studies that prove that teachers, and lawyers, and doctors, and dentists have better driving rates than other folks. We have never seen that. We think that if that information exists, it should be readily available to the public, and to consumer organizations, and others to look at and see if that actually -- what -- who's done the research, and what it shows.

If a student has the misfortune of having a parent who had their job outsourced to India, or they lost their job due to an event such as an employer's insolvency or a natural disaster, that student may actually have to quit high school to help out the family. Why does it make this former student a worse driver than someone with a higher education? It just doesn't seem fair.

The response to our concerns -- which have been raised publicly in the press -- has been, "Well, we have competition in New Jersey. If you don't like what the insurance company is using, or what factors they're using, just go to another insurance company." Well, insurance companies need to stay competitive. That's what they tell us. And right now, in New

Jersey, we have four companies-- We have Liberty Mutual, New Jersey Skylands, Electric, and AMEX Insurance that are currently using occupation and education, or both, in setting their rates. Allstate has also begun to do this in several other states. We believe that as time goes on, other insurance companies are going to be able to phase in these factors, and there won't be a choice for a consumer to go to a company who doesn't do this.

We saw this happen with credit scoring. And I know this is not about credit scoring, but we were very much opposed to credit scoring. We were able to get some protections put into credit scoring. We still are seeing credit scoring having adverse affect against minorities and low-income people. So it seems that each one of these things that we're giving -- that the State is giving to insurance companies to help them to stay here is something that has a negative effect on a particular segment of the community. That could be looked at as being discriminatory.

So we would want you to take a really strong look at this and begin to move legislation through your Committee that would ban this practice.

Thank you.

SENATOR GILL: Thank you.

Before you--

Any Senators have any questions of the witness?

Senator Cardinale.

SENATOR CARDINALE: You have made an assertion that doctors, dentists, and attorneys aren't better risks, essentially, than some others. I think you said welders. I forgot the other two categories.

MS. SALOWE-KAYE: Wait staff and water filter salespeople.

SENATOR CARDINALE: Okay.

Do you have any statistical data that would support that statement?

MS. SALOWE-KAYE: No, I don't. But I believe that the Consumer Federation of America has some information. But I don't think there is any information that shows otherwise, that's been done by an independent agency.

SENATOR CARDINALE: But you're making an assertion.

MS. SALOWE-KAYE: Yes.

SENATOR CARDINALE: And you don't have anything other than anecdotal.

MS. SALOWE-KAYE: That it's unfair.

SENATOR CARDINALE: And you just think it's unfair.

MS. SALOWE-KAYE: Absolutely.

SENATOR CARDINALE: The impact on some people creates an unfairness. The impact of using these criteria creates an unfair situation.

MS. SALOWE-KAYE: I am not an actuarial. I'm not an insurance actuarial expert. But in this instance, I don't believe that anything exists that has been done by an independent, outside -- not an insurance company -- that shows that a lawyer is a better driver than a wait staff person. And if it does, if there is something -- there is information that exists that shows -- and I'll quote this.

For example, race-based premiums-- It's illegal to use race and income for insurance. And yet there is actuarial information that shows that people of certain races have a lower life expectancy, which would then make the issuance of life insurance -- using that factor -- as something you could do. And, yet, that has also been made illegal in the United States.

SENATOR CARDINALE: We're not talking this.

MS. SALOWE-KAYE: But it's--

SENATOR CARDINALE: This hearing doesn't deal with life insurance. We're dealing with automobile insurance.

MS. SALOWE-KAYE: I understand that. But if there was such actuarial information -- which either way-- Which I don't have. And I do not have proof that a lawyer is a better or worse driver than a worker -- wait staff person.

SENATOR CARDINALE: Not necessarily driver, but risk.

MS. SALOWE-KAYE: Risk. I do not have that information. But if information does exist that, for life insurance, an African-American is a poorer risk -- has a lower life expectancy than a Caucasian -- and we can't use -- not, we -- the insurance companies are prohibited from using that in setting rates. So one would be effective on the other.

But, no. To answer your question, I don't have that information.

SENATOR CARDINALE: But none of these criteria that you mentioned are race. They are not using race. You are not asserting that they're using race.

MS. SALOWE-KAYE: Well, if you look at the statistics of how it breaks down, in terms of education, you would know that 26 percent -- that the number of Caucasians, African-Americans, and Latinos-- If you look at those numbers and see what percentage of those have higher education, you would see that the impact ends up being race. And if you look at their earning capacity, you would see that at the end of the day that -- that in those three categories, the African-American and Latino has a much -- who doesn't have a higher education -- has a lower income expectancy.

SENATOR CARDINALE: So you're objection is not that they're using a criteria which they believe is risk-related. Your objection is that the bottom line on it is that people of certain backgrounds or educational levels will tend to suffer from that criteria being used.

MS. SALOWE-KAYE: It's both.

SENATOR CARDINALE: Then you went on to say that in order to remain competitive, the companies which are not now doing this will begin to do it. They will be forced to begin to do it in order to remain competitive. That's what you said. Did I understand that right?

MS. SALOWE-KAYE: In order to get higher income business, yes.

SENATOR CARDINALE: Well, you said in order to remain competitive.

MS. SALOWE-KAYE: Right, in the higher income market, because they will want the doctors and the lawyers to get their boat insurance or their other insurance through them. So, yes, I think we will begin to see that happen.

SENATOR CARDINALE: So if this is not risk-based, at least -- and I haven't seen the data either. We may get some data today, but you're the first witness.

In order to remain competitive, other companies will have to use similar criteria, according to your thought process. If it is not risk-based, how does that affect their competitive position?

MS. SALOWE-KAYE: You should ask the companies and not me that question. Because we have seen four companies now begin to use it. We have talked to other companies who tell us that they will have no choice but to do it. I think that some of those companies have been invited to testify. I'm not an insurance company. I don't want to speak for them.

SENATOR CARDINALE: Well, it's interesting.

SENATOR GILL: Senator Cardinale.

SENATOR CARDINALE: Yes.

SENATOR GILL: Just for your point of information, there will be people from the trade who will be able to address that. And I think there will be others who will be able to address the more specific points of the actuarial and the risk. I think that this testimony was from the consumer's standpoint, and the impact being we haven't seen the risk. But even if we haven't seen the risk, it violates constitutional prohibitions against a disparate impact that doesn't have to-- You don't need intent. It is the result of a policy that may--

And I think that's what your position is. And we can get to the more--

SENATOR CARDINALE: But one more observation, with respect to the testimony of this witness.

SENATOR GILL: Okay.

SENATOR CARDINALE: And that is occupation. I've been advised that occupation is used in life insurance in setting rates.

MS. SALOWE-KAYE: But income is not allowed.

SENATOR CARDINALE: Occupation is used in that. And what we have-- What you're objecting to are two criteria, one of which is occupation. And in life insurance -- just to turn the same example back on you -- it is permitted to use occupation.

MS. SALOWE-KAYE: And perhaps that's why there are still suits and settlements concerning life insurance going on right now.

SENATOR GILL: Well, we will--

MS. SALOWE-KAYE: This is not about life insurance.

SENATOR GILL: I don't normally interrupt. There are a lot of people to testify. This is specifically focused on auto insurance. And, of course, to the extent that any example can be clarified, to the extent that it gets off on another subject matter, I will have to step in. So we're not going to talk about life insurance. This is auto insurance, with respect to those criteria.

Do you have any other questions, Senator?

SENATOR CARDINALE: No, I don't. Thank you.

SENATOR GILL: Senator Lesniak, do you have any questions?

SENATOR LESNIAK: Thank you, Madam Chair.

I certainly don't purport to be a constitutional scholar. And I do agree with the Chair and Phyllis's testimony that if these criteria are not based on legitimate risks, they would be invalid.

However, on impact, I do know that-- For instance, we have rating caps in territories. And that is to spread the risk. The impact on that is beneficial, certainly to the minorities I represent in my community. So I am-- I don't-- I'm certain that-- As I said, I don't purport to be a constitutional scholar. But the disproportionate impact, in and of itself-- I don't see how it can be a constitutional violation. I remain open to be convinced of that.

But as I said, we do have a very, very substantial impact -- beneficial to the folks I represent -- already in place, in terms of automobile insurance.

SENATOR GILL: The constitutional issue that's also -- we understand, in GEICO, is being-- You have a suit in the Federal district court in Minnesota, specifically on the issue of race and its impact on this. And we do know that in the constitutional law -- I don't mean to be a constitutional scholar, but I do do a lot of constitutional litigation -- it is the negative impact. It is the disparate impact that gives rise to what may be a constitutional issue. But we can discuss that later.

Do you have any further questions? (no response)

Senate Scutari.

SENATOR SCUTARI: Thank you, Madam Chair.

Why is it then that some of these companies utilize these two factors in order to set their rates?

SENATOR GILL: I think the companies can answer those more detailed questions.

SENATOR SCUTARI: I would like to know what she thinks, from a consumer standpoint, why they -- if they have a theory on why it is that they utilize that.

MS. SALOWE-KAYE: I would not even begin to answer why an insurance company does something. I just don't think I'm the right person to do it. I just know that by doing this-- I believe it's going to have a very harmful affect on the people that we represent.

SENATOR SCUTARI: Fair enough. Thank you.

ABIGAIL CAPLOVITZ: Hi.

Abigail Caplovitz, New Jersey PIRG.

I appreciate this opportunity to testify. And I appreciate very much this Committee taking so seriously -- looking into this issue. Because auto insurance in New Jersey, as we all know, is awful at best, and hopefully getting better.

I stand side-by-side, though, with Phyllis, and also with the comments that the Chair was making at the beginning, that what's at stake here is a matter of fundamental principle and who is being affected by it.

Without a doubt, I bet an actuary could give me statistics that showed race and income had risk relationships. There's all sorts of things in life that you can find a risk relationship around. At some point you decide what are your fundamental values, and what are you going to allow to be measured as a risk basis. So the question to me isn't really, is there some potential correlation on risk?

I mean, the old joke is, you can ask an actuary what's one and one equal, and he'll say, "What do you want it to equal?" I mean, you can find risk correlations at the margins for a lot of things. The question is, is it an allowable thing to measure? And we've decided, as a State, that race and income are not allowable to measure.

So then the question is, occupation and education. And I would suggest that these two factors are proxies for income, and perhaps proxies for race, because of the statistics. So I think it's a less-direct intention at getting at race, although it has that impact because of the statistics.

So the question is, why do you want this data? And you will have to ask the insurers that question, because I don't do their calculations. But it seems to be -- the only thing they very substantially correlate to-- The obvious thing -- if I were to ask you, what do you think correlates with educational attainment, and what do you think correlates with job status, you're going to say income. And I bet if I told a census person somebody's educational attainment and their job, they could ballpark their income for me. Could they ballpark their driving record? I doubt it.

Again, at the margins, could you establish a correlation? Sure. But then you get back to first principles. What is it that we allow each other to be judged by? And we happen to think that education and occupation are not appropriate. We think they are proxies for income. They are potentially proxies for race. And that's just not what you score people on when you give insurance.

Spreading risk is a purpose of insurance. If you allow every potential factor to be used in assigning risk to people, you can put out, to the sixth decimal point, what somebody's risk is going to be. But then that person can't afford insurance, and somebody else can get it dirt cheap.

And in terms of the question as to why do other companies need to copy this to be competitive-- Phyllis was getting at it. The higher income market that gets subsidized by the low income market -- think of the perverse inequity in that. The high income market that gets subsidized by the low income market, as a result of proxying income, has a lot of other business that you want. So maybe you even have a loss leader. Or if maybe it's not a loss leader -- but maybe it's not your most profitable piece of business, because you want to sell these people all kinds of other pieces of business. And so the question is-- To stay competitive, you're going after that upper income market.

So we think that, just as a matter of first principles, what kind of society are we? What are the factors that you allow people to be judged on for risk or other things? We don't think you should be judging educational attainment. We don't think you should be judging job status. Although the Senator over here is a living example -- they don't always correlate. You didn't complete college, but you are a State Senator. I mean, their proxies are not great proxies. I mean, at the end of the day, proxies are not the real thing.

SENATOR LESNIAK: He married well. (laughter)

MS. CAPLOVITZ: So, all that said, New Jersey PIRG just stands on principle. This just isn't what it's about.

That said, we encourage you to move carefully. New Jersey consumers -- and we represent consumers -- are very grateful that insurance has gotten better. And we don't want to do anything to make it get worse.

So please be careful in how you do this. And thank you for bringing in all of this testimony today.

And I'm happy to take any questions you might have.

SENATOR GILL: Do we have any questions that are not of an actuarial nature?

You don't mind, Senator Vitale (*sic*), if I call Senator Singer first? We can keep balance--

SENATOR CARDINALE: I am Senator Cardinale. (laughter)

SENATOR GILL: I know Senator Cardinale, and you are Senator Cardinale. (laughter)

Senator Singer, please.

SENATOR SINGER: That's okay. He didn't marry well. (laughter)

Just one comment. I just take a little bit of exception.

I really think the Department and the members of this Committee have worked on automobile insurance in the last four or five years, and it is a far better market than I've ever seen before. It is not something I'm getting phone calls on constantly, "I can't place insurance." If you remember, for a while there, we had only very few companies operating in the State of New Jersey. You couldn't place your insurance. Today you can place that insurance.

Second of all, it's the first time I know in many, many years that now you see people be competitive about it, advertising lower rates. "I can beat these rates by a couple hundred dollars." And that's a positive fact.

I'm not saying that this criteria should be used or not. We're going to hear that today and make a decision. But let's not knock the marketplace. We've come an awful long way. And at least we've taken it off the radar screen in being the number one priority for a lot of people -- not being able to get automobile insurance. They can get it now. The question, is it fair or not, is a different issue. But let's not--

I think the Department, members of this Committee who have worked on issues, have gone a long way in making this a very positive market.

MS. CAPLOVITZ: Senator, we fully agree. And that's why we're glad you're doing this in the thorough way that you are, and not rushing forward. New Jersey consumers would not dispute that it is a much better market today than it used to be. And we appreciate the hard work this Committee has done in making it that way.

SENATOR GILL: Any further questions of the witness? (no response)

Thank you very much for your testimony.

SENATOR CARDINALE: I--

SENATOR GILL: Oh, my goodness.

Senator.

SENATOR CARDINALE: You had passed me over, in terms of getting--

SENATOR GILL: That is my mistake, Senator Cardinale.

SENATOR CARDINALE: I want to reemphasize everything that Senator Singer has said. I've been on this Committee for more than 20 years, and this is the best climate that I've seen in a long time.

But wherever we have gone with the regulations or the laws that we passed, I think we've been cognizant of the fact that however we make these criteria, there are always going to be some drivers who are going to be subsidizing other drivers. Because, either within a particular group or when you take all of the groups and compare them to one another, there are going to be a spread of folks who drive well, and a spread of folks who drive poorly, however you try to set up these criteria.

And I'd just like to clarify one point that you said, because I'm not quite sure. I think I know what you were saying. Do you have any evidence, or any anecdotal notion, that a doctor who also happens to be a minority is treated differently than other doctors?

MS. CAPLOVITZ: I didn't make that suggestion, and I have no basis to make that. I think, first and foremost, these are proxies for income. And I think, because of the way income and educational attainment are distributed across races, it has a disparate race impact. But I have no indication that there is a purely racial component to this, whatsoever. And I would not suggest that you would expect two similarly situated doctors, one who happens to be black, to be treated differently.

SENATOR CARDINALE: Thank you very much.

MS. CAPLOVITZ: Yes, sure.

SENATOR CARDINALE: I have nothing further.

SENATOR GILL: Thank you for your testimony.

The next witness, please.

MR. LORETTE: The next presenter before the Committee today will be Eric Poe, Vice President of Operations with the insurer New Jersey Citizens United Reciprocal Exchange, commonly referred to as NJCURE.

ERIC S. POE, ESQ.: Good afternoon.

SENATOR GILL: Good afternoon. Thank you for appearing.

MR. POE: My name is Eric Poe. I'm actually now the Chief Operating Officer of New Jersey CURE auto insurance.

New Jersey CURE auto insurance was founded in 1990 by the former New Jersey Insurance Commissioner James J. Sheeran. And we insure close to 50,000 vehicles. And we are the fifth largest direct writer in the State of New Jersey.

I'm a licensed attorney, as well as a certified public accountant. I've been working in the private passenger automobile insurance industry for over 12 years.

What I hope to testify today is -- really narrowing and clarifying this topic down to three subjects and, hopefully, addressing each one. Number one, why we are here representing a competitor in the marketplace; number two, why we can prove that it should not be used as a writing criteria in the State of New Jersey; and, number three, we are going to prove how it will not affect the health and profitability in competition in the marketplace.

Addressing the first one, why we are here. The reason why we are here is because when we learned that GEICO, entering the state in 2004, used education and occupation as sole base factors to determine whether somebody was eligible for their preferred insurance company, we were appalled. We were forced to do one of two things: Make an action to try to let the public know that they are being judged in this fashion. Anybody who goes on GEICO.com that is a blue collar worker, or categorized in their non-preferable group, is being rejected by their preferred companies, and not even being notified that they're being rejected by those preferred companies, on their Web site, on the basis of their education and occupation alone.

So complaints to the Department of Insurance on this basis does not make any sense. Because if you are a blue collar worker, and you went to GEICO.com, and you put down that you are a minimally skilled U.S. Postal clerk, you're not going to be told that you're rejected based on the fact that you are a U.S. Postal clerk, or that you have a high school diploma. You're just going to see a rate that's twice what you're paying. And you're going to say, "GEICO is not the place I want to go, because they're not going to save me any money."

Why we're here is because we don't want to adopt these practices, because we think that they are unfair. We think that they have discriminatory impacts on racial minorities. And we simply do not believe it's necessary in order to underrate risk.

The second subject of proving why it shouldn't be used: Number one, this classification of education and occupation is classifying people with the use of socio-economic factors, influences that we do not use in our current, valid classification system. If you ask insurance carriers what we are allowed to use to determine rates, we're allowed to use the person's age, the person's gender, the person's marital status, the person's territory, and the person's usage of that vehicle.

Out of all the factors that I just named, not one of them has a socio-economic impact. Everyone has the equal opportunity to use their car differently. Everyone has the equal opportunity to decide to move to a different, less densely populated area in the State of New Jersey. Everyone has the opportunity to improve their driving record. And, believe it or not, everybody has the opportunity to get older. And everybody has the equal opportunity to get married or divorced. I know some people don't believe that.

But this would be the first rating factor that would actually use a classification that does not give every single person in the State of New Jersey the equal opportunity to change. If someone is going to argue that everyone has the equal opportunity to get a four-year college degree, I think you'd have a major, major debate in this room.

The second reason why it shouldn't be allowed -- and we can prove it -- is based on the interpretation of the regulations that are currently in place. According to the New Jersey Administrative Code 11:3-35.3c7, we currently have a regulation in place that states, and I quote, "No underwriting rule should be based on the lawful occupation or profession of an insured." To my knowledge, the only reason why no other carrier in the State of New Jersey does not use occupation as a rating factor is because we abide by this regulation. GEICO is the only carrier that I am aware of that does not abide by this regulation.

The second topic, based on education-- According to the same subchapter, the regulation states, "An underwriting rule shall be based on a reasonable and demonstrable relationship between the risk characteristic--" and that is the key, "the risk characteristic of the driver and the hazard for which the insurance is provided."

My best example I learned was about -- last week, to give to everybody -- and that is, that it is not sufficient for an insurance company to simply say, "I have actuarial loss data," and show a certain group has higher losses than others. That does not justify its use as a rating factor.

An example is, if everybody in this room -- we were to group the two groups into people with brown eyes and people with blue eyes. You would, without question, have-- If we took all the loss costs for everybody with brown eyes versus blue eyes, you'd have a group that has one higher loss number than the other. Does that give you the ability, as an auto insurance carrier, to determine risk and rate, based upon the fact that one of those groups has higher losses? No.

That's why this regulation is in place. Because it requires that you show that the characteristic of that driver is correlated to the risk. You cannot show that because somebody has blue eyes or brown eyes that they're actually a higher risk, just because their loss has that data.

The best example I can give from an insurance standpoint is this. In 2006, the Quality Planning Corporation -- which is a subsidiary of ISO, which is the largest rating bureau in the world -- studied 15 million policyholders and 2 million claims. And they came up with a study that said if you live within a mile of a restaurant, a car dealership, a liquor store, or an elementary school-- They showed that there was 18 to 30 percent higher losses for those people that live within a mile of those establishments.

Now, from a layperson's standpoint, you would read that and say, "Well, that seems like a good reason for car insurance companies to ask me if I live within a mile of one of these establishments." But according to the regulation, you have to show reasonable and demonstrable correlation between the characteristic trait. There is no characteristic trait of somebody who lives within a mile to make them a higher risk. This is what we call a *redundant classification*. The reason why this would never pass muster, if you use this test, is that it is not the fact that you're living within a mile of these restaurants, or elementary schools, or liquor stores, or car dealerships that make you a higher risk. This is already accounted for in the classification of territory. The people that live in urban areas always live within a mile of a restaurant, car dealership, elementary school, and liquor store. So to classify the person -- that you've already charged a higher rate in these urban areas -- an extra higher classification because they live within a mile of one of these establishments makes no logical sense.

The exact same reason is why you cannot use education. Because the reason why -- probably -- education has some small percentage of a correlation to losses is because when you make more money and you are a higher educated person in the State of New Jersey, you do not live in the urban areas of Newark, Camden, Trenton, and Jersey City. The people who live in the suburbs are the people that are more affluent, typically -- I'm not saying every single person -- but are typically more affluent and have higher educations. That is why this, categorically, should not be allowed.

Now, my third and last topic is to prove how and why this passage of this bill would have absolutely no impact on the competition and health of this marketplace, like I know our trade organizations are going to try to testify about.

The fact is this: There are 33 insurance carriers in the State of New Jersey. Four of those insurance carriers use education. One of those carriers uses education and occupation. Together, those four carriers only amount to 19 percent of the entire market share in the State of New Jersey. It would be impossible to say that if you pass a bill to prohibit the use of what only four out of 33 carriers use, you would actually threaten the entire profitability of the marketplace.

I'd like to commend the entire industry regulators and legislators for what they've done in their 2003 reform act. It made meaningful change to us. It allowed us to compete. But what we're here to say now is that we are all for competition and health, but we're not for competing on these discriminatory grounds. And that's exactly what's going to happen if you do not pass a bill like this.

SENATOR GILL: Any questions from anyone?

Senator Lesniak, are you looking at me over you eyeglasses? (laughter)

SENATOR LESNIAK: Did you drink any Red Bull before you gave this testimony? (laughter)

MR. POE: Unfortunately, that's just the way I am. I'm sorry. I actually don't drink caffeine, which is really sad.

SENATOR LESNIAK: I commend you for your passion.

MR. POE: Thank you.

SENATOR GILL: Was that a question?

SENATOR LESNIAK: No question.

SENATOR GILL: Senator Cardinale.

SENATOR CARDINALE: You can always rely on me, Madam Chairwoman.

SENATOR GILL: And it's always good to have a good, reliable Republican.

SENATOR CARDINALE: You indicated that-- I think the last words you said were that if we don't pass some sort of bill that prevents this, your company is going to be forced to use the same practice.

MR. POE: Correct.

SENATOR CARDINALE: Is that correct?

MR. POE: Yes.

SENATOR CARDINALE: Why?

MR. POE: Because if you look at, for example -- we've studied this -- the number of the largest population of our insureds that leave to a carrier like GEICO are ones that -- when we go and look at how long we've insured these people, how good of a driver they are-- We absolutely cannot compete unless we start realizing that when we look at their occupation or education -- that we either have to adopt those rates, or we're going to lose every single time to those particular drivers.

SENATOR CARDINALE: Now, if there's no rate advantage to keeping those drivers, why would you mind losing them?

MR. POE: Well, first, there is nothing to say that we wouldn't want to keep them. We would like those insureds. There's no question about it, which is why we want to actually lower our rates for those particular people.

Are you saying that -- why do we -- why would an insurance carrier care about losing what you would say is an underpriced policy? The reason why is because this, automatically, is now subsidizing carriers that have national presence with multiple lines of insurance to offer. You're giving them a competitive advantage, because they can go after the rich person, take as a loss leader their car insurance, sell them financial planning, yacht insurance, umbrella insurance, and choose to actually artificially charge those drivers less.

So, yes, we could apply for filing for insuring other lines of business in order to do that. But basically what you're doing is, you're doing the opposite of what most people think, and you're subsidizing the lower -- the higher income person with a lower income person which, typically, no one ever accuses auto insurance carriers of ever doing.

SENATOR CARDINALE: You've lost me. I have to tell you that. (laughter)

MR. POE: Sorry.

SENATOR CARDINALE: Because my question is-- You want to keep those folks. You said you want to keep those folks. You object--

SENATOR GILL: Senator, I'm sorry. So that we -- I understand -- who is those folks? Maybe we can--

SENATOR CARDINALE: The doctors, the people with greater education. You want to keep them.

MR. POE: Right.

SENATOR CARDINALE: The people that GEICO is stealing from you now.

MR. POE: Right.

SENATOR CARDINALE: And they're stealing because they're giving them a lower rate.

MR. POE: Right.

SENATOR CARDINALE: You say that you're going to have to-- If you want to keep them, you're going to have to start giving those folks a lower rate.

MR. POE: Correct.

SENATOR CARDINALE: Now, if there was no risk justification for that lower rate, why would you mind losing that?

MR. POE: I think--

SENATOR CARDINALE: Or why would you want to keep them by giving them a lower rate? Let's put it in the other direction.

MR. POE: Okay. Because we don't--

SENATOR CARDINALE: You're not in the business of losing money, or attempting to lose money.

MR. POE: Right.

SENATOR CARDINALE: You're not establishing your policies on a basis that you want to assure folks lower premiums at the expense of your stockholders, or however your company is arranged. So why do you want to prevent someone else from getting them if the premise is that there is no risk relationship there? Are you charging them too much and, therefore, you want to keep charging someone more than the risk entitles you to charge?

MR. POE: I think I'll relate back to what the representative from PIRG said. If you have-- If you want, you can actually go find, to the sixth decimal point, what every single risk is correlated to the amount of. And, yes, we would be artificially charging them-- Maybe we're charging them the exact amount by lowering-- Maybe there is a correlation, and maybe there is a reason for -- that you could show that-- If you actually prove that education was correlated to what losses we had, we would adopt them. But the fact is, insurance is pooling.

I don't know if I'm really answering your question. It's a zero sum game. We can't afford to lose. And no insurance carrier, whether it's State Farm, whether it's Allstate, whether it's any carrier that doesn't use these practices -- cannot sit by and watch all of their highly educated, suburban, high-income drivers that have an affluent background to simply leave their carrier.

Now, I don't know whether or not every-- I mean, every carrier makes profits or they wouldn't stay in business. I mean, obviously, in any given year, we could lose money. But I guess what I'm trying to say is, no carrier wants to lose people that don't get into accidents, that are affluent drivers, to other carriers.

SENATOR CARDINALE: Okay. I think you've come around to my way of thinking -- at least in what you're saying.

MR. POE: Okay.

SENATOR CARDINALE: You seem to be supporting the notion that I have, that these folks are lower risk drivers.

Now, in case you don't agree with that, can you have -- can you produce any evidence -- I'm going to ask this of the other companies, too, I'm not singling you out--

MR. POE: Right.

SENATOR CARDINALE: --that would undercut the notion that these folks are actually lower risk drivers, the doctors, the highly educated people.

MR. POE: Well, I guess-- See, the difference between the way I terms things-- I think there's a correlation to losses. I don't believe there's a correlation to risk. And that's the basis of this entire thing. There is a big difference.

SENATOR CARDINALE: How do you determine risk except by doing--

MR. POE: Like I said, you can group any class in the world and say, that group of losses-- "We have this group of brown-eyed people. They have lower-- They have higher losses." Does that mean they're a higher risk because they have brown eyes? No.

So I'm saying, yes, there is a correlation to losses with education. But that does not mean that there is a correlation to risk. And there is--

SENATOR CARDINALE: What is the-- Can you quantify the correlation to losses?

MR. POE: I'm sorry.

SENATOR CARDINALE: Can you quantify? You say there is a correlation to losses.

MR. POE: I said there could be. I don't have that data. Just so you know, out of the majority of carriers in the United States of America, we never ask education and occupation. It's not required. So any data that's even purported today, by GEICO or any company, is their own data. When is the last time anybody in this room got auto insurance, and they made it a mandatory requirement that you tell them how far you got in college, or how far you got in high school, and what occupation you have, which can change in any given year? So whatever data they have, I can tell you that it's probably their own data. I don't think there's any data from an independent study. If there is-- The only data I know is of the Quality Planning Corporation, that showed the contrary of what they're saying -- which is, that out of all 40 occupations that they studied, out of 15 million policyholders, the two highest, outside of students, were attorneys and doctors -- with the highest accidents per thousand vehicles insured. And the lowest were homemakers and firefighters. So, yes, if you wanted stats, those are some stats I can give you.

SENATOR CARDINALE: You, I think, asked me a question. When did we see these kinds of things begin to happen? And I think when we passed our last legislation, and we got some new companies in that began to cure some of the problems in New Jersey, is when we saw these things happening.

MR. POE: Well, actually--

SENATOR CARDINALE: And those things are happening. And it's a high correlation, with me, with the resolution of some of the problems that we have previously experienced in a long history in New Jersey.

And I don't want to belabor this.

SENATOR GILL: Right.

SENATOR CARDINALE: I know the Chairwoman wants to get on with the rest of the witnesses.

MR. POE: Thank you.

SENATOR CARDINALE: That's all that I have.

SENATOR GILL: And I would like to say, for the record, that I did an OPRA request, on behalf of this Committee. I did ask for the specific information. It was deemed to be proprietary. And although we sought to challenge it, we moved ahead with this Committee hearing. So I asked specifically for that information so that the Committee could have it in order to determine if there was a correlation of the characteristic trait being segmented to the risk of loss -- had a relationship. And I think that is crucial information. The Department of Banking invoked that segment on my OPRA request.

So I hope that we will be able to get to that in some way that does not violate the proprietary claim, but still allow some transparency so we could determine what happened with respect to DOBI, and what was the information presented. Because on one segment, that is so vital to the assumptions that we're all making here, either pro or con.

So I just wanted that to be clear.

Any further questions? (no response)

Thank you very much.

MR. POE: Thank you.

MR. LORETTE: The next presenter today will be Hank Nayden, the Vice President and Legislative Counsel with the Government Employees Insurance Company, commonly referred to as GEICO.

HANK NAYDEN, ESQ.: Good afternoon.

SENATOR GILL: And I'd like to, before you testify, make it clear to you that this is not GEICO-bashing. You have-- We're open to any objective information. We understand that it is a business that you participate in, and this is your business model. And we further understand that it is a legislative body that determines if it is valid, based upon what our public policy determinations are.

So I want you to be comfortable. And, certainly, we welcome your testimony.

MR. NAYDEN: Thank you, Senator Gill.

Chairwoman Gill, ranking member Cardinale, members of the Committee, my name is Hank Nayden.

SENATOR LESNIAK: Whoa, ranking member.

SENATOR CARDINALE: Wow.

SENATOR GILL: He didn't say rank, so don't worry. He wasn't talking about you, because he said ranking.

MR. NAYDEN: I am Vice President and Legislative Counsel for the GEICO group of companies. I appreciate this opportunity to be here to talk about the benefits that competition and choice have brought to New Jersey drivers.

First, let me start by thanking the members of this Committee, and the entire Legislature, for the auto insurance reform legislation--

I'm sorry. Is that better? Have you heard anything that I've said to this point? (referring to PA microphone)

SENATOR SINGER: We heard the ranking member. (laughter)

SENATOR GILL: I also heard my name, so you're on good stand. (laughter)

MR. NAYDEN: --for the auto insurance reform legislation of 2003.

I also want to credit former Governor Jim McGreevey. The newly competitive market that has brought more choices and lower rates to New Jersey auto insurance buyers is a result of Governor McGreevy's vision and leadership. Without his commitment to competitive reforms, GEICO and other companies would not be in New Jersey, and New Jersey drivers would be paying significantly more for their auto insurance.

GEICO is excited to be back in New Jersey. Since our return 21 months ago, GEICO has gone from zero vehicles insured to more than half a million. Even better, according to over 27,000 policyholder surveys, the average annual savings for New Jersey GEICO policyholders is over $675. In total, based on our policyholders' reported savings, last year alone GEICO saved New Jersey drivers over $200 million. These savings are being enjoyed by our customers across all cities, and towns, and all demographic groups.

In this short period of time, GEICO has also become one of the largest insurers of urban drivers in New Jersey. GEICO's 2006 growth rate in urban areas is over 50 percent annually. We insure over 170,000 vehicles in these urban areas. And more than half of these vehicles are insured in GEICO's preferred companies.

In addition to saving drivers over $200 million in premiums, I am proud to say that we have created 240 new jobs and opened a new office in New Jersey.

Over the past few months, there has been an orchestrated campaign of misinformation regarding GEICO's business practices. This misinformation has caused a great deal of confusion, and we are grateful to this Committee for an opportunity to set the record straight and to explain how our business practices benefit consumers with lower prices.

GEICO was founded in 1936 to serve only government employees, just as other companies were founded to serve only military officers, farmers, teachers, or lawyers. Over the years, GEICO has broadened its marketing and underwriting model to include all drivers, but the companies have used occupation as an underwriting criterion for over 50 years.

GEICO didn't get to be the fourth-largest auto insurance company in America and New Jersey, and one of the largest urban underwriters nationwide, by being unfair to anyone. GEICO is succeeding in the New Jersey marketplace because drivers in every demographic are saving money.

The overwhelming majority of GEICO's business is done over the phone or the Internet. We don't use brokers or agents in New Jersey. Any customer, anywhere in the state, can log onto GEICO's Web site or call our toll-free number 24 hours a day, seven days a week to purchase a policy. And just to clarify, GEICO only underwrites auto insurance, not other lines of business.

GEICO bases its pricing on decades of data collection and analysis, and our risk selection criteria have been actuarially validated. The New Jersey Department of Banking and Insurance has reviewed and approved all of GEICO's business practices, as have regulators across the country.

In a recent press release, one of our competitors in the state alleged that GEICO bases auto insurance rates and eligibility -- and I quote -- "solely upon education and occupation." This allegation is categorically false. The fact is that GEICO uses more than 20 factors, not just one or two, in determining rates for auto insurance. No single factor is ever used exclusively, or even primarily, to determine a rate.

The Insurance Commissioner of Maryland, our state of domicile, has dismissed this allegation against GEICO as being without foundation. And to address the comment earlier, regarding whether or not there was data available and had actuarial evidence been presented, the answer is yes.

In a recent in-depth analysis of GEICO's underwriting practices, the Maryland Insurance Department and an independent actuary stated that GEICO's use of education and occupation is predictive, actuarially objective, and legally valid under Maryland's insurance and anti-discrimination laws.

The use of education and occupation is not a new concept in insurance pricing. Insurers, including GEICO, use these factors throughout the country, and have done so for many years, because these factors, along with the more than 18 other factors that GEICO uses, are accurate predictors of loss.

GEICO's occupational groupings are based on decades of data that show that people in some occupations, like teachers, are less likely to be in accidents than other occupations. Gender, marital status, age, driving history, and vehicle type are all other factors that GEICO uses in determining rates. A change in any factor may result in a change in risk and price.

In New Jersey and across the country, GEICO writes auto insurance through its preferred, standard, and nonstandard companies. Our competitor has alleged that the only coverage offered to individuals with a high school education or lower occupation is through one of the sub-standard companies. This is absolutely false. In New Jersey, in 2005, GEICO wrote 125,000 new policies in our preferred companies. More than one in three of these preferred GEICO policyholders falls into a so-called lower occupational group or has a high school education or less.

Conversely, over 25 percent of new policyholders in our standard and nonstandard companies are from so-called higher occupational categories or have more than a high school education. These statistics prove that having a particular occupation or educational attainment is no guarantee of getting the best or worst rate. Education and occupation are merely two of many, many factors.

In conclusion, I'd just like to say Governor McGreevey and the Legislature created a very competitive marketplace that has benefited New Jersey drivers. However, the reforms are still in the early stages. Companies, not just in New Jersey but across the nation, are watching to see if these reforms stay in place or if changes are made to reverse them.

I hope that the information provided today will help the Committee and the Legislature continue the progress and protect the reforms that have resulted in more competition and saved New Jersey drivers millions of dollars in auto insurance costs.

I appreciate this opportunity to set the record straight, and I'd be happy to answer any questions.

SENATOR GILL: Any questions from any Senators?

Senator Scutari.

SENATOR SCUTARI: I'll defer to the ranking member. (laughter)

SENATOR GILL: The ranking member has deferred to you.

SENATOR SCUTARI: Oh, thank you, Doctor.

What other companies in New Jersey use the criteria that we're discussing today, besides yourself?

MR. NAYDEN: I don't have the list with me, but I believe the representatives from the Department of Banking and Insurance do.

SENATOR SCUTARI: Do you have an estimate of how many companies utilize it?

MR. NAYDEN: I know there is at least a handful operating in New Jersey now.

SENATOR SCUTARI: And there's how many companies doing business in New Jersey in the auto market?

MR. NAYDEN: That I don't know. I know there are a lot more today than there were three years ago.

SENATOR SCUTARI: The criteria that we're discussing, which is essentially education and occupation -- correct? Those are the two criteria.

MR. NAYDEN: Yes.

SENATOR SCUTARI: Are they not covered by other criteria within your rating system? Is it redundant to utilize education and occupation?

MR. NAYDEN: According to our actuaries, and independent actuaries, absolutely not.

SENATOR SCUTARI: What is your company's position with respect to the correlation of education as it is to risk of loss?

MR. NAYDEN: What we found is that, over time, these criteria are predictive, as are many other criteria that we use.

SENATOR SCUTARI: They're predictive, based upon the statistics.

MR. NAYDEN: Yes.

SENATOR SCUTARI: But what would the reason be that someone with a four-year degree or a master's degree is less likely a loss or a better driver than someone who doesn't--

MR. NAYDEN: Senator Scutari, I'm a lawyer, not an actuary. I honestly cannot answer that question.

SENATOR SCUTARI: As Senator Lesniak pointed out, it may not matter, I guess. But my question is, why? Why is someone's employment determining their riskiness as a driver; or someone being more educated -- they're less risky than somebody who is more-- How would that -- other than-- I guess what you're saying is that data that's been collected over the years has shown that someone with a higher education is less likely to be involved in losses than somebody who has less education.

MR. NAYDEN: I know that companies over time -- and for GEICO that's been decades -- collect and analyze the data on their policyholders, and keep very close records on their losses.

SENATOR SCUTARI: So a person's occupation and person's level of education is helpful in determining how risky they are as an insured. Is that right?

MR. NAYDEN: Our data has shown that, in addition to the many other factors that we use to predict risk of loss.

SENATOR SCUTARI: So you can-- Two of the factors that you utilize to predict loss would be someone's occupation or someone's level of experience. And that's based upon historical data that you've collected.

MR. NAYDEN: That's correct.

SENATOR SCUTARI: But you can't tell me why that is.

MR. NAYDEN: Again, Senator, I'm not an actuary.

SENATOR SCUTARI: Do you think anybody could tell me why someone--

MR. NAYDEN: I don't know the answer to that question. What we do know is that the data are persuasive. And independent actuaries have looked at our data and have agreed they are predictive and actuarially justified.

SENATOR SCUTARI: I guess-- I'm not saying it's correct or not. I'm just trying to work this through. Someone who is a 17-year-old driver is generally now deemed to be a riskier driver than someone who is a 40-year-old driver. Would you agree with that?

MR. NAYDEN: I think those are the indications, yes.

SENATOR SCUTARI: And I guess-- I gather that we can determine that the 17-year-old driver is less experienced, or just engages in riskier driving habits. At least that's my thought on why that would be determined.

MR. NAYDEN: I think that would be accurate, yes.

SENATOR SCUTARI: But I'm grasping to figure why one occupation would be riskier than another, in terms of their driving habits. That I'm trying to figure out.

MR. NAYDEN: There is a very large number of personal characteristics, for example, gender, age, marital status. And I'm not sure that I could answer that question for any of those characteristics.

SENATOR SCUTARI: Fair enough.

So there may be a lot of criteria that may be difficult to get the causation between driving habits, besides the two that we're talking about.

MR. NAYDEN: There, more than likely, would be. But, of course, that's speculation as an attorney, not an actuary.

SENATOR SCUTARI: How many individual criteria is utilized in your rating particular drivers?

MR. NAYDEN: We use well over 20 criteria to underwrite and to rate risk.

SENATOR SCUTARI: Thank you very much.

Thank you.

SENATOR GILL: Senator Cardinale.

SENATOR CARDINALE: There was a time, not too long ago--

And, by the way, flattery is very welcome. (laughter)

But there was a time, not very long ago, that I used to get very frustrated by hearing GEICO's ads. I was a GEICO customer when I first came to New Jersey. And when I would hear how you can save all this money by going to GEICO, and then hear the tag, "Not available in New Jersey," it was a source of great frustration to me.

That changed not too long ago. And you came back to New Jersey. And, one, welcome back.

MR. NAYDEN: Thank you.

SENATOR CARDINALE: But was the ability to use these criteria a factor in the decision made by GEICO to come back to New Jersey?

MR. NAYDEN: It was one of the many, many factors that we took into consideration on return, yes.

SENATOR CARDINALE: Was there a prearrangement with the Department that you would be able to use these factors?

MR. NAYDEN: We simply came in and had initial discussions with the Department and, basically, showed them our entire business model, and asked them to review it and to approve it, which they did.

SENATOR CARDINALE: And they did approve it.

And so you haven't snuck this thing past anyone. You've done all of the things that were required in order to have your business model approved in New Jersey.

MR. NAYDEN: That's correct, Senator.

SENATOR CARDINALE: Thank you.

I don't have any other questions.

SENATOR GILL: I have a couple questions.

The data that you say the actuarials have provided-- Does that data show a correlation in the characteristic traits of a person who has less education -- and risk -- not the correlation, but simply between -- loss between groups -- but the characteristic of having less education directly relates to risk?

MR. NAYDEN: Senator, I'm not sure, again, as I'm not an actuary. I'm not sure I have the answer to that question.

SENATOR GILL: I understand what you are, but I do understand that you're here to--

MR. NAYDEN: What I can--

SENATOR GILL: Wait a minute.

I understand that you are here to represent GEICO. Now, we may have to ask this of others. But I know you're a lawyer. I'm a lawyer. We won't hold that against either one of us.

MR. NAYDEN: Thank you.

SENATOR GILL: You're welcome.

SENATOR CARDINALE: Speak for yourself now. (laughter)

SENATOR GILL: That's a non-lawyer.

Did GEICO provide the actuarial information to show two things: One, with respect to their underwriting, that there is a reasonable and demonstrable relationship between -- and I'm quoting from NJAC 11:3-35.3c2, Subchapter 35. "An underwriting rule shall be based on a reasonable and demonstrable relationship between the risk characteristic of the driver insured and the hazard insured against."

So did GEICO provide the correlation to show that the characteristic of being a high school graduate -- that characteristic, by itself, is a relationship to the loss that you are insuring against?

MR. NAYDEN: Senator, I do know that we provided our entire model and all of our data to the Department of Banking and Insurance for their review. I'm not familiar with the New Jersey gloss on the term of our reasonable and demonstrative relationship between risk and hazard -- under New Jersey law. But I believe that when the Maryland Insurance Administration hired their actuaries to review the correlation, this was precisely the kinds of things they reviewed.

SENATOR GILL: We're talking about New Jersey.

MR. NAYDEN: Yes, ma'am.

SENATOR GILL: And you know why I have that concern? Because we know that GEICO is being sued in Federal court, in a class action suit in Minnesota, based upon the use of occupation and education as a violation of the constitutional rights of minorities. And we also know that in several states, legislation is being introduced -- and has been introduced -- where GEICO operated with education and occupation. Legislation is being introduced to prohibit that.

So what Maryland says is not disparate here. I would like to know-- And maybe I will also ask the Department of Banking. And that's a crux -- that's, I think, a serious issue for all of us on the Committee. At least for me. And if the actuarial information was simply part of the business model, or was it an independent assessment-- And I ask you that question, because we know there has been the study that's been done that says just the opposite, based on the actuarial determination -- I think you're aware of it -- that the drivers who are the people who are the worst drivers happen to be the doctors and the lawyers. And it's the blue collar workers that are the safest. So there seems to be, in the marketplace, a complete opposite. And I wanted to know if it was an independent actuarial, or was it simply your business model you submitted to the Department of Banking and Insurance, or you don't know.

MR. NAYDEN: Senator, we submitted all of our data for review.

SENATOR GILL: And that is-- That goes to another point. Why, under the -- my OPRA request, we asked for that information, or information that contained that information, to which the Department entered an objection -- and this is just for the record, not for you to answer -- entered an objection to that. And if the Legislature can't get that information to determine if there is a valid risk factor, that's a real issue.

But let me go on to another question, with respect to GEICO. GEICO, it's my understanding, is a holding company, correct? And it has four -- three or four GEICO subsidiaries.

MR. NAYDEN: We have two preferred companies with exactly the same coverages and rates. And then we have a nonstandard and a standard company.

SENATOR GILL: And does the nonstandard and the standard company have higher or lower rates than the preferred?

MR. NAYDEN: Generally, with GEICO -- and this is fairly standard in the industry -- the preferred company has, generally, lower rates. The standard company has slightly higher rates. And the nonstandard company has slightly higher rates.

SENATOR GILL: When a person makes an application to GEICO, and they are accepted, does GEICO tell the consumer which subsidiary they are being insured by?

MR. NAYDEN: That's correct.

SENATOR GILL: They do?

MR. NAYDEN: Yes, we do.

SENATOR GILL: Okay.

Now, if you had all factors being equal-- You had a 30-year-old who lived in the suburbs, a good driving record, and 18 of the 19 factors -- 20 factors you talked about -- a blue collar worker, lived in the suburbs, 18 of the 20 factors were exactly the same as the doctor or lawyer -- two factors are different: occupation and -- education and occupation. All factors being equal except those two, would the doctor pay a rate higher or lower than, or the same, as the blue collar worker?

MR. NAYDEN: Senator, I'm going to have to say maybe. And the reason I have to say maybe--

SENATOR GILL: Maybe as to which, *A*, *B*, *C*, or *D*?

MR. NAYDEN: It's possible that they might pay exactly the same rate. First of all, it's highly unlikely -- and there's a very, very small percentage of risk -- persons to be insured who would have all of the same characteristics with the single exception of education or occupation.

Secondly, even if that were the case -- and this is a very narrow hypothetical -- it could be that, under our model, they would get exactly the same rate. For example, driving characteristics -- a person's driving history: how long they've been driving, what their DMV and accident record are -- are weighted very heavily under our model.

SENATOR GILL: And I'm saying that those -- all of those factors are equal. Would the doctor pay less than the blue collar worker?

MR. NAYDEN: Depending on what all the factors were--

SENATOR GILL: All of them-- The 20 that you talked about--

MR. NAYDEN: Senator, I understand that.

SENATOR GILL: --18 of them are exactly the same.

MR. NAYDEN: What I'm-- I'm not communicating very clearly. What I'm trying to say is, depending on what the other 18 factors were--

SENATOR GILL: You said that there were 20 factors that come into consideration.

MR. NAYDEN: More than 20.

SENATOR GILL: More than 20. So if it's more than 20, what's the number of factors GEICO considers in underwriting insurance in the State of New Jersey?

MR. NAYDEN: More than 20.

SENATOR GILL: Okay. What is more than 20? Is it 30?

MR. NAYDEN: I believe it is less than 30.

SENATOR GILL: And where is the--

SENATOR LESNIAK: It's bigger than a breadbox.

SENATOR GILL: I don't know. I'm a lawyer, so those high school examples go right over my head. (laughter)

Now, what I'd like to know is, where are-- Where's the information that states exactly what criteria the 20 -- more than 20, and less than 30, and a little bit bigger than a breadbox -- where is that information memorialized?

MR. NAYDEN: The New Jersey Department has our entire underwriting and rating model.

SENATOR GILL: And do you consider that information proprietary?

MR. NAYDEN: Yes, we do, as would every insurance company in the country.

SENATOR GILL: So that at this point here (indiscernible) we have no information as to what criteria you use, in terms of from the one to 30. We don't have a complete listing, do we?

MR. NAYDEN: I don't believe you do have a complete list, Senator.

SENATOR GILL: Because what you do show, as to your underwriting, is certainly not 20 to 30 characteristics that you use, that the public is aware of, correct?

MR. NAYDEN: We have made entirely public our entire model, all of our data for both underwriting and rating, to the regulator.

SENATOR GILL: And so the regulator has it. And I'm not faulting you, so I don't want you to think my direct approach in my voice is that. The underwriter has these 20 characteristics that the public does not -- 20 to 30 characteristics that the public does not have, correct? The regulator has it.

MR. NAYDEN: That's correct.

SENATOR GILL: And the reason I ask you this is because we're going to the issue here of transparency.

The regulator has them. You say you utilize them. The public doesn't know what it is. And the regulator won't give it to this Committee. So, of the 20 or 30, if all were equal except two, would the blue collar worker pay more than the doctor?

MR. NAYDEN: Under some scenarios, absolutely not.

SENATOR GILL: And under some scenarios, absolutely?

MR. NAYDEN: Perhaps.

SENATOR GILL: Well, under what scenarios? Can you tell me what factors would outweigh occupation and education so that the blue collar worker and the doctor make (*sic*) the same?

MR. NAYDEN: The driver's driving history -- and that would be length of time driving, DMV record, accident history -- has a greater weight than either education or occupation in our model.

SENATOR GILL: In your model.

MR. NAYDEN: That's correct.

SENATOR GILL: In your model, is there a company where those people have left education-- Because in your-- And I would like to ask you that. You do, in your guidebook, talk about those professions. In your index of filing, you talk about those professions that are-- You group them, correct?

MR. NAYDEN: Yes, we do.

SENATOR GILL: And you group them based upon education, and you group them based upon income.

MR. NAYDEN: No, we cannot group by income. That's not correct.

SENATOR GILL: You group by occupation and education, excuse me.

MR. NAYDEN: Yes, we do that.

SENATOR GILL: And in your filings, where you talk about -- and I would be referring to Page 4 of the GEICO -- education risk -- who have achieved at least a high school diploma or it's equivalent, are more favorable than those without a high school education. Bachelor's, master's, other advanced degrees are considered most favorable. Level of education is not a risk factor in occupation group 7 and 8. So in groups 7 and 8 -- and you know what group -- it is not a risk factor. But in all other groups, it is. And your group-- You know what groups 7 and 8 consist of, correct?

MR. NAYDEN: Yes.

SENATOR GILL: That's the undergraduate degree, graduate degree, and the professional class, more or less, correct?

MR. NAYDEN: I'm sorry.

SENATOR GILL: The professional class.

MR. NAYDEN: Groups 7 and 8?

SENATOR GILL: Yes.

MR. NAYDEN: No, that's not correct.

SENATOR GILL: Okay. Group 7 is college students, undergraduates, grad students, professional nurses, as well as those who have graduated within the last three months and they're continuing to look for occupation, or they're continuing to look-- And then it's the military, correct?

MR. NAYDEN: That is accurate, I believe.

SENATOR GILL: And in the military, the occupation determines -- because I think it is, what, E2? E2 is not a favorable group, correct?

MR. NAYDEN: Senator, our--

SENATOR GILL: No, I mean-- I'm just looking at your-- I'm simply looking at your guidelines.

MR. NAYDEN: Senator, first of all, I have no idea where you acquired that. And I don't know how old or recently issued it is.

SENATOR GILL: I will tell you where I acquired it, but that's of no moment, because I did it under the Open Public -- OPRA. And it's called "GEICO's Automobile Group to Company Placement (*sic*)," right? Are you aware of this? I don't want to question you on something--

MR. NAYDEN: Oh, absolutely. We do have underwriting guidelines, and they are filed with departments all across the country.

SENATOR GILL: I don't want to question you on anything you're not aware of, because I'm not doing ambush here. We understand where we are in this document, correct?

MR. NAYDEN: Yes.

SENATOR GILL: Okay. And in the issue with the groups and the education factors, a private in the Army is considered to be not favorable under GEICO's placement, correct?

MR. NAYDEN: If the data that we've collected over time showed that their loss experience is higher than other occupations, that would probably be true.

SENATOR GILL: And by defining it as an E2, you--

MR. NAYDEN: That would be the military's classification, not ours.

SENATOR GILL: That's the military's. But you use the military's classification. And I think it's E2. And you know, at E2, the poor private makes about $24,000. So by classifying it in the military terms, and saying an E2 is not a favorable risk, you know what the income of the E2 is -- is $24,000, correct?

MR. NAYDEN: I'm not aware of what the income of an E2 is.

SENATOR SINGER: Madam Chairwoman, when I was E2, we made $120 a month, so I don't know when--

SENATOR LESNIAK: Me, too. That's what I got.

SENATOR SINGER: I don't know where you got $24,000, but it isn't close. (laughter)

SENATOR GILL: Okay. Well, the E2--

I am a lawyer, so you will forgive me on arithmetic, but I'm quite sure the point has been made.

The E2-- It does not-- You know, by classification of his military status -- his or her military status -- what that person's income is, correct?

MR. NAYDEN: Yes, I suppose so, Senator.

SENATOR GILL: And in your placement, you say that those people -- somebody who may be a private in Iraq, fighting today -- in this placement, they are considered to not be favorable, correct?

MR. NAYDEN: Senator, you're reading from the guidelines. I don't have them in front of me.

SENATOR GILL: Well, let me summarize what the guidelines say. And for those who need to see them -- because I won't take you through them. It's the "GEICO Auto Group Guide to Company Placement," revised as of 07/05/04.

And GEICO talks about those groupings by occupation and education that are not considered favorable. One large group they talk about is blue collar and gray collar. Do you know what definition -- at least by example -- for the least favorable grouping or placement that a gray collar job would consist of?

MR. NAYDEN: For example, bartenders would be in that category.

SENATOR GILL: Would secretaries without college degrees--

MR. NAYDEN: They might be.

SENATOR GILL: Would construction workers without college degrees--

MR. NAYDEN: Yes, they could also be in that category.

SENATOR GILL: Would a home health aide without a college degree be in that category?

MR. NAYDEN: That's entirely possible.

SENATOR GILL: And would a Senator without a college degree be in that category?

MR. NAYDEN: No, they would not be.

SENATOR GILL: Why?

MR. NAYDEN: If--

SENATOR GILL: They didn't have a college degree.

MR. NAYDEN: If a legislator--

SENATOR CARDINALE: You get their other ones.

MR. NAYDEN: I said they wouldn't be. I should probably hold my thought on that and say it's entirely possible that a legislator -- legislative member would be in another category.

Senator, the important thing that I want to--

SENATOR GILL: I'm going to let you speak, but I do have some questions of definition that I would like to pursue. Because they are in the written placement for GEICO.

What would be an example of a blue collar job that is not favorable?

MR. NAYDEN: If, by not favorable, you mean has a higher indication of loss propensity--

SENATOR GILL: Well, it says *not favorable* in your--

MR. NAYDEN: And I think that's with-- And, again, that's an extract of the guidelines, which address not only occupation and education, but all of the other many, many factors that we use to underwrite.

SENATOR GILL: Oh, it does?

MR. NAYDEN: But I would say to you that--

SENATOR GILL: Just an example of a blue collar that would fit in that.

MR. NAYDEN: For example, an electrician might be an example of "blue collar."

SENATOR GILL: And does GEICO rate based upon -- or have in their least favorable-- If you have a job that only requires a college education -- only requires a high school degree. But let's say your job downsized, and you have a college degree. So now you're in a job that only requires a high school degree. Would the education aspect be determined by the level required for the job duty, which would only be a high school diploma, even though I have a college degree?

MR. NAYDEN: Senator, I don't have the answer to that question. But I can certainly forward that to your office. And I will get that answer.

SENATOR GILL: That would be extremely important, because I know that -- if I can use myself for an example. My legislative director has a law degree from Pepperdine. But since the job description does not call for an advanced degree -- although we can say that the work load does -- the job description does not call for an advanced degree. Would my legislative director be rated on the level of degree required by the job?

MR. NAYDEN: Senator, I can't give you a snap answer, but I will absolutely get that information and get it to your office.

May I--

SENATOR GILL: Because I would like to-- And you said that this document contains the characteristics of the 50 or so -- or your characteristics.

It says that the factors are grouped into three categories: driving record, drivers in vehicle -- and they talk about accident, theft, convictions, license suspension, age, occupation, number of drivers, driving experience, current insurance, current limits -- and years with your insurer. This document that gives the underwriting criteria does not contain the 20 or 30 criteria that you say is utilized. Is there a reason why?

MR. NAYDEN: Senator, again, I don't have that document in front of me. I believe that's an extract from our underwriting guidelines and our rating guidelines. And I will say that to price our insurance products, GEICO uses more than 20 underwriting factors.

SENATOR SINGER: Can I ask you one question, Madam Chairperson?

SENATOR GILL: I would like for you to--

Yes.

And I don't have-- I'll let somebody else question.

Can I have an attendant, please? I know you're guarding the door, but--

I'd like to make sure that you get an opportunity.

MR. NAYDEN: Senator, the other thing that I would like to just say is that every single occupation that you've mentioned -- in fact, every occupation -- has the preferred companies available upon underwriting. In other words, every single occupation, depending on the other factors, can be underwritten in our most preferred company.

SENATOR GILL: But we do know that when you start off, you start off saying these occupations are not favorable. And I had the attendant give you what I was reading from. So I just would like you -- just so the record is clear and complete -- to take an opportunity to look at that. Is it what it says it is?

MR. NAYDEN: It appears to be, at least, an extract from our placement guide.

SENATOR GILL: Is it an extract or-- When you say extract-- That document is given to whom? Is it given to DOBI, is it given to the public? If you know--

MR. NAYDEN: Senator, I'm not sure. I'd have to sit down and go through every page in this document to try and determine--

SENATOR GILL: So you don't know if it's an extract or if it's the complete document, with respect to the underwriting characteristics.

MR. NAYDEN: I really cannot speak to this document.

SENATOR SINGER: Madam Chairwoman, can I just ask you one question?

SENATOR GILL: Yes.

And if you can return the document--

And I will let Senator Singer--

SENATOR SINGER: No, I have a question for you, Madam Chairperson.

SENATOR GILL: Oh, it's a question to me.

SENATOR SINGER: Yes. I'm glad I wore my white shirt day.

Let me just ask you one question. It is my understanding -- and I don't sit on Judiciary. I know that both yourself and the senior member here, Jerry Cardinale, do.

SENATOR LESNIAK: Ranking member.

SENATOR SINGER: Ranking. (laughter)

But it's my--

SENATOR CARDINALE: Senior has other connotation.

SENATOR SINGER: Well, ranking, senior, doctor.

It is my understanding, in the Judiciary, that in the case of looking at a judge's reappointment, you have the right to look at -- just follow me. Give me a little bit of leeway. You have the right to look at certain information that is not public information under -- and not available to other Senators or other people -- to look through in a special way, because you sit on Judiciary.

Would it be possible, as a Senator sitting on the Commerce Committee, that the Department would allow us to sit down with them and go over confidential information in their presence without the public, so that we would have a better understanding ourselves of what is going on, since we are not allowed to get information, publicly, since it's proprietary -- but yet to look at it, because we sit on this Committee? Could you not request that of the Department for us?

SENATOR GILL: I will certainly request that of the Department. And I think it goes to an even broader issue of the need for transparency. And it would be very good that we know about it. But then we would be restrained from discussing it in public, because we -- the proprietary objection would only be waived to the limited extent that we can look at it. But we can work that out. But I do think this goes to -- and your suggestion is well-taken. And we have the Commissioner here.

But it also goes to the heart of transparency, with respect to setting rates. And I think that your suggestion is excellent. I will proffer that. And I do think that that's something--

Anyone else have any other question?

SENATOR LESNIAK: Madam Chair, on that issue--

SENATOR GILL: Yes, please, Senator Lesniak.

SENATOR LESNIAK: It would appear to me that the rating criteria, in and of themselves, should not necessarily be proprietary. I mean, this is not-- I mean, everybody basically knows what the rating criteria are that insurance companies use.

Now, what they-- The factor that they-- And I may be wrong on that. But it seems to me, when you say something-- Look, every proprietary decision -- every decision as to whether something is proprietary or not is not a black and white thing. You have to weigh how much it is exclusive to that particular business.

Now, on the other side of that coin is what weight they give to each criteria. That's certainly proprietary. I mean, without a doubt. But the general classifications-- It would seem to me that that's something that we should know. And, quite frankly, I think it would be good for the insurer to quite frankly -- for us to know so that we can actually see the broad picture that's painted that allows many of the people who I represent, who don't have college degrees, who aren't doctors or lawyers -- are insured by preferred rates by GEICO. It would certainly paint a better picture, I think, for me to understand. And I think it would inure to the benefit of the -- of GEICO and other insurance companies, as well.

SENATOR GILL: I think it is crucial that we know what weight is given by GEICO to occupation and-- Not just that we use 20 to 30 different things, but what weight is given. Because if we, as a committee of legislators -- we don't have that information. And if you give 95 -- let's just say -- 95 percent of the weight goes to occupation and education, then that cancels out, in terms of the determining factor, the other 20 or 30.

And the reason I say that, Senator Lesniak, is because we have a stated public policy, that this Legislature passed with the reform act, that says you cannot use race and income. And in order to understand -- and it may or may not be. If this is being circumvented by giving more weight to income and education, you have circumvented the very things we put in place to prohibit discrimination, both on income--

So we ask for that information. And I think that's vital, given the tenor.

You don't know, and you're not an actuarial. So I think it's important that we do know that very information.

SENATOR SINGER: Madam Chair, the only reason why I would like to look at--

SENATOR LESNIAK: Senator, if I may, because that was a response directly to my statement.

I just want to make this clear. I didn't suggest that it wasn't important. I suggested that it would be proprietary. I just want to make that clear.

SENATOR GILL: Okay. I get it.

SENATOR SINGER: Just to add one thing to that, Madam Chair, just to clarify is, my next door neighbor is a plumber, and his house is bigger than mine. So I'm not quite sure how you guide jobs sometimes.

SENATOR GILL: Are there any other questions of GEICO? (no response)

Thank you very much.

MR. NAYDEN: Thank you, Madam Chair.

SENATOR GILL: Oh, I do have one question.

MR. NAYDEN: Yes, ma'am.

SENATOR GILL: If we prohibited the use of education and occupation, would New Jersey still be a competitive market? Or do you need those two things in order to be competitive?

MR. NAYDEN: Senator, I think that--

SENATOR GILL: Profitwise, we're talking about. Can you make a profit that makes you competitive without the use of education and occupation?

MR. NAYDEN: Senator, I think that anything that the Legislature does to roll back these reforms would move toward making the market less competitive than any-- If companies have fewer legitimate underwriting tools to use, yes, that would make the market less competitive.

SENATOR GILL: And I do like your qualifying factor of legitimate underwriting tools. Of course that's to be determined by us.

Thank you very much. Thank you for being in New Jersey.

And we understand that all of the reforms-- They have worked. Some of them haven't. And that's what we're getting here.

But thank you very much for your testimony.

MR. NAYDEN: Senator, thank you very much for allowing me to speak today.

SENATOR GILL: Thank you.

The next witness, please.

MR. LORETTE: The next presenters before the Committee will be a panel of representatives from the Department of Banking and

Insurance, including the Commissioner of the Department, Steven Goldman; the Director of the Division of Insurance for the Department, Donald Bryan; as well as the Assistant Commissioner of Property and Casualty within the Division of Insurance, Bill Rader.

SENATOR GILL: Thank you very much, Commissioner. I understood that you would be in D.C., but you made different arrangements so you could be here. So I'd like to say, in advance, that the Committee really appreciates that -- and to the rest of the members who will testify.

But thank you very much for changing your schedule.

COMMISSIONER STEVEN M. GOLDMAN: You're welcome.

Thank you, Madam Chair and members of the Committee.

I think they've already been introduced, but let me again introduce the Director of Insurance, Don Bryan, who is to my immediate right; and the Assistant Commissioner for Property and Casualty, Bill Rader, who is to his right, who will help to respond to the Committee's questions today.

The purchase of insurance transfers the risk of an uncertain, infrequent, and future event of significant consequence in exchange for a known premium payment. The nature of the insurance product thus requires a degree of regulation to protect purchasers.

This involves three separate but related goals. First, to promote sound financial practices in order that insurers remain solvent and able to pay claims. Second, to promote fair trade practices by oversight of insurers' marketing and claim practices. And, third, to promote a healthy market of available and affordable insurance products that meet consumers' needs by prudent oversight of the products they offer. True consumer protection requires simultaneous consideration of all three goals. And this is the Department's aim as it carries out its regulatory responsibilities.

Auto insurance is only one of two lines of insurance where the purchase of the product is mandated by law. When the force of the law mandates that the general public purchase insurance, government establishes a captive market for the suppliers of the product. In this circumstance, government has a unique and special responsibility to assure that the product is both available and affordable.

Before I specifically address rating, I'd like to provide a brief background on auto insurance regulation in New Jersey.

From about 1972 through 2001, the focus of public policy was to try to make auto insurance affordable for the people that were required to buy it. This is a daunting task, as we found out.

New Jersey is the most densely populated state in the nation. The cost of auto insurance is high in New Jersey because of high traffic density, which promotes accidents; generous medical benefits that fund our excellent trauma care system and the health care associated with the aftermath of accidents; the relative wealth of our residents who purchase high limits of coverage; and newer, more expensive cars that cost more to fix or replace -- and for other similar reasons.

To try to maintain affordability, New Jersey enacted a series of laws that sought to control every important aspect of this business. Since the easiest way to keep insurance affordable is to control the price, New Jersey required prior approval of insurance rating systems. In doing so, it established a rate-making formula that restricted return on invested capital. Laws were enacted that established internal subsidies. We developed data filing and review processes that prevented or delayed increases.

And on the other side of pricing, the Legislature enacted an excess profit law that tightly capped return on investment over a three-year look-back period, when the industry norm is to determine results over a longer period of time.

When this assigned risk plan resulted in high prices, the Legislature created a State supervised residual market mechanism known as the JUA. When that failed, New Jersey lawmakers mandated that all insurers provide coverage to all drivers except those with the very worst driving records. Finally, the law compelled insurance companies to remain in the market by restricting their withdrawal through a process that could take six years or more.

Although these restrictions were undertaken in good faith, and many were aimed at addressing a particular problem at a particular time, their accumulation over 30 years resulted in a steady erosion of insurance companies willing to make the capital investment necessary to meet the personal auto insurance needs of New Jersey's drivers. Some insurers withdrew from the market, and many insurers created New Jersey-only companies with limited capital. Companies that remained in the market sustained losses and became insolvent, or so financially stressed that they were forced to cease writing new business.

In 2001, the market was in crisis after two major insurers with more than 20 percent of the market -- over a million cars -- announced their intention to stop doing business in New Jersey. No new market entrants were replacing them. Despite the take-all-comers law, the supply of auto insurance product was disappearing, and the public policy concern was availability.

That crisis created the will to address our market problems in a fundamental way, and resulted in the auto insurance regulatory reform laws, which were enacted with strong bipartisan support in 2003, and the complementary regulations adopted by this Department to implement those laws. The 2003 reforms did not repeal the regulatory structure, but they revised them so as to provide a framework for the development of a competitive market which held the promise of better availability and affordability.

Regarding pricing, the Legislature did not repeal the prior approval rating law, but revised the rate review process to make it quicker and more certain. Nor did it repeal the excess profits law, but it revised it to make it less likely to interfere with normal investment decisions. The reforms didn't repeal the take-all-comers statute, but phased out their effects over five years for insurers that met growth targets, and thereafter limited its reinstatement to times of severe market availability problems based on objective criteria. The law didn't repeal restrictions on withdrawal, but made the process shorter and more certain so that restrictions on market exit were not a significant deterrent to market entry.

The results have clearly benefited consumers as the Legislature intended. Companies planning to withdraw suspended these plans, and are now reinvesting in our state. Companies are competing for new business through advertising in all media forums. Companies have reduced rates or issued special policyholder dividends in excess of half a billion dollars.

Significantly, the reformed New Jersey market has attracted new entrants, including some of the largest, nationally recognized auto insurers in the country. And there are more, I might say, who are considering coming.

But we need to recognize that the reformed market is still in transition. Business practices that have developed over 30 years are still being adjusted to this new competitive environment. We need to ensure that recent entrants into the marketplace remain, and that the reformed market continues to attract new competitors, including small and niche market insurers. In doing so, we need to appropriately encourage the positive affects of free markets, such as price competition and incentive for investment, while preventing the unfair and imprudent behaviors that unregulated markets can produce.

A significant feature of the history of insurance regulation is the tension between the general goal of a highly efficient market, on the one hand, and the desire to accomplish specific societal objectives on the other. The desire to achieve specific societal objectives can result in rate setting based on factors other than actual loss costs.

While there can be compelling society reasons to force insurers to charge a given group of consumers less in premiums than that group costs in claim payments, doing so can create market distortions. At the least, that means charging one group of consumers more than is justified based on their claims and risk profile, and charging another group of consumers less than is justified based on that group's claims and risk profile.

Generally speaking, premiums need to cover claims payments, business expenses, and a reasonable return on the capital required to be invested in order to license the insurer. Since the main cost of providing insurance is paying claims under the policies that are issued, it is in the business interests of the insurer to distinguish between, and charge the right amount of premium, to each and every group that it insures.

While it is theoretically possible to charge all insureds at the same rate, different insureds present different risks of loss. One can see why it's important to charge the right premium to each group when one realizes that charging a low risk group too much money sends members of that group to competing insurers, where the price is more appropriate. That leaves the insurer with a disproportionate number of high risk customers, a situation that can lead to insolvency. On the other hand, charging a high risk group too little money attracts more members of that group to the company, creating the same situation, a financially unhealthy balance of customers that can lead to insolvency.

Two simple examples illustrate the point. Take life insurance. Smokers have a different life expectancy than nonsmokers. And since they present a higher risk, they are charged more. In this example, a life insurer that charged both groups the same would be charging too much to the nonsmokers and too little to the smokers. Nonsmokers would tend to purchase coverage from other competitors who charged less, and the smokers would be attracted to the single-rate company. This scenario illustrates that in order to accomplish the three goals of insurance regulation I previously mentioned, it's important for the regulatory framework to allow insurers to charge an appropriate rate, given the probable frequency of the loss payment presented by the risk.

In auto insurance, a second stark example would be an insurer that charged the same amount for comprehensive coverage to the owners of a Cadillac and a Chevrolet. While the risk of both cars being stolen might be the same, the payment to replace the more expensive car would be much higher, and so its owners pays a higher premium to reflect the potential claims cost. This scenario illustrates that in order to accomplish the regulator's goals that I mentioned, it's important for the regulatory framework to allow insurers to charge an appropriate rate for the severity of the potential claim, in addition to taking into account the frequency or likelihood of the loss payment that I illustrated with the smoking example.

Thus, in regulating rates, the Department's role is to evaluate the soundness of each insurer's proposed rating system in order to ensure that those systems reflect the frequency and severity of loss to the extent allowed by law. The essence of the regulatory responsibility is reflected in N.J.S.A. 17:29A-4. That statute requires that rates be neither unreasonably high nor inadequate for the safety and soundness of the insurer, nor unfairly discriminatory between customers presenting essentially the same level of risk and expense. This standard, which is used across the country, is important not only for assuring that companies remain financially strong enough to pay claims, but to assure that each class of customer is charged rates that are fair, with respect to the risk of loss that they present.

The degree to which a proposed rating factor seems intuitive or obvious is inconsequential. What is consequential is the degree to which a rating factor actually -- and by that I mean in a mathematically demonstrable way -- predicts the probability of losses.

It's important to understand that there is no single characteristic that causes accidents, or stolen cars, or other kinds of loss. Having a claim one year does not cause you to have a claim the next year.

Being 17 years old does not cause you to have an accident any more or less than having a college education, being single or married, male or female, or working as a lawyer or on an assembly line. It is the mathematically demonstrable correlation between one or more of these characteristics, and the frequency and severity of losses, that makes a particular factor worthy of consideration for purpose of insurance rating.

Causation is an unworkable concept for the purpose of insurance rate setting and regulation. In the end, there really is only correlation. No one correlation is more driving related than any other. What distinguishes one correlation from another, from an actuarial point of view, is its predictive power.

Finding the highest degree of predictive power is a perpetual goal of insurers, and methods for achieving that goal have evolved over the decades, along with technology and the sophistication of actuarial science. Some factors that seem commonplace today looked strange when they were introduced. Indeed, some factors that are well accepted today can be made to seem strange again, depending upon the perspective from which they are viewed.

For example, we all tend to accept that 17-year-olds should pay more, because they are riskier drivers. But couldn't one argue that they also have faster reflexes and that helps them to avoid accidents? As new drivers, couldn't one assume that they would be more reluctant to engage in risky behavior likely to cause an accident? And one might expect that they would be extra cautious, because their use of the family car -- their long-awaited privilege of driving -- is on the line.

The statistics demonstrate that young drivers, on average, generate three to four times the claims of all drivers. The point is that, depending on your perspective, we can argue that this or that group is more or less risky. In the end, only the statistics tell you for sure. So that is what insurers look to in analyzing the risk characteristics of certain drivers as a means of predicting the frequency and severity of their claims. To approve these rating factors, regulators require statistical support that demonstrates the correlation.

The goal of maximizing predictive power through statistics is why modern rating systems have evolved to use many, many factors, sometimes resulting in millions or billions of combinations or permutations in a single rating system. Indeed, so many factors can be in play that drivers with a couple of so-called *bad* characteristics still end up with some of the best prices, because a lot of good things are being measured, as well.

Basing rates on a few characteristics doesn't tend to work well for either insurers or consumers. Focusing on auto accidents is insufficient, because accident-producing claims are infrequent occurrences. Of 100 cars, on average, only seven will produce collision claims per year, and only one will produce a bodily injury claim.

As members of the Committee may recall, New Jersey tried, but then quickly abandoned, such a narrow approach more than a decade ago, when it legislated, and then replaced, a mandate that accidents and violations be the primary rating factors.

The eligibility point surcharge system that grew from this approach was unsuccessful, because it was perceived that the significant surcharges unfairly penalized drivers for minor infractions. You may also recall that the eligibility point surcharge system was replaced by what was called *tier rating*. As initially implemented, tier rating grouped a number of rating characteristics together into a few tiers. Again, consumers were dissatisfied when a change of circumstances moved them to a higher tier, because the cost differential between tiers was often significant.

While New Jersey was dealing with eligibility point surcharges and tier rating, insurers in other parts of the country were developing more sophisticated rating systems that used technology to analyze the predictive power of a whole host of new rating factors. These modern rating systems have demonstrated their success in the marketplace through the growth and success of the companies who use them, and the satisfaction of the customers who pay fair and reasonable rates when buying their products. Insurers tend to succeed when they predict well, and run into trouble when they don't.

We, in New Jersey, didn't have much chance to see these examples of success firsthand before the auto reforms of 2003. Until then, our failure to progress along with the rest of the country had hurt not only insurance companies and their capital investment in New Jersey's auto insurance market, but the thousands upon thousands of New Jersey drivers who paid higher rates than they do today, when they were able to find coverage at all.

Members of the Committee may recall that the crisis that sparked reform was one of availability. But the regulatory changes that brought new insurers here to deal with that crisis have resulted in lower rates as well, and that is telling.

Insurers have put more than one-half billion dollars back into the pockets of our drivers. This has occurred broadly, with premium reductions or special dividends for about 75 percent of policyholders. The question of whether or not to prohibit this or that rating factor out of the multitude now in use, despite a mathematical correlation to losses, must be viewed in the context of modern rating systems in use across the country, and now in New Jersey, as well.

When, following the reforms, the Department was confronted with new entrants to our market that sought to use the rating systems by which they competed in other states throughout the country, it approved those elements of the systems that were actuarially supported and not prohibited by our statutes. Doing so was, and continues to be, consistent with the object of the reforms: to attract new carriers and new capital to our market so as to address the crisis in availability. Not only was that legislative purpose served, but the competition that it has spurred has measurably improved affordability, as well.

New Jersey drivers have more choice and availability in auto insurance today than ever before. In a competitive market, with different insurers using different rating factors, consumers are able to shop and compare prices. The fact that an individual insured finds that a particular insurer's rates, based on its combination of rating factors, yields the most competitive prices for that person does not mean that another individual insured pays more. The second consumer can purchase coverage from a different insurer that uses a different set of rating factors that result in a better price for them.

So, in trying to ascertain the costs of potential changes to the current approach, it's helpful to look to New Jersey's not-too-distant past, a time when auto insurance was far more problematic than it is today. The Department strongly urges the Committee and the Legislature to allow the reforms of 2003 to continue to their conclusion and to permit the newly competitive market to fully stabilize, rather than inadvertently returning to the piecemeal regulatory approach of the '70s, '80s, and '90s.

Thank you, again, for inviting the Department to testify. We'd be happy to take any questions.

SENATOR GILL: Thank you very much, Commissioner.

Are there any questions?

Senator Cardinale.

SENATOR CARDINALE: It's not really a question, Commissioner, but an observation. And you gave a very thorough history of my whole tenure on this Committee. I lived through all of those. And you were very right. And I would like to perhaps even paraphrase what you said and say it a little more succinctly.

When we try to manipulate, as legislators, factors -- probably in any business, but particularly in insurance -- that we really don't know an awful lot about-- We could be on this Committee forever, and we really don't know enough to effectively try to make the kinds of changes that perhaps the people in the Department, who deal with this on a much more in-depth basis -- they can't even do it very well. I think the companies are the best people to create those factors, because they have something to lose. And they're careful about whether they're going to win or lose in any given year, or over a period of time.

I want to thank you very much for your presentation to the Committee. And I think there's nothing -- and I listened very carefully -- there's nothing that I could find to improve in your presentation.

Thank you.

COMMISSIONER GOLDMAN: Thank you, Senator.

SENATOR GILL: Senator Lesniak.

SENATOR LESNIAK: Thank you, Madam Chair.

And I'm sure the Chair's going to follow up on this line of questioning that we kind of concluded with, with the representative from GEICO, with regard to what is proprietary and nonproprietary information.

It occurred to me that if I were a competitor of GEICO, it probably would be a simple thing to set up a computer program, hook it up to their Internet system, and quickly determine, just by running a series of permutations, what their criteria is, and get a pretty good idea even of what their weighting system is.

What's your view on how proprietary is the underwriting criteria that the Chair has asked for?

COMMISSIONER GOLDMAN: I think the general criteria, the rating factors, are not necessarily what I would consider to be absolutely proprietary. But, certainly, the methodologies each company designs and applies to their various criteria, I think, would be highly proprietary. I think they've developed a very sophisticated computer model, after a lot of expenditure, to determine how to weigh certain factors, and how they weigh them in certain markets. And that's pretty essential, I think, to their business model. So I think every company would find that sort of information to be very highly proprietary.

SENATOR LESNIAK: One other follow-up question that the Chair asked -- and that is-- And I don't necessarily disagree with your answers. Actually, it's the answer I gave. But the Chair raises a good point.

GEICO is stating that there are over 20 but less than 30 criteria that they use.

SENATOR GILL: Size of a bread basket.

SENATOR LESNIAK: And maybe one of its competitors that have made some charges -- that they have categorically denied, in terms of them being the sole -- education and occupation being the sole criteria that they use -- could allege that they're hiding behind these 20-plus, when really 98.9 percent are education and occupation.

Staying within those proprietary guidelines, could we receive some level of assurance, with regard to the relativeness of -- not even interrelated, but the overall weight of the two criteria that could be, if abused -- could be considered objectionable?

COMMISSIONER GOLDMAN: Well, Senator, I'm sure you know, and I'm sure the Chair knows, that the basis of the submission of the information to the Department is on a confidential basis. To what degree we would be permitted, by law, to release that is something that I couldn't answer without, frankly, getting a legal opinion on. The regulatory function requires a great deal of proprietary information to be submitted. It's submitted in order to allow the Department, as the regulator, to carry out its function. It's not generally intended for public dissemination. And so before that, we could consider to what degree that might be permitted. We'd have to understand what the legal limitations and the ramifications, obviously, for ongoing regulation are. I mean, it's necessary to continue to perform the regulatory function. And if the submitters of the proprietary information felt, at some point, that in the future it's possible that information could become public, it would make the regulation function pretty much impossible.

SENATOR LESNIAK: Thank you.

I fully understand that answer.

And one last question, Madam Chair.

Obviously though, any information that was proprietary, based on the confidentiality agreement, could be made-- (interference from PA microphone)

You remember Morse Code? Were you in the Army with me? (laughter) It goes back to World War I -- I don't go back that far.

Certainly anything can be made, under that agreement, on proprietary, based on the agreement with the Department and whoever the applicant was, correct?

COMMISSIONER GOLDMAN: We would-- Again, I would want to make sure we were complying with whatever legal obligations we had before I answer that question.

SENATOR GILL: Any other questions of the Commissioner? (no response)

I just have a few.

A competitive market does not take -- does not trump a violation of underwriting if it's based upon race or income, does it?

COMMISSIONER GOLDMAN: A competitive market does not--

SENATOR GILL: Trump the consumer protections that you should not use in scoring. That you should not use, or cannot use, or consider race or income.

COMMISSIONER GOLDMAN: That's correct. But in approving the rating system, we obviously are very well aware of what the law permits and doesn't permit, in terms of the rating factors. And so we obviously take that into account when we look at the rating factor.

SENATOR GILL: And so when you looked at the rating factors, with respect to GEICO, did you analyze it to determine if those rating factors circumvented the prohibition against using income and race? Did they result in being able to use race and income by using occupation and education?

COMMISSIONER GOLDMAN: Well, I have two responses to that, Senator.

First of all, when the rate proposals were first presented to the Department, they were new to the Department. As I said in my testimony, these sorts of rating systems were new to New Jersey when they were presented. And so we had no history, then, of the potential -- I guess -- substitution or proxy of any of the factors for race or income. They were new. They hadn't been used in this state at all.

SENATOR GILL: Well, even though they had not been used in the state before, they had certainly been used in other parts of the country.

COMMISSIONER GOLDMAN: They had been approved widely across the country.

SENATOR GILL: And in other parts of the country, there had been challenges to the use, based upon the implication of race and income. Were you aware?

COMMISSIONER GOLDMAN: I don't know what the timing of that was, Senator. So I'm not-- I don't know.

SENATOR GILL: But even though the rating system may be new, don't you vet it to determine if that rating system would violate or circumvent the use of race, income, ethnicity, and the other prohibitions that are in the statute?

COMMISSIONER GOLDMAN: My understanding -- and I'm going to let Don Bryan address it.

SENATOR GILL: Okay.

COMMISSIONER GOLDMAN: My understanding was, and remains, that at the time that the rate system was presented, it was compared to the legal requirements that existed, including the preclusion of using race or income as a basis for rating. And it was found to be compliant. But I'll let Don address it further.

DONALD BRYAN: Thank you.

Just briefly, Senator, the insurers have not, for many decades, captured data about race as part of insurance applications. As far as income, that is not something that they capture in order to develop a correlation with income, etc. We don't have any data that can compare those factors with rates. What we do get is income -- excuse me. What we do get is data that addresses the requirement, under our law, that the rating system -- the rating factors demonstrably show the correlation between the risk of loss and the rating factor. And that's what we get.

SENATOR GILL: Do you take it one step further, like you would -- assume to be required here -- to see if-- Even if it's a correlation-- Let's say, for the sake of argument, that you can show the correlation between the risk factor and the characteristic. But that rating factor has an impact on -- a disparate impact -- on a racial group, and that those rating factors, by asking occupation, circumvent the prohibition of income. Was that a basic inquiry made by the Department of Banking?

MR. BRYAN: No, it was not. We do not have the data or the capability to be able to do a disparate impact factor, assuming that it would be relevant to our decision whether to approve the rating system or not.

SENATOR GILL: I would think -- correct me if I'm wrong -- that it would be -- should be extremely valid to your decision -- if something is race-based or income-based, because that's what is directly prohibited by DOBI, in order to protect the consumer.

That kind of evaluation was not made. And you say you don't have the ability to do it.

COMMISSIONER GOLDMAN: The problem is, Senator, we would need race data in order to be able to compare the impact.

SENATOR GILL: Can you tell me--

COMMISSIONER GOLDMAN: And we're not permitted -- and we don't think we ought to be -- to collect that sort of data.

SENATOR GILL: No, not that you collect it. But do you see if it has a disparate impact?

For example, we know that -- and we read the statistics about the college degrees, and the income level, and how GEICO puts certain blue collar, gray collar workers as least favorable. Did you make an analysis--

What weight was given to income? What weight was given to occupation and education in the rating by GEICO? What weight do they give those characteristics?

COMMISSIONER GOLDMAN: That's the proprietary information, Senator, that we didn't turn over to you, pursuant to your OPRA request.

SENATOR GILL: And did you, with that information that you had -- knowing what weight is given to income -- not income -- knowing what weight is given to occupation and education by GEICO-- Did you vet that to see if it violated the race and income statute?

COMMISSIONER GOLDMAN: In order to make the analysis you're suggesting that we make, we would have to make assumptions about the steps from education and occupation to income, and then from education, and occupation, and income to race. And we did not do that analysis, because we can't work on those sorts of assumptions. We have to work with the data -- the statistical data that's presented to us. And so we're--

SENATOR GILL: If you took the census -- and assuming what weight is given that you say we can't know -- and you're not telling because of these restrictions-- No one here knows. But we do know that, with respect to education, we don't have-- Seventy-four percent of the people in New Jersey don't have a college degree. And we know that, with respect to minorities, it's 87 percent.

Given that factor, you could just look on the census to see if they're going to use -- if they're going to weight -- whatever weight is going to be given that you can't tell the public, but the public is going to have to pay the price-- Whatever weight is given to this, let's look at the occupation, let's look at the education to see what -- because it's education as to degrees, it's not just one or two years. Let's see what potential impact, statistically, that could have. Because it is a factor that really the insured can't change. I mean, it is what it is.

So let's see if GEICO is giving it 10 points, those people who could be affected by it. And does it circumvent our public policy. You don't have to collect race data. All you have to do is go to the census, and you could go to the board of ed, or the board of higher education, or the Department of Education in New Jersey. They can tell you the racial breakdown, as well as the other breakdowns.

COMMISSIONER GOLDMAN: Let me respond a couple of a ways, if I might.

First of all, while we have not tracked the effect of the data as you suggested, we do keep track, by territory, of the results of rates, average premiums. What we have seen-- And we do that across the entire state. What we have seen is that in 12 of the 14 urban territories, rates have gone down. And we have seen that in the two urban territories where rates have not gone down, there have been very modest increases on average premiums in the range of $6 or $8. And we have seen that, on a statewide basis, premiums--

SENATOR GILL: Go ahead, I'm sorry, Commissioner.

COMMISSIONER GOLDMAN: That's all right.

And what we have seen, on a statewide basis, is that New Jersey consumers -- pretty much across the board, as I mentioned, 75 percent or so

-- have saved significant amounts of money as a result of the competitive market, which has grown directly out of the 2003 reforms.

SENATOR GILL: And how long has GEICO been using rate -- the criteria of education?

COMMISSIONER GOLDMAN: Since their entry into the market in 2004.

SENATOR GILL: In 2004.

COMMISSIONER GOLDMAN: Yes.

SENATOR GILL: So your data doesn't show the impact, yet, of what the policy may be, correct?

COMMISSIONER GOLDMAN: Well, I can't say that we have tracked the specific impact of those two rating factors, if that's your question.

SENATOR GILL: Yes, because--

COMMISSIONER GOLDMAN: No, we haven't. And we don't track the impact of any particular rating factors. But when we look at the market in whole, we see a very positive effect on the market, including, as I said, in the urban areas.

SENATOR GILL: Are you aware--

Are there any other questions?

I just have two more.

Are you aware of the class action suit filed against GEICO in Minnesota, based upon the effect of the occupation and education as a discriminatory factor, with respect to minorities?

COMMISSIONER GOLDMAN: I'm aware that it exists. I have not seen the complaint.

SENATOR GILL: Do you think that that would be an important item -- or at least to look at the complaint, to look at the documentation? Because it is, actually, a class action suit for all African-Americans in the United States, which would include New Jersey, and its impact.

So has the Department, as you know, made an investigation of that complaint?

COMMISSIONER GOLDMAN: We have not seen the complaint. No, Senator.

SENATOR GILL: Okay.

Senator Scutari-- Is that okay? You had a question.

Oh, he's going to defer to you, since you--

You have questions?

SENATOR SCUTARI: Just a couple, briefly.

Can you tell us what other companies utilize those factors, now, in New Jersey?

COMMISSIONER GOLDMAN: Education is used by eight companies in New Jersey.

SENATOR SCUTARI: Eight?

COMMISSIONER GOLDMAN: Eight.

Education and occupation, together, are used by two.

SENATOR SCUTARI: Can you tell me which companies those are?

COMMISSIONER GOLDMAN: GEICO, Electric Insurance, AMEX Insurance, Liberty Mutual, Liberty Insurance, New Jersey Skylands Insurance Association, New Jersey Skylands Insurance Company, Esurance

Insurance Company, and AmeriStar Insurance Company use education. GEICO and Electric Insurance use both education and occupation.

SENATOR SCUTARI: And how many companies do we have in New Jersey, currently, writing insurance?

COMMISSIONER GOLDMAN: Approximately 70.

SENATOR SCUTARI: There's 70 different companies now?

COMMISSIONER GOLDMAN: Yes.

SENATOR GILL: Are you two--

SENATOR LESNIAK: I'm sorry.

SENATOR GILL: Do you have any more questions?

SENATOR SCUTARI: I'm sorry.

Would education and occupation be covered in any of the other criteria that these companies utilize? Would it be-- Meaning, is that redundant? Is that a redundant factor, education and occupation, as opposed to some of the other factors?

MR. BRYAN: No, it's not. We have them do what's called a *multi-vari* analysis to show that each of the factors are -- stand alone, and are considered by themselves in being approved in their rating system.

SENATOR SCUTARI: Thank you very much.

SENATOR GILL: Senator Lesniak.

SENATOR LESNIAK: That does prompt -- thank you, Madam Chair -- this question, because I thought that in analyzing the rating criteria used to ensure that it's consistent with our statutory mandate, and particularly with regard to the prohibition against using race and income as criteria, that-- And I thought we were a little bit off base in focusing just on the occupation and education components -- that you really need to -- and I may be wrong on this. You really need to look at the impact of all of the criteria together. Because there may be other criteria that have an impact, intentional or unintentional, in the opposite direction.

Is that a fair assumption, that really all the criteria combined result in an impact, in terms of the market that each company is seeking, and whether it may or may not be violating any prohibitions in an indirect way?

MR. BRYAN: It's a difficult question to respond to. When we review a rate filing, we look at the separate rating factors and the support for the use of each one of them.

SENATOR LESNIAK: I understand.

MR. BRYAN: As far as the ultimate results-- A very interesting question is, does this mean that at the end of the process, is there an overall disparate impact on the whole system? I don't know how we could get that, because as I said, the insurers themselves don't collect race or income data. So we can't get it from the insurers. Whether you could get it from some other source, I don't know.

SENATOR LESNIAK: Thank you.

SENATOR GILL: Are there--

Oh, I'm sorry, Senator Cardinale.

SENATOR CARDINALE: You keep looking over to the other side of the room. (laughter) We are here.

SENATOR GILL: Are they--

SENATOR LESNIAK: At the beginning of the hearing you got all the questions.

SENATOR GILL: Are they to my left?

SENATOR LESNIAK: And first, as the ranking member.

SENATOR CARDINALE: I like that title, you know. Will you continue using it?

SENATOR GILL: Senator Cardinale.

SENATOR CARDINALE: You said that you don't collect racial data. What is the reason for that?

MR. BRYAN: I think it has been not collected by insurers at least since the 1950s. A few years ago, an issue came up about -- that dealt with inappropriate rates charged, based on race, among certain life insurers that we looked at. We looked back through our archives, and the closest thing we could find that was relevant was a bulletin from the commissioner in 1962, which referenced that this data hasn't been collected in some years, but that there was apparently some continuing results of that in rating systems. And he was directing that insurers eliminate that. That was 1962. And so I would not think that the use of that -- use of racial data would be appropriate to be collected because of the possibility of it being misused.

SENATOR CARDINALE: If you were to issue a directive to all of the companies that report to you, and require them to provide racial data, would there be any law in New Jersey that we would be violating if you did that?

COMMISSIONER GOLDMAN: Well, since the law prohibits them from collecting it, I don't know how they could comply with such a demand in any case. So I don't know.

My answer to your prior question, I think, would be a simple one. It was in an effort to make sure that the relationship between a potential insured and the company was not based on race. And so, therefore, you didn't want the data collected.

SENATOR CARDINALE: It's my impression of the law in New Jersey -- and not being a lawyer, sometimes I don't know all of the answers to the questions I ask.

But my impression is that it would be bordering on, if not an actual violation of the law -- if the Department worked backwards to try to create a racial component to their approval process. If we're not allowed to use race, and then we evaluate the various criteria with respect to the impact on racial groups, that would seem, to me, to violate if not the letter, certainly the spirit of the law. We don't want to make race a factor in the determinations of the Department. And it occurs to me -- and I don't think it's intentional. But I think what the Chair has asked you -- were you able to do it if you even had the data on which to do it -- would be an improper exercise under the law.

SENATOR GILL: That wasn't my question, but it would be-- That was not my question.

SENATOR CARDINALE: I misunderstood your question.

SENATOR GILL: That's okay.

But I do have this question. We're not asking to collect racial data, because you can't collect racial data the same way you can't use an underwriting technique to circumvent the prohibition against race. So that's why it is important. But you can look to other statistics, with respect to income level and education, to determine, based upon the weight given by the insurer, if this violates our policy, circumvents it, with respect to race and income.

So it is not the issue -- kind of like a red herring -- of collecting racial data. It is to look at the criteria and see if it has a racial impact -- disparate racial impact, which is very easy to do -- and to look at the income requirement -- or look at the occupation requirement and see if it violates the prohibition against income.

So I'm not asking that the insurers collect racial data. I'm saying that you -- since we have a public policy -- that you vet the criteria against that public policy to see if it violates it in any way. And that's the thrust of my position. I'm not asking you to collect, but certainly to be able to make some determination if it violates it in any way.

SENATOR SINGER: Madam Chairwoman, even though I sit on your right, just one--

What I'm trying to figure out is, if you took a look at the census, which is public information and something you have access to, and you take my district, which has the high percentage of noncollege graduates, which is probably -- statistically, probably 15 percent minority in my district -- my district-wide is only about 15 percent minority -- and took a look to see the percentage of people that are insured by one of the insurers, based on their criteria; and then you went to Senator Cardinale's district, who is probably--

What percentage of minorities are in your district?

SENATOR CARDINALE: About eight or nine.

SENATOR SINGER: --8 or 9 percent, with the highest percentage of college graduates. And then you went to the Chairwoman's district, and so forth, and so on. By just taking a look there, you could see if, by using those two criterias, there's disproportionate less people in, for example, the Chairwoman's district being insured by that company than in my district, or vice versa. And taking a look at that, get some type of criteria to determine whether, based on just strictly the census, you're seeing that that criteria is used in an improper way to give people with less college degrees nonaccess to discount insurance, or people -- minorities less access to that. By not violating any laws, by not using any information that's not public information, but just using statistics of our five districts -- to have some portion, to see if there is any disparity based on that.

COMMISSIONER GOLDMAN: I'm neither a statistician or an actuary, so I don't know how broad a base you would have to sample in order to make a valid determination of those kinds of numbers; or what kind of formulation, in order to have a valid approach to it, you'd have to have in order to do it. I can tell you that we in the Department are not equipped to do it.

SENATOR GILL: But you are charged with doing it.

COMMISSIONER GOLDMAN: Well, we're charged--

SENATOR GILL: And you're charged-- You're charged with saying that you cannot discriminate.

COMMISSIONER GOLDMAN: We have not seen, Senator, in the information we've gotten, any sense that this sort of discrimination that you are expressing your deep concern about is happening out there. We have gotten nearly no complaints on either criteria.

SENATOR GILL: People don't realize. That's why you haven't gotten complaints, because people don't realize.

COMMISSIONER GOLDMAN: But they've also seen reductions in their rates.

SENATOR GILL: People don't realize that they're being charged with respect to education.

But I have one more question, and then we'll move on.

COMMISSIONER GOLDMAN: Sure.

SENATOR GILL: Did the Department simply accept the actuarial information provided by GEICO, or did the Department undertake an independent actuarial review, or did the Department use an independent actuarial review or information to compare the legitimacy or correctness of GEICO's business plan information?

COMMISSIONER GOLDMAN: We did not independently verify with GEICO; and we don't independently verify, with any submission, the information that we are given. And the reason for that is because that same information is what the company uses in order to make its determination on pricing decisions. That determination has ripple effects, in terms of what it reports in its financial statements to its -- in the case of a public company -- the Securities and Exchange Commission. It's what the management of the company relies on in formulating its business.

So if we're-- First of all, we're without the resources to undertake that depth of examination. And we feel we have a pretty good basis to accept the validity of the information, because it's the premise upon which the company is operating.

Now, I guess if they're fraudulent in submitting it to us, and the ramifications of that are fraudulent elsewhere in their model and throughout, they're going to run into trouble at some point in the not-too-distant future. And we'd see it then. But we certainly don't have the resources to undertake the kind of independent verification you're suggesting.

SENATOR GILL: And I only have one more question.

The issue is not that it's fraudulent. But across the country, we understand and see that the use is having a disparate impact, in that the-- If you simply accept what any insurance company states, without any independent verification mechanism, then I would suspect that the Department of Insurance becomes a rubber stamp without being able to determine, in advance, if the insurance company is violating the public policy and the prohibitions as stated in the statutory scheme. Is that a correct statement?

COMMISSIONER GOLDMAN: I don't think so. There were-- And I'm going to let Don address it.

But we do ask for changes in what's filed. We don't just rubber-stamp it and send it out the door. We do have meetings, we do confer with the companies. We don't just accept the plans as filed. If I gave that impression, that's a misimpression.

SENATOR GILL: But you don't have any independent actuarial information in order to determine if the information given you, with respect to the risk of the characteristics of a particular group, is verified in a way that's appropriate? DOBI has no way of having an independent assessment?

MR. BRYAN: Just briefly, we do get premium, and loss, and other statistical data, from statistical agents, that are filed. We do get information from several different companies that file data with us in support of various rates. We do have a financial examination process that we use. That's a periodic exam every three years or so. We occasionally, in response to specific kinds of issues or problems, do a market conduct examination, where we go in and seek more detailed verification of data that we get. If that's helpful in responding to your inquiry--

SENATOR GILL: It is, because it answers my question that you don't get independent verification. You have no idea as you sit here, I would assume, if the risk characteristic presented by GEICO as to the education level or occupation is, in fact, valid. The risk characteristic -- not the correlation, but the risk characteristic. As you sit here today, we don't have an independent assessment of that?

COMMISSIONER GOLDMAN: Well, when you say we don't have a validation of the risk characteristic, what's presented to us is an actuarial analysis -- a statistical analysis -- of that correlation between what the characteristic is and its reflection in lost costs.

SENATOR GILL: And you have no way to determine if that is, in fact, accurate.

COMMISSIONER GOLDMAN: We have no way to determine the veracity of it, is that what you're asking?

SENATOR GILL: Yes.

COMMISSIONER GOLDMAN: We do not independently, as I said, determine it.

SENATOR GILL: And are you aware that there is a statistical study that was completed that indicates just the opposite? That the people who -- the five professions that are the worst risk: doctors, lawyers, clergy, and two others. And the people who have the lowest risk factor, by characteristic, are housewives, blue collar workers, and others. So in the marketplace, there are two completely different statistical, actuarial conclusions. And I would assume DOBI was aware of those.

COMMISSIONER GOLDMAN: That would not be correct. We are not aware of the second one that you referred to. We've never seen it. The first I heard of it was today.

SENATOR GILL: Well, you know, I would be more than happy to supply it to you.

COMMISSIONER GOLDMAN: That would be fine. We would like to see it.

SENATOR GILL: Good. And then perhaps we can have a further conversation on the validity of what was given in the beginning, what is out there now, and what DOBI may intend to do or not intend to do to actually vet it.

So I will have my staff supply it to you by Thursday. I think we're back again on Thursday.

COMMISSIONER GOLDMAN: Thank you. We would appreciate that.

SENATOR LESNIAK: Madam Chair, may I--

SENATOR GILL: Oh, yes.

SENATOR LESNIAK: One last point, because it all-- Now things are starting to become a little bit clearer here.

It makes a lot of sense to me that there would be two different studies on this. You testified earlier that only a handful of companies use education and occupation, or both of them. And many of them do not. Well, it makes sense to me that there would be two different studies out there. And if the study that GEICO is using is right, they're going to make money. If the other study is right, they're going to lose money. And they'll adjust accordingly. And that's what the whole reforms are all about, in terms of bringing competition in. And people can choose what they think is best to service the populous. And that seems, to me, to be the best way that we get the results that you talked about, in terms of premiums going down, or certainly not increasing at the alarming rate that they have been over the previous decades. And I certainly see that in my district.

I just want to make a point, Madam Chair, that this gets to be a little dicey. Not as much with regard to the disparate impact on race, which I don't understand completely the constitutional law on that -- whether that alone, in and of itself, is unconstitutional. But on the income factor, which is statutory in nature, and not constitutional in nature, I'm just looking at-- What if a company wanted to, and they may, weigh against 17- to 25-year-olds, weigh very much in favor of 45- to 60-year-olds, and very much against 65-year-olds and up? That certainly would have a disparate impact on income. I could say that 17- to 25-year-olds aren't making that much money, and 45- to 60-year-olds are. The over 65 maybe aren't. Now, does that mean that because I do that, that I am violating the statutory prohibition against using income? No.

Statistics are very, very, very tricky, as we in politics know, in terms of polling and other things that we use in terms of elections. I just wanted to make that point.

COMMISSIONER GOLDMAN: There is one point that you make, Senator, that I think is worth keeping in mind. And that is that, if certain companies decide that a particular statistical model is going to be the basis for what they determine to price their products based upon, and they're wrong, the market is going to tell them that they're wrong, because they're going to be losing money. And if the statistical model that you referenced is the correct model, and the result of the people who use that model is that they're right, then the market is going to tell them that they're right, because they, hopefully, will be making money.

So I think you have an objective measure of how well these models do or don't work, based upon whether or not their success in the marketplace-- And I think the point that I was trying to make in my testimony was that what we've seen since the reforms is that the marketplace is telling us that the reforms have been successful, because a very, very wide swath of the people who buy auto insurance in New Jersey have benefited greatly. And that's the principal point.

SENATOR GILL: And I think that if we use that analysis, and take it to its logical conclusion, red-lining a district with -- let's say in the mortgage industry -- was profitable, because the mortgage companies did not have to give mortgages in urban areas, because they said there was a risk factor. However, there was a public policy that said it is an act of discrimination, because it has a disparate racial impact on a group of people.

So it is not simply that they can make a profit. But a public policy here is, how do you make that profit? And you cannot make that profit off of the impact on race in the use of income. And that is where DOBI, I think, becomes crucial. Because it's not GEICO's fault. They're here to make it however they can make it, with respect to the regulatory powers and sanction.

And we do know that the other insurance company says, "If GEICO can do it, we are going to do it." And so that is why DOBI is -- and that's why transparency is so important. You are the only thing standing between the desire to make money -- this is why we're not GEICO-bashing -- and protecting our public at the same time. And so that's how I see it, and that's how I see the position of DOBI. So it's not the insurance companies, because they're here to make a profit. It's our obligation to say, "You can make a profit, but you can't make it this way."

COMMISSIONER GOLDMAN: Senator, we agree with you. We are keenly aware of our responsibility to protect the consuming public. And we do everything that we can to make sure that that happens. So I don't have a single disagreement with you about the obligation of the Department to regulate, in a way.

And I think, as I mentioned early on in my testimony, there were three factors. And consumer protection was one of those three, and maybe the most important of those three. But all of them interrelate, and we can't have-- (interference with PA microphone)

SENATOR LESNIAK: I didn't do it. (laughter)

COMMISSIONER GOLDMAN: Part of consumer protection, as I said, is to make sure that the product, particularly where it's mandated by law, is available and it's affordable. But I don't, for a moment, intend by anything I've said to minimize the responsibility of the Department to protect the consuming public. We're keenly aware of it.

SENATOR LESNIAK: Madam Chair, if I may just-- Please.

I did not hear everything that you heard from the Commissioner. I heard him say-- I didn't hear him say that profitability was the key. He said that in our districts, in urban areas, that insurance has become more affordable and more available. So it's not exclusively the profitability of the insurance companies. I certainly wouldn't lend that as the criteria that we should make our decision on.

SENATOR SCUTARI: You told me earlier that there were 70 companies writing automobile insurance in New Jersey today?

COMMISSIONER GOLDMAN: Approximately. I think the actual number is 69, but I'm not sure.

SENATOR SCUTARI: Does that count GEICO more than one time, or is that--

COMMISSIONER GOLDMAN: Yes, that includes all of GEICO's companies.

SENATOR SCUTARI: What I'm saying is, in that figure of 70, is GEICO counted four or five times, or GEICO once?

COMMISSIONER GOLDMAN: They've got three, I believe.

SENATOR SCUTARI: Three.

COMMISSIONER GOLDMAN: They have three different companies -- GEICO does -- who are writing insurance in New Jersey.

SENATOR SCUTARI: Okay.

SENATOR GILL: I have no further questions, except I want to hope that we will get -- we will write you formally to ask for the weighting factor. And we will ask you formally, in writing, if at least this Committee can see what is determined to be the proprietary information, with respect to how much -- the weight given to education and occupation.

And we would also provide to you the new study and ask that you respond, in terms of the validity of the information that we're not allowed to see, and you're not allowed to talk to us about, and the public doesn't know but for which they are rated and, ultimately, for which they will pay. So we will do that formally in writing.

I'd like to thank you. I'd like to thank you for your patience.

Thank you very much for appearing.

COMMISSIONER GOLDMAN: Thank you.

SENATOR GILL: Do you have any further questions? (no response)

Thank you very much.

COMMISSIONER GOLDMAN: Thank you.

SENATOR GILL: We have one last panel of witnesses, and we'll take them all at one time.

MR. LORETTE: For the last presenters, it's a panel of four representatives of insurance trade associations. The panel consists of Chuck Leitgeb, Vice President with the Insurance Council of New Jersey; Richard Stokes, Regional Manager and Counsel with the Property Casualty Insurers Association of America; Paul Tetrault, Northeast State Affairs Manager with the National Association of Mutual Insurance Companies; and, finally, Richard Van Wagner, for the American Insurance Association. And also present at the table is Magdalena Padilla, the President of ICNJ.

SENATOR GILL: Thank you.

You can identify yourself for the record.

MAGDALENA PADILLA, ESQ.: Good afternoon.

My name is Magdalena Padilla, and I'm the President of the Insurance Council of New Jersey.

I'll take this opportunity and note that to my right is our Vice President, Chuck Leitgeb, who is normally before your Committee. And out of courtesy to one of our fellow colleagues, who doesn't have a seat at the podium, Chuck has graciously agreed to let one of our other colleagues come up instead. The trades work very closely with each other.

RICHARD J. VAN WAGNER: Thank you, Madam Chairwoman, members of the Committee.

I'm Richard Van Wagner, on behalf of the American Insurance Association. I appreciate, I think, the invitation to speak here today.

I'll be brief. I don't have a tremendous amount to add.

We certainly believe, and I think it's been stated many times here today, that this is a healthy, and healing, and competitive marketplace. I understand completely, and would never minimize, your desire as a body and as a Chairwoman of a very significant Committee, to look into issues that you think may not be all that adequate, or may not be addressed adequately in the marketplace.

I would suggest though-- We feel that something that's really increased in the several years in New Jersey is capacity in this marketplace. And I hesitate to sound glib when I say this, but four years ago, when we started to lobby this -- and I think Senator Singer put it best when he opened up earlier and said, "I don't get the calls anymore in my office." And as we pursued that reform act, if someone said then, "Hey, four years from now, here's where you're going to be at, though," I'd still take it. Because we've come that far in this market.

So I would just caution that while I understand, and certainly respect and appreciate, your inquiries and investigations into the market, and hope they all work out satisfactorily-- Before we go jumping in and enacting more statutory restrictions on insurers ability in the marketplace, remember easing them several years ago. It's really helped. And today is pretty much, I think, a product of the successful reform you all passed several years back.

And with that, again, I don't really have any more specific comments. I'm certainly here to answer any questions.

SENATOR GILL: Thank you very much.

We're not here to actually turn back the reforms. But we are here to address the statutory requirements. And one of which is that no underwriting rule shall be based on the lawful occupation or profession of an insured. And that is a statutory responsibility that was part of the reform for the industry.

And so that is our inquiry at the Committee. It's not to create more regulations, but to understand if the regulations that are in place are being followed. And so when we have that regulation in the Banking administrative code that says no underwriting rule shall be based on the lawful occupation or profession of an insured, and we have information that it is being based on that, in whole or in part, what we are here doing is to find out if the regulations that we passed, in conjunction with the changes in the market, are being followed.

So it's not an addition, it's an enforcement. And that is the perspective that we are inquiring.

MR. VAN WAGNER: And just my last note on that--

Madam Chairwoman, I would agree. And also, I think that even before the reform act, there were statutory -- there is statutory authority for the Commissioner to always look into individual issues -- rating, underwriting plans, whatever they may be -- and whether or not they amount to discriminatory, race-based underwriting, or whatever the case may be.

So I appreciate your comments. Thank you for the line.

SENATOR GILL: And so for all of you.

I assume that that will be the testimony for all.

MS. PADILLA: Yes.

Senator, we would also just like to add that the Insurance Council of New Jersey -- that the signals that New Jersey sends are very important, not only to the rest of the country, but the citizens here in New Jersey. And in 2003, the signal sent in June was that the State was ready for competition. And so while we certainly recognize that all of the questions raised today are very important, it's equally important to continue sending the right signal, continue sending the message that New Jersey is ripe for competition in New Jersey, and that we do want to encourage the kind of competition we have seen since 2003, and we don't want to go backwards.

SENATOR GILL: And we don't want to have competition based on race, and we don't have to have competition based upon violation of our own underwriting laws.

So there are messages that we are sending. And I think both are important. But I don't think, under our -- and I've worked closely on that insurance reform -- they're not mutually exclusive. We say, "You can have competition, but you can't discriminate in this way." They're not mutually exclusive, nor does it impact on the market. Because we already analyzed that before we passed the reform. And we said, "You can have competition, but you can't discriminate." And that is the basis. If you look at all the insurance reform, that's the basis of the competitive nature that we allow to exist.

So we'll follow through. And we do thank you for your testimony.

MR. VAN WAGNER: Thank you, Madam Chairwoman, members.

MS. PADILLA: Thank you.

SENATOR GILL: Any other comments? Any other witnesses? (no response)

Thank you very much.

You're adjourned.

(HEARING CONCLUDED)

APPENDIX

NEW JERSEY CITIZEN ACTION

Testimony
Senate Commerce Committee
Phyllis Salowe-Kaye
Executive Director, New Jersey Citizen Action

New Jersey Citizen Action is very concerned that the Government Employees Insurance Company (GEICO) is using rating methods and underwriting guidelines that have serious adverse effect on minority consumers and lower income New Jersey residents . These practices might also be discriminatory under federal or state civil rights laws. We believe that state legislation is need to rectify the harm that has been done by a regulation that was promulgated by the New Jersey Department of Banking and Insurance in an effect to urge insurance companies do business in New Jersey. I am here asking you to ban the use of rate making methods that directly base eligibility and premiums upon the educational background and occupation of consumers. The use of this information results in unjustified increases in insurance rates for many lower income and minority residents of New Jersey.

GEICO, the nation's 4th largest auto insurer, has adopted rating methods and underwriting guidelines that directly base rates and elibilbity solely upon education and occupation in 44 or 50 states. New Jersey is one of the states. GEICO's underwriting guidelines not only directly harm lower income Americans, but also have an indirect negative effect on minority consumers. Under the criteria used by GEICO a factory worker without a four-year college degree in New Orleans would pay 90.75 percent more than an attorney with a graduate degree. Nationally the average "surcharge" being applied by GEICO for being poor is over 40 percent. In Princeton, New Jersey, a blue collar worker pays 32.49% more than a white collar worker ($455.00 vs. $604.00) for the same coverage.

A facially neutral practice that has an adverse and disparate impact on a protected class of people has been found to be a violation of civil rights laws. (For example, race-based premiums for the issuance and pricing of life insurance are prohibited in the United States, despite actuarial and statistical evidence that exhibits different life expectancies for different races. Although most life and property and casualty insurance companies nationwide stopped selling race-based policies in 1966, when basing rates on race became illegal under federal law, several life insurance companies were recently found to continue to use underwriting and pricing methods based upon race and were sanctioned accordingly.)

GEICO has concealed the negative effect of their practices on minority and lower income consumers through the use of underwriting guidelines based solely upon education and occupation. They are pulling an underwriting "slight of hand" that allows the company to get around the use of income and race to determine insurance rates. And in this case eligibility is based on a technically. Education and occupation are directly linked to income, and cannot be used in determining insurance elibility or rates because it would have a serious adverse impact on lower income and minority consumers. Yet GEICO is allowed to do this. Americans who hold a Bachelors' degree can earn an average $65,442 compared to $26,593 for those who have not graduated high school or $36,700 for those with a high school diploma but no higher education. According to U.S. Census data, high school completion for Hispanics aged 22-44 was only 64 percent, compared with 91 percent for Caucasians and African-American, respectively. These figures illustrate the disparate of nature GEICO's underwriting practices. Not everyone has the ability or opportunity to receive an education. Why should they be penalized and have to pay a higher insurance rate?.

GEICO uses four separate insurance companies- GEICO, GEICO General, GEICO Indemnity and GEICO Casualty. Each of these companies charges drivers different base rates. If a driver does not qualify for the preferred GEICO insurance company, that driver will get a quote from one of their sub-standard insurance companies and pay substantially higher rates.

GEICO places individuals whose highest level of education is a high school diploma in a group that is ineligible for the preferred rates at the GEICO company. The only coverage offered to this group by GEICO is through one of the sub-standard companies, which has significantly higher base rates. These individuals are not even informed that they are being rejected by the preferred GEICO company due to their educational or occupational status alone.

If a student's parent has the misfortune to have a job outsourced to India or lost to an event such as an employer's insolvency or natural disaster, that student may have to quit school to help the family. Why does this make the former student a worse driver?. This is just not fair. The response to our concerns has been, "Now that more companies are doing business in New Jersey consumers can shop around. They can choose an insurer who doesn't use education, occupation or credit scores in computing there rates".

The fact is, that in order to stay competitive, insurance companies will begin to use these factors in setting rates. In New Jersey, Liberty Mutual, N.J. Skylands, Electric and Amex Assurance are currently using occupation education or both in setting their prices. Allstate has also begun to use factors in four states.

If an insurer sees a competitor doing this and believes the competing will take away their richer clients, to whom they could sell home, life, boat insurance and banking products, the insurer may feel forced to adopt this approach. Low income and minorities are the ones who will get the short end of the stick it this happens.

We urge you to prohibit this practice before <u>all</u> insurance companies in New Jersey adopt this criteria. This use of occupation and education is simply a method to by-pass the deletion of "income from credit scores. This was to prevent any bias towards minorities and lower income individuals. Unfortunately, GEICO has found a way to get around this. The Legislator needs to be act quickly to correct this unfair situation.

NJCURE

A BETTER STATE OF CAR INSURANCE.

Eric S. Poe, Esq., CPA
Chief Operating Officer
NJ CURE
June 7, 2006

Dear Senator Gill and Respected Senators:

My name is Eric Poe and I am the Chief Operating Officer for NJ CURE auto insurance. NJ CURE is a direct writer of auto insurance founded in 1990 by former NJ Insurance Commissioner James J. Sheeran (1974-1982) and nationally renowned actuary Lena Chang, PhD. NJ CURE currently insures nearly 50,000 vehicles in New Jersey, collects nearly $50 million annually and ranks as the fifth largest direct writer in the State. I have worked in New Jersey's private passenger auto insurance industry for more than 12 years and am responsible for overseeing the operations of our 200 employee staff. My experience includes in-depth involvement with implementing rate filings, adopting and implementing new regulations, and dealing with the Department of Insurance on regulatory matters. I am a licensed attorney in New Jersey as well as a Certified Public Accountant.

In my opinion, a ban of the use of education and occupation as a factor to determine rates and underwriting rules for auto insurers is necessary to prevent discrimination against those who are less educated or work in blue collar industries that may have excellent driving records. This type of discrimination undeniably has a disparate impact on lower income and racial minorities. Furthermore, such a ban will pose no threat to the health and competition of the current New Jersey auto insurance marketplace.

This issue was brought to light through the discovery of the practice by GEICO when they re-entered the State of New Jersey in the Fall of 2004. Upon their re-entry, it was discovered through GEICO's company documents, that given identical information of a driver such as identical clean driving records, residential location, age, use and vehicle type, GEICO will reject drivers with lower education levels from their preferred companies and charge them higher rates. Similarly, GEICO will also reject drivers from their preferred companies on the basis that they are considered "blue and gray collar workers." Notably, the rejection of this driver from the preferred companies on the basis of their education or occupation alone is done without any notification to the applicant.

GEICO Example: In Newark, a male driver, age 31, without any accidents or tickets in 14 years of driving, owns a 2002 Ford Taurus LX. As a vice president white collar executive with a masters degree, he will be charged $1,596.60 annually for car insurance. In contrast, all conditions held constant, except this same clean driver simply chose to work in construction and had only achieved a high school diploma, GEICO would charge that same clean driver $3,279.60; an increase of over 105%.

For those unfamiliar with the auto insurance industry, it should be noted that any rating or underwriting practice approved for use by one auto insurer in the State can be adopted by all other insurers in New Jersey. In fact, this is the reason we support a ban of the practice, because we, as a car insurer in New Jersey, do not wish to be compelled to adopt such discriminatory practices in order to compete.

The ability for all carriers to adopt other competitor rating and underwriting methodologies should dispel any statements that attempt to isolate this into a "competitive choice" issue for consumers. If education and occupation are permitted as factors to determine rates and eligibility, every insurer in New Jersey can, and most certainly will, be forced to adopt the same underwriting practices, leaving those who are disadvantaged by this rating methodology without any choice to avoid higher rates.

The pressure to adopt these practices by other industry carriers will result because insurers will otherwise risk losing their educated drivers to competitors who use these factors to rate their policies, similar to the grand sweeping use of insurance scores, which was introduced in New Jersey in 2003.

My testimony will address two reasons that I hope will clarify why this legislation is necessary, and why it poses no risk to the profitability and health of the auto insurance industry in New Jersey. The two reasons are:

I. EDUCATION AND OCCUPATION STATUS DO NOT MEET REQUIREMENTS TO SEGREGATE INTO AN UNDERWRITING AND RATING CLASS;

II. THE BAN OF THIS DISCRIMINATORY PRACTICE WILL NOT AFFECT THE PROFITABILITY OR COMPETITION OF THE NEW JERSEY MARKETPLACE BECAUSE ONLY 4 COMPANIES CURRENTLY USE THIS DISCRIMINATORY METHOD

I. THE USE OF EDUCATION AND OCCUPATION AS AN UNDERWRITING AND RATING CLASS

Prior to GEICO's re-entry into the State of New Jersey, the use of education and occupation was never used by an insurance carrier to determine rates and eligibility.

According to N.J.A.C. 11:3-35.3 (c) 7, New Jersey auto insurers are prohibited from using a driver's lawful occupation as a class factor. This regulation currently states "No underwriting rule shall be based on the lawful occupation or profession of an insured...". Therefore, this regulation currently in place clearly identifies the use of occupation as prohibited as an underwriting or rating criteria.

Aside from the apparent deviation from this regulation, the reasons why education should not be approved as a rating class is explained as follows:

Subchapter 35, under N.J.A.C 11:3-35.3 (c) 2 states, "An underwriting rule shall be based on a reasonable and demonstrable relationship between the risk characteristic of the driver(s) insured and the hazards insured against."

Based upon this language, before a group of drivers can be separated and classed as a category of drivers which can be given different rates, the class itself must show more than simply a correlation to loss but it must also show that **the characteristic trait of the driver** being isolated is correlated to the **risk of loss** for which the insurance is purchased to protect against.

It is rather simple for a car insurer to claim it has "actuarial loss data" by simply showing that there are losses that can be drawn based upon a certain class and attempt to support the segregation of that class. However, the key is that they must also show that the characteristic trait of that class of drivers are correlated to risk.

> **ILLUSTRATION**: Recently, Quality Planning Corporation, a subsidiary of the Insurance Services Office (ISO) published a study of more than 15 million policyholders and two million claims that showed that those who live within one mile of a restaurant, car dealer, elementary school, or liquor store would have an increase in physical damage claims than those who did not. Their study showed that the increase in loss costs for people who lived within a mile of those establishments were between 18-30% higher than those who did not. On its face, it seems that this data would be the "actuarially supported data" that could be used to class drivers and charge them higher rates for car insurance.
>
> However, in New Jersey, a driver's residence (territory) is already used to calculate a driver's rate. So a study such as this which proposes that living near certain establishments justifies classing people in different rating tiers would be a **redundant classification** because urban city drivers, as opposed to suburban drivers, typically reside within one mile of a restaurant, car dealer, elementary school, or liquor store and to rate these same urban city drivers **again** into a higher rate class simply because they live within one mile of a certain establishment common in city areas would be unreasonable. Simple loss statistics of a specific group does not justify its use to class a group separately because an insurer still must show that the "characteristics" of drivers in that class, in and of itself, correlate to the risk and hazard of auto insurance. And merely living within one mile of a restaurant does not make someone a worse driver. In reality the reason losses are higher for those who live within a mile of such an establishment is because typically most urban drivers will live within a mile of a restaurant.

In order for an auto insurer to legally adopt the use of education level or occupation as a rating and underwriting tool, it would need to show evidence that higher education itself correlates directly to a lower frequency of moving violations, incidents, accidents or other hazards. A 2004 study done by Quality Planning Corp. matched Department of Motor Vehicle records with its own database of 15 million auto insurance policies to match incidents, drivers and occupations. It found the worst drivers by rank-- students, medical doctors, attorneys, and architects -- had twice as many accidents as the safest -- homemakers, politicians, pilots, firefighters and farmers - providing strong evidence that education is NOT correlated to risk.

II. THE BAN OF USING EDUCATION AND OCCUPATION FOR RATING AND UNDERWRITING WILL NOT HAVE AN EFFECT ON NEW JERSEY'S PROFITABILITY OR COMPETITION

Although the New Jersey Auto Insurance Consumers Choice Act (NJ AICCA) of 2003 provided a positive impact on the auto insurance industry for a number of reasons, it should be clear that the favorable profitability results in 2003 and 2004 are not a result of allowance by insurers to use discriminatory practices such as the use of education and occupation. In fact, NJ AICCA never even addressed the use of education and occupation as a rating and underwriting factor, so tying this legislation with this issue is illogical.

Education and Occupation are Socio-Economic Rating Factors That Have A Disparate Racial Impact

What distinguishes the use of education and occupation from other permitted rating factors such as age, gender, territory, driving history and usage – is that these permitted factors are not impacted by any socio-economic influence. Not everyone has the ability or opportunity to receive an education. In contrast, every driver has the same opportunity to get older (age), to move to a different area (territory), to improve their driving record through time (driving record) and use their vehicle in different manners (usage), which are valid classifications of risk by an auto insurer. According to 2000 U.S. Census data, the percentage of people age 25 and older who had a bachelor's degree was 24.4%. Overall, however, 26% of the White population over the age of 25 holds a bachelor's degree compared to only 14% of adult Blacks, and only 10% of Hispanics.

This is important because if insurance companies are permitted to provide lower rates to those with higher levels of education they would be knowingly, on average, providing better rates for car insurance for more Whites than Blacks and Hispanics regardless if each of these drivers had perfect driving records.

In conclusion, we urge the legislature to ban the practice of using education and occupation because we believe other auto insurers, such as ourselves, would be pressured to use these methods of rating, or risk losing all of our highly educated drivers to carriers that do use these methods. Without a specific legislative ban of this practice, the drivers of New Jersey may be subject to the incorrect regulatory interpretation of how certain classes of people can be segregated.

NJ CURE is proof that an auto insurer can grow successfully without the use of education and occupation. In fact, 4 out of the top 5 largest carriers in New Jersey have successfully insured nearly 44% of the cars in New Jersey without the use of this discriminatory practice. With only 4 insurers currently using education or occupation as an underwriting or rating factor, which comprises less than 19% of the entire market, such a ban will not affect the health and competition of the marketplace.

NJ CURE is a strong proponent of competition in the marketplace, just not a proponent of competing on these discriminatory grounds.

Eric S Poe

Sincerely,
Eric S. Poe, Esq. CPA
Chief Operating Officer
NJ CURE Auto Insurance

Insurance Council of New Jersey

ICNJ

ICNJ Statement to the Senate Commerce Committee
June 12, 2006

Good Afternoon Madame Chair and Members of the Committee. On behalf of the Insurance Council of New Jersey's member companies, I respectfully submit the following statement to the committee for its review and consideration.

The Insurance Council of New Jersey (ICNJ) is a nonprofit, insurance, research, information and advocacy organization representing 27 New Jersey licensed property /casualty insurance companies. Collectively, ICNJ member companies underwrite 93 percent of automobile insurance policies, 64 percent of homeowners' insurance policies, 34 percent of commercial insurance policies and 65 percent of worker's compensation policies in New Jersey.

Today, the Insurance Council of New Jersey is in somewhat of a unique position regarding certain issues relating to the use of education and occupation as rating factors used by insurance companies. GEICO and NJCURE, who have differing views on this issue, are both members of the ICNJ.

ICNJ's role today is to discuss the effect of competition in general and not to focus on any particular competitive issue -- such as how individual companies establish their premiums.

ICNJ believes the market reforms implemented in 2003 are working and benefiting New Jersey consumers. In the 10 years prior to the enactment of the reforms, more than 40 insurance companies left the state and two major carriers – State Farm and AIG were planning to follow suit. And consumers were finding it more and more difficult to purchase insurance. In short, the state was facing a crisis.

The Legislature's bold, bipartisan decision to reform the automobile insurance marketplace and ease some of the excessive government regulation promoted a healthier and productive business environment that allows companies to compete for business while offering consumers unprecedented choices and options when purchasing insurance.

Needless to say, the reforms implemented in 2003 have been working. State Farm and AIG both announced plans to stay in New Jersey. And for the first time in decades, we have seen saw new insurance companies coming to New Jersey to do business – 17 at last count.

In 2003, Mercury Insurance began writing policies in New Jersey. Esurance, an internet-based company, entered the market in 2005. We also witnessed the return of prominent national carriers like GEICO and Progressive.

In addition, companies already doing business in New Jersey – such as Liberty Mutual, First Trenton (now Traveler's of New Jersey), High Point and New Jersey Manufacturer's announced plans to expand business operations. Companies opened additional sales offices and appointed more then 1,500 agents and sales representatives statewide, creating more job opportunities for citizens.

More importantly, this new competitive market has resulted in a downward pressure on rates. To date, a half-billion dollars has been returned to state policyholders through dividends and rate reductions.

Because New Jersey now has a competitive marketplace, companies compete differently for consumers. ICNJ believes the diversity of rating programs offered by companies is a product of the 2003 reform law that started the transformation from a dysfunctional, non-competitive marketplace to a more competitive one. Perhaps it is no surprise that such a transformation inevitably would lead to some of the questions that are being asked by the committee.

In a vibrant and competitive marketplace new and different business techniques are utilized by companies so they can actively and aggressively compete for consumer business.

Companies are not all the same and the 2003 reform law recognized that a one size fits all regulatory approach was not effective and discouraged competition. Insurers should be free to compete and develop rating programs that make sense for their company and offer consumers real and meaningful choices. It is important to remember that these rating programs must be actuarially justified, reviewed and approved by the Department of Banking and Insurance.

It is equally important to remember that the 2003 reform law has empowered consumers and that a policyholder who is troubled with rates, services or practices of his or her current company now has a variety of companies to choose from in the market. The consumer is now in the drivers seat. And that is what competition is all about.

ICNJ respectfully urges the Legislature to refrain from imposing new restrictions on New Jersey's competitive marketplace and to let this dynamic market continue its growth and transformation.

We believe it would be a mistake to return to the days of a dysfunctional market that does not promote competition and choice. ICNJ believes it is imperative that this new competitive market be allowed to continue evolving under the watchful eye of the Department of Banking and Insurance.

Thank you for your attention.

PCI
Property Casualty Insurers
Association of America
Shaping the Future of American Insurance
28 West State Street, Suite 719, Trenton, NJ 08608

Testimony before the Senate Commerce Committee Regarding Underwriting Factors and Rating Systems Used by Auto Insurers

June 12, 2006

Chairwoman Gill and Members of the Committee:

Thank you for this opportunity to comment. Again, my name is Richard Stokes and I represent the Property Casualty Insurers Association of America or PCI. PCI is a national trade organization representing over 1,000 major insurers that provide insurance to policyholders in all property-casualty lines.

PCI is pleased to be here because of the positive impact that auto insurance reforms have had on consumers. We recently released a report on the impact of the reforms that we have attached to our testimony. Since the reforms were signed into law in 2003, 17 new companies have entered the New Jersey marketplace, the number of top 20 national companies has doubled, and over 1,500 new agents have been appointed by the carriers throughout the state.

We have also seen $343 million returned to policyholders and 47,000 new drivers, providing an additional $58 million to the support of the system.

More importantly, the 2003 auto insurance reforms have benefited all consumers, especially those in the urban areas. They have lower and more stable auto rates, greater ease in obtaining coverage, and there is greater competition in the system. This all provides greater choice and access to insurance products.

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It was only a short time ago when State Farm announced its plans to leave the state and actually started non-renewing more than 4,000 policies a month. For policyholders during this time, finding any company with capacity to provide coverage was difficult.

We think the changes we have seen in three short years are no less incredible and an important preface to the tools insurers use to underwrite and rate policies. How your determine risks and what part of the market you consider, are all important criteria insurers use to develop their markets. A part of this is their ability to use objective and credible underwriting and rating criteria.

PCI supports the ability of our members to consider underwriting and rating criteria that are objective, supported by statistical evidence and do not unfairly discriminate. A company's ability to properly underwrite risks is a critical component of a company's ability to succeed in the market. And when insurers are able to more accurately predict losses, the consumer benefits with lower rates, more choices in the market and greater market stability. All elements that we so desperately needed and wanted during the insurance crisis of a few years ago.

This is in our view what competition is about: permitting insurers to determine the risks they will undertake and permitting consumers to choose the insurance company they want to do business with. Not all companies use the same underwriting and rating tools and, as has been seen today, some companies may actually disagree about what tools to use. But we support the right of companies to decide which tools work best for them and their customers. We think this is positive and important as long as the overall goal is to benefit consumers. Anything less than the use of actuarially justified rating and underwriting factors create subsidies among consumers and eventually harm the marketplace by stifling competition and innovation.

We would be happy to answer any questions that you may have. We are unable, however, to discuss any specific company practice or activities.

Richard Stokes
Regional Manager and Counsel
609-396-9601

PCI
Property Casualty Insurers
Association of America
Shaping the Future of American Insurance

The Impacts of the New Jersey Automobile Insurance Competition and Choice Act (NJAICCA)

The Positive Effects of the New Jersey Auto Reforms of 2003

May 31, 2006

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- New Jersey consumers are benefiting from lower or more stable rates, more coverage availability, and greater ease in buying insurance.
- Urban drivers have more options in coverages and services, and can now buy insurance at more competitive prices.
- Thousands more previously uninsured drivers are now insured, contributing to the auto insurance system.
- New insurance investments are revitalizing the New Jersey economy and creating more jobs for workers.

Future Challenges

Executive Summary

For many years, New Jersey's auto insurance market was in a crisis mode, much to the detriment of its motorists. "Thousands of drivers were unable, for months at a time, to find companies willing to sell them policies."[1] Now with the passage of the 2003 New Jersey Automobile Insurance Competition and Choice Act, *"consumers are in the driver's seat"* throughout the state, especially in urban areas.

This paper describes some of the positive effects that have taken place as a result of the New Jersey Automobile Insurance Competition and Choice Act (NJAICCA), enacted on June 9, 2003. Certain provisions of this new law include the ability to get rate filings approved more quickly [i.e., the Department of Banking and Insurance (DOBI) must act on filings within a designated time period]; abolishing the "take-all comers" requirement; implementing strong anti-fraud measures; and offering additional tools to help consumers shop efficiently and effectively for insurance.[2]

New Jersey's drivers are the clear winners, thanks to the passage of the 2003 auto reforms. Not only are they receiving cost savings in terms of lower or more stable insurance rates and are getting more product and service options, but they also have the benefit of selecting from a wider array of insurance companies, including prominent, national carriers. Furthermore, consumers are able to shop more easily for insurance and readily understand what they are buying, and there are fewer uninsured motorists driving on the roads.

The NJAICCA has encouraged more insurance companies to set up operations throughout the state to serve a variety of market segments. This movement is especially significant in urban areas, as residents in the cities now have greater selection among carriers and coverages at competitive prices. The urban markets have additionally been bolstered as a new "Special Auto Insurance Policy" was created, making insurance more affordable for drivers with limited financial resources.

Indeed, new insurance investments are being made in all of New Jersey and more jobs are being created for workers, revitalizing the state's economy.

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[1] *The Record* (Bergen County NJ), "Car reform plan wins final OK; Victory for McGreevey," May 16, 2003

[2] Other provisions of the NJAICCA include: allowing insurance companies to use generally accepted industry methods of determining risk; allowing companies to retain more of their surplus before distributing dividends to policyholders or giving them rate reductions; lengthening the experience period used to compute "excess" profits; and establishing a 13-member commission to set up consumer information guidelines and monitor unfair and anti-competitive insurance practices.

Introduction

Greater Competition Among Insurance Companies Provides Greater Choice and Greater Access to Consumers

Competition in the market has improved since the NJAICCA went into effect, giving consumers greater choice among financially sound, national insurance firms and more availability of products and services. Larger companies have decided to enter or re-enter the state's auto insurance market. Of note are GEICO (the fourth largest insurer group in the country) and Mercury General Company that began offering auto coverage in 2004 and 2003, respectively. Mercury, a large carrier on the West Coast, was the first major insurer to enter the New Jersey auto market in over 30 years. This company, which operates in underserved urban areas, announced a commitment of $100 million in new capital to aid the troubling market[3] and is now writing thousands of policyholders.

Furthermore, after a 22-year absence from the state, the nation's third largest auto insurer, Progressive Group, returned creating two new entrants (known as Progressive Drive Insurance and Progressive Direct)[4] in late 2005. The mandate that regulators act more quickly on filings was the primary appeal influencing its comeback.[5] In addition, as of mid-April 2006, Unitrin, Inc. began transacting business in the New Jersey auto market through its direct subsidiary. Unitrin, whose philosophy is to better serve the needs and interests of consumers, attributes its decision to write business here to the passage of the NJAICCA.[6] All of these companies are among 17 auto insurers (including AMEX Assurance Company, part of the American Express Property and Casualty Group, and Esurance Insurance) that have become licensed to write business in New Jersey since the new reforms took place three years ago.[7] Not only does the entry of these insurers mean more coverage options for the citizens of this state, but it means more employment opportunities for workers as well.

In a statement made by the New Jersey DOBI, the number of top 20 national companies writing business in the state almost doubled since 2002.[8] Prominently known companies such as American International Group, Inc., State Farm and Travelers all abandoned their plans to leave the state after the NJAICCA became law; State Farm even decided to stop canceling 4,000 policyholders a month.[9] Now, all major carriers in New Jersey are striving to increase their presence in the market by writing new policies and/or expanding their insurance products, thanks to the NJAICCA.[10]

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[3] *Insurance Journal*, "Mercury to Travel N.J.'s Roads to Auto Competition," August 8, 2003
[4] Progressive Group
[5] *The Record* (Bergen County NJ), "Another auto insurer returns; Progressive's presence will give drivers more choice and possibly lower rates," October 4, 2005
[6] A.M. Best *Newswire*, "N.J. Auto Reforms Lure Direct Writer Unitrin to Market", April 18, 2006
[7] National Underwriter Insurance Data Services/Highline Data (National Association of Insurance Commissioners database)
[8] New Jersey Department of Banking and Insurance, *New Jersey Consumers are....In the Driver's Seat: 2004 Milestones and A Look Ahead to 2005*, February 2005
[9] State of New Jersey, "Governor's Auto Insurance Reforms Materializes," 2004
[10] New Jersey Department of Banking and Insurance press release, October 3, 2005

As an example, the state's largest auto insurer, New Jersey Manufacturers (representing 15 percent of the auto insurance market), recently expanded its operations by setting up a new 57,000 square-foot branch office in Hammonton, N.J. Drivers living in the southern part of the state now have more coverage availability, while at the same time more than 150 residents in the area have been able to find employment in this new facility.[11]

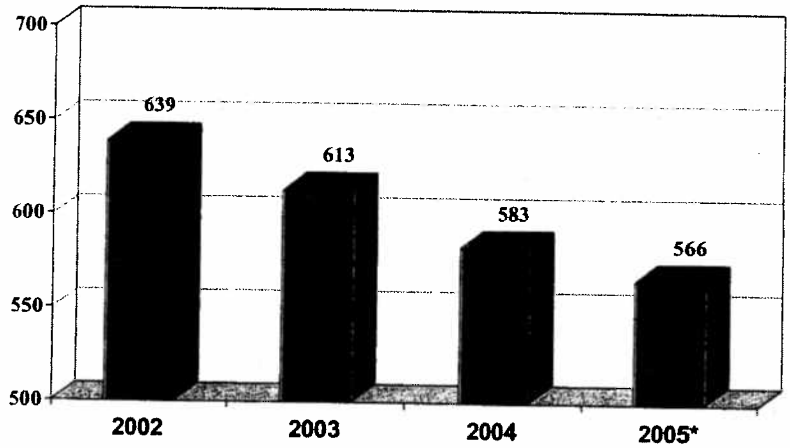
The city of Paterson is seeing additional rewards from the passage of auto reform, as Royale Insurance Agency became the first auto insurance agency to open in this area in over 20 years. Since Royale caters to the urban insurance market,[12] residents here are the beneficiaries of more products and services. According to agency president, Remberto Perez, "The 2003 auto insurance reforms are making a positive impact in urban communities. The reforms have resulted in more options for urban drivers. We are now able to offer these residents the ability to choose their insurance company, rather than companies deciding whether to choose them."[13]

In total, over 1,500 new agents have been appointed by carriers throughout the state, making insurance more accessible to New Jersey motorists.[14] By opening up new facilities and sales offices throughout the state and hiring more personnel, insurance companies and agencies are making new, much needed investments in the market to help bolster the economy.

The entry of the additional insurance companies along with the companies that have decided to remain have helped improve the competitive level in the state. According to the U.S. Department of Justice, the Hirschman-Herfindahl (i.e., Herfindahl) index used to measure market power shows that the level of concentration in the auto insurance market is becoming lower and lower (see Figure 1). This is a positive sign, as it demonstrates that no one insurance company or small group of companies is dominating the market and unduly influencing prices and availability. The lower the Herfindahl index, the greater the amount of competition which in turn places downward pressure on insurance rates.

[11] New Jersey Department of Banking and Insurance press release, April 4, 2004
[12] Royale Insurance Agency also operates in Guttenberg and Jersey City, New Jersey
[13] *Insurance Journal*, "N.J. Auto Agency Makes Drive for Success in Paterson," June 10, 2005
[14] New Jersey Department of Banking and Insurance press release, June 10, 2005

Figure 1
New Jersey Auto Insurance Market is Becoming More Unconcentrated (as Determined by the Herfindahl Index) Due to Auto Reform



Note: 2005 database is incomplete.
Source: PCI, based on National Association of Insurance Commissioners data

New Jersey consumers have benefited from lower or more stable insurance rates.

About $343 million have been returned by auto insurance companies to the nearly two million insured drivers in the state.[15] Specific examples of auto reform-related savings given by companies to their insured drivers include:

- United Services Automobile Association's overall auto insurance rates were reduced by 4.8 percent, lowering the average amount by $56 per vehicle for its 139,000 policyholders.[16]
- Liberty Mutual has returned over $28.5 million in dividends and rate reductions since the NJAICCA was enacted.[17]
- Allstate New Jersey returned $15 million to more than 200,000 policyholders in the form of dividends.[18]
- New Jersey Manufacturers decreased rates for 548,500 policyholders, saving them $4.5 million;[19]

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[15] *Philadelphia Inquirer*, "Time to deregulate N.J. auto insurance: The climate has improved since changes were enacted in 2003. The next step: Let the market do the driving," April 17, 2006
[16] State of New Jersey, "Governor's Auto Insurance Reforms Materializes," 2004
[17] Liberty Mutual Insurance Company
[18] *Insurance Journal*, "Allstate Returns $15 Million to NJ Drivers," July 19, 2004
[19] *Insurance Journal*, "N.J. Governor Again Hails Auto Improvements," April 7, 2004

- State Farm Indemnity Company put into effect a fourth rate reduction for its policyholders in 2005, saving them more than $132 million;[20]

- Selective Insurance Company also lowered its rates by 4.3 percent last year, saving its policyholders more than $6.4 million;[21]

- Chubb Insurance Company gave a 10 percent credit amounting to more than $1.1 million to a group of its drivers in 2005;[22] and

- Unitrin Direct's streamlined marketing efforts, as found in other states in which it operates, are expected to result in cost savings up to 20 percent if drivers switch to this company.[23]

The latest available data (2004) compiled by the National Association of Insurance Commissioners[24] show that the personal auto liability loss ratio in the state has greatly improved since the reforms. Although insurers still have not made an underwriting or operating profit on this line over the last decade, the trend in liability loss experience (see Figure 2) is an indication that rates for this coverage will not increase as much as in the past, or possibly become lower.

New Jersey's 2004 loss ratio of 69.9 percent (of earned premiums)[25] is substantially less than its 10-year average (1995-2004) of 81.3 percent. Lower loss ratios typically mean lower rates and, as highlighted above, this is precisely what policyholders in this state have seen since the NJAICCA went into effect.

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[20] New Jersey Department of Banking and Insurance, *New Jersey Consumers are...In the Driver's Seat: 2004 Milestones and A Look Ahead to 2005*, February 2005

[21] Ibid.

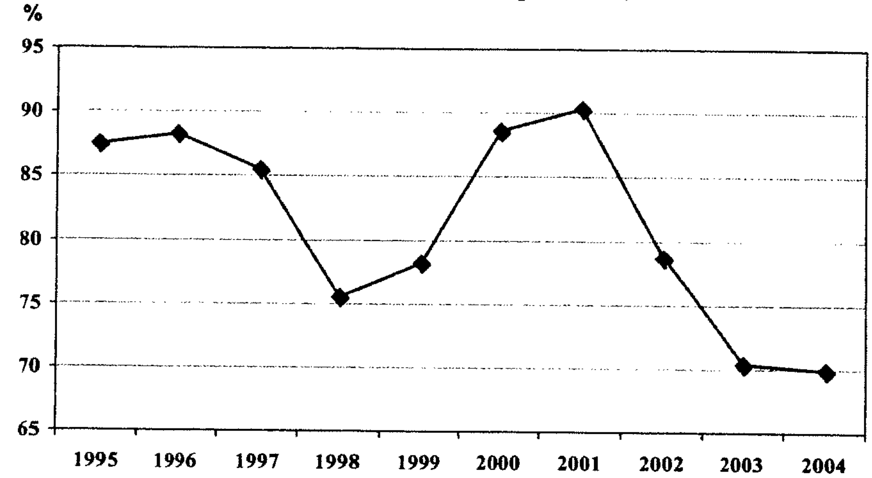
[22] Ibid.

[23] Automotive.com, "When Auto Insurance Competition Heats Up, Garden State Residents Win - Auto News from April 18, 2006"

[24] NAIC, *Report on Profitability by Line by State, 2004*

[25] A 65 percent loss ratio is typically the cut-off point where insurance companies are said to break even in underwriting.

Figure 2
New Jersey
Trend in Personal Auto Liability Loss Ratio
(as a percent of earned premium)



Source: NAIC

Even financial guru Warren Buffet, chairman of Berkshire Hathaway, claims that the New Jersey auto market is significantly improved compared to what it was prior to reforms.[26] ***Consumers now have access to an online program to give them information to better understand coverages, making buying decisions easier.*** Through the Auto Insurance Purchasing Planner, not only is there greater ease in buying insurance and more knowledge of what customers are getting for their money, but there also are more options in coverages and products available to them.

In addition, 47,000 previously uninsured drivers are now insured and contributing more than $58 million to the system.[27]

Part of this influx is due to drivers wanting to take advantage of more affordable coverage. Another reason for a greater number of motorists obtaining insurance is the Special Auto Insurance Policy introduced in October 2003.[28] This plan, which is especially helpful to low-income drivers (many who live in urban areas), is yet another successful consequence of the auto reform initiative intended to reduce the number of uninsured drivers in the state.

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[26] *Philadelphia Inquirer*, "Time to deregulate N.J. auto insurance: The climate has improved since changes were enacted in 2003. The next step: Let the market do the driving," April 17, 2006

[27] New Jersey Department of Banking and Insurance press release, November 22, 2004

[28] The Special Auto Insurance Policy (SAIP) is available only to those drivers eligible for federal Medicaid with hospitalization. It provides $15,000 of emergency care and $250,000 of medical coverage if the driver suffers a catastrophic injury. The driver's Medicaid benefits provide any non-emergency medical care. SAIP provides a higher and more certain level of reimbursement for trauma centers, which helps reduce the cost of the first-party personal injury protection coverage for other drivers. A portion of the premium for each of these policies goes toward a fund that compensates drivers who are injured by uninsured motorists. The policy also provides a $10,000 death benefit.

According to the latest PCI statistics (2001-2003)[29] available, New Jersey has an uninsured motorist (U.M.) population of about 24 percent. The recent increase in drivers with coverage has helped to lower the U.M. population in New Jersey; not only does this mean a healthier insurance environment as more drivers are protected and more money is being funneled into the pool, but it also helps to lower U.M. rates or keep them stable. Furthermore, it eliminates any time and hassle it may take for some insured motorists and pedestrians who are hit by uninsured drivers to get recovery for injuries or damages.

Future challenges

Clearly, the vastly increased competition resulting from the NJAICCA has dramatically improved the auto insurance market for New Jersey motorists, especially those in the urban areas. Although this three-year old law has revitalized the New Jersey economy and poured more insurer investments into the state, there is more to be done:

- A personal injury protection medical fee schedule still has yet to be adopted to help control medical costs. Auto carriers are, in many cases, paying exorbitant medical payments for surgical and ambulatory procedures that should be regulated by a schedule;

- The cost effects stemming from the weakened verbal threshold as a result of the June 2005 New Jersey Supreme Court ruling (in *DiProspero vs. Penn*) have not been addressed; and

- A new territorial rating regulation which has not been changed in over 50 years needs to be adopted to ensure fair and accurate rate levels throughout the state.

Although the auto insurance reforms are moving ahead for the benefit of consumers, the past – i.e., when the New Jersey auto insurance market was plagued with significant problems – should not be forgotten. In order to maintain a stable marketplace with competitive prices, it is important that the continued success of the 2003 NJAICCA reforms be ensured.

The Property Casualty Insurers Association of America (PCI) is a trade association consisting of more than 1,000 insurers of all sizes and types, and representing 40.7 percent of the total property/casualty insurance business and 52.0 percent of the total personal auto business in the nation. In New Jersey, PCI members represent 65.1 percent of the personal auto market.

[29] Property Casualty Insurers Association of America, *2004 Auto Compilation*

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Statement of Paul Tetrault, Northeast State Affairs Manager
Before the New Jersey Senate Commerce Committee
June 12, 2006

Thank you for this opportunity to express NAMIC's views regarding insurers' use of underwriting factors in private passenger automobile insurance. NAMIC is a full-service national trade association with more than 1,400 member companies that underwrite 43 percent ($196 billion) of the property/casualty insurance premium in the United States. In New Jersey, 113 NAMIC members including 25 companies domiciled in the state write approximately 27 percent of the state's direct written premium including approximately 27 percent of the auto insurance direct written premium.

NAMIC supports underwriting freedom and opposes limitations and restrictions on insurers' ability to underwrite freely. Underwriting, involving the assessment, analysis and pricing of risk, is the most fundamental function of insurance. Insurers need to be able to engage in this function as freely as possible in order for insurance markets to work properly, which ultimately benefits consumers and society in general Limitations and restrictions on underwriting freedom stifle innovation and thereby hamper competition, ultimately harming consumers and society in general.

NAMIC believes underwriting restrictions are cause for concern wherever they are proposed, but such concern should be particularly high when underwriting restrictions are proposed where there is a history of marketplace troubles. Prior to passage of the 2003 reform law, New Jersey offered a case study in the kinds of problems that can befall an insurance marketplace when insurers are not allowed to underwrite freely and compete effectively. Coverage was more expensive, it was harder to obtain, and insurers were trying to leave the market. The reform law has been successful in enhancing competition precisely because insurers have been given the freedom to underwrite they need in order to innovate and compete. Placing restrictions on insurers' ability to underwrite would threaten to reverse the substantial gains achieved and would therefore constitute a misguided step backwards for New Jersey.

NAMIC's views on this critical issue are more fully addressed in a NAMIC public policy paper that I have submitted to the Committee. The paper, "The Case for Underwriting Freedom: How Competitive Risk Analysis Promotes Fairness and Efficiency in Property/Casualty Insurance Markets" authored by NAMIC Director of Public Policy Robert Detlefsen, Ph.D., comprehensively discusses the role of underwriting freedom in the context of the insurance underwriting process, the benefits of underwriting freedom, and the detrimental effects of restricting that freedom.

Issue Analysis

A Public Policy Paper of the National Association of Mutual Insurance Companies September 2005

The Case for Underwriting Freedom:
How Competitive Risk Analysis Promotes Fairness and Efficiency in Property/Casualty Insurance Markets

By Robert Detlefsen, Ph.D.
NAMIC Director of Public Policy

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Executive Summary

In many states, property insurance prices are artificially manipulated through government regulation, ostensibly to make insurance more affordable and available to consumers. However, regulation that curtails insurers' freedom to set prices stifles competition and deprives consumers of the benefits that naturally flow from competition. The most obvious form of insurance price regulation is state-administered "rating laws," which require insurers to seek the approval of state insurance departments whenever they wish to raise or lower premiums. However, government-imposed underwriting restrictions – rules that curtail the ability of insurers to assess and classify risk – also strongly affect the price that consumers pay for insurance. Regulation that limits the ability of insurers to engage in risk assessment and classification has far-reaching implications for the entire insurance system.

Underwriting Freedom Benefits Consumers and Society

In jurisdictions where underwriting freedom prevails, insurers compete by trying to assess individual risks more accurately than their rivals do, and by refining their systems of risk classification, which permits them to more precisely forecast the losses that any given individual is likely to experience. Competitive, risk-based underwriting facilitates fairness in pricing, prudent conduct, widespread availability of coverage, and risk sharing among insurers:

- **Competitive Underwriting Leads to Equitable Pricing.** An insurer whose risk classifications are more refined than those of its competitors will be able to more closely align premiums with the actual level of risk that a policyholder presents. Low-risk individuals will be grouped together and offered premiums that are lower than those offered by insurers who lack accurate risk classification systems. High-risk individuals will be similarly isolated and charged higher premiums that reflect their higher loss costs. If other insurers do not respond by refining their own classification systems, they will lose their low-risk policyholders to their competitor's offer of lower premiums. Competitive underwriting is thus critical to insurers' ability to offer the lowest possible price to each insured, based on the level of risk he presents.

- **Competitive Underwriting Creates Incentives for Risk Reduction**. Competitive risk assessment and classification provide incentives for high-risk individuals to take actions to control losses, because doing so may result in lower premiums. Further, since risk classification involves the pooling of large numbers of similar risks, the insurer is often better able than any individual insured to discover less risky courses of conduct than those its insureds currently follow. Thanks to their superior access to loss experience statistics and greater ability to finance

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TURNING ISSUES INTO POSITIVE RESULTS

The National Association of Mutual Insurance Companies is a full-service trade association with more than 1,400 member companies that underwrite 43 percent ($194.6 billion) of the property/casualty insurance in the United States.

research into loss prevention methods, insurers may be able to suggest specific changes in behavior that will reduce risk and lower premiums.

• **Competitive Underwriting Increases the Availability of Insurance.** To market its products effectively, an insurer must utilize a risk classification system that will allow it to offer insurance to as many potential customers as possible. While competition is generally most intense for low-risk insureds, insurers seeking to improve their market penetration will also wish to compete for high-risk insureds within the same market. Increased market penetration provides economies of scale in the marketing and distribution of insurance, as it does for any product. Competitive risk classification therefore serves to increase the availability of insurance even for high-risk individuals, because the economic advantages of superior market penetration will accrue to those insurers whose refined risk classification systems permit them to price coverage in accordance with the expected costs of each identifiable class of risks within the markets they serve.

While competition is generally most intense for low-risk insureds, insurers seeking to improve their market penetration will also wish to compete for high-risk insureds within the same market.

• **Competitive Underwriting Facilitates Risk Sharing Among Insurers.** By accurately assessing particular risks, insurers can avoid situations in which they absorb more of a particular kind of risk than they are capable of indemnifying, effectively sharing such risk with other insurers. For example, competitive underwriting among insurers has led to the development of sophisticated risk-assessment techniques such as catastrophe risk modeling, which allows individual property insurers to avoid over-concentration in geographic areas prone to natural disasters.

Negative Consequences of Restrictions on Underwriting Freedom

Government restrictions on underwriting freedom ostensibly guard against unfair business practices and ensure that insurance will be available to meet market demand. In many instances, however, these regulatory interventions only create dysfunctional market conditions that are detrimental to insurance consumers. Among the more harmful distortions to the competitive insurance system caused by underwriting restriction are adverse selection, moral hazard, and cross-subsidies:

• **Adverse Selection**. Adverse selection occurs when low-risk insureds purchase less coverage, and high-risk insureds purchase more coverage, than they would if the price of insurance more closely reflected the expected loss for each group. When an insurer is unable to distinguish between individuals who have a low probability of experiencing a loss – either because it lacks the ability to accurately assess and classify risk, or because it is prevented from doing so by regulation – adverse selection is the likely result.

• **Moral Hazard**. Underwriting restrictions that prevent insurers from accurately assessing risk can create incentives for policyholders to conduct their affairs in a manner that is less risk averse than if they had no insurance. The most effective method of addressing moral hazard is to accurately assess and classify risk, varying the price of coverage according to the expected loss of each class of insureds. By making it more difficult for insurers to deal with the problem of moral hazard, restrictions on underwriting freedom increase overall claim costs, thereby driving up the price of coverage for all insureds.

• **Cross-Subsidies**. Underwriting restrictions weaken the link between expected loss costs and premiums, creating cross-subsidies that flow from low-risk insureds to high-risk insureds. In addition to the injustice entailed by such compulsory wealth transfers, cross-subsidization of insurance rates has a number of adverse consequences. When high-risk individuals do not pay the full marginal costs they impose on the insurance system, they lack incentive to take precautions to avoid loss. The net effect of misguided attempts to lower premiums for high-risk individuals through cross-subsidies is likely to be an increase in accident rates and insurance loss costs, adding to the inflationary pressures on insurance premiums.

Conclusion

The efficiencies that result from competitive, risk-based underwriting lead to increased price competition, and make possible the development of new coverage options tailored to the specific needs of particular consumers. By eschewing underwriting restrictions and allowing competitive insurance markets to flourish, state regulators would realize their common goal of ensuring that property insurance rates are "adequate, not excessive, and not unfairly discriminatory." Insurance rates that are determined by competition among insurers to assess risk with the greatest possible rigor, and to group similarly situated insureds into precisely constructed risk classes, cannot, by definition, be unfairly discriminatory. Nor could rates established through competitive, risk-based underwriting be considered "excessive," because the same competitive forces that promote underwriting accuracy also conspire to drive down prices. Far from improving the lot of property insurance consumers, government-imposed underwriting restrictions prevent consumers from enjoying the full range of benefits that come from unfettered competition.

Introduction: Underwriting Restrictions and Insurance Pricing

Most businesses operating in the United States enjoy complete freedom in deciding how much to charge for their products and services. The classic exception is the handful of industries in which exclusive private ownership of essential network facilities and equipment (such as pipelines, telephone lines, and rail lines) gives rise to "natural monopolies" that are impervious to the forces of market competition. The "market failure" that results from these circumstances provides a theoretical justification for government regulation of prices.

That justification is notably lacking with respect to property/casualty insurance. As numerous commentators have observed, insurance markets have none of the features of a natural monopoly; indeed, competition among insurers is robust in every line and product category. Nevertheless, in many states, insurance prices are artificially manipulated through government regulation. Invariably the intent of such regulation is to make insurance more affordable and available to consumers. However, what is true of other goods and services is true of insurance as well: A competitive market system is the most effective guarantor of low prices, widespread availability, superior service, and product innovation. Put simply, regulation that curtails insurers' freedom to set prices stifles competition and deprives consumers of the benefits that naturally flow from competition.

Insurance markets have none of the features of a natural monopoly; indeed, competition among insurers is robust in every line and product category.

The most direct method of insurance price regulation is the patchwork system of state-administered "rating laws," which require insurers to seek the approval of state insurance departments whenever they wish to raise or lower premiums. However, there is another component of many states' insurance regulatory regime that also strongly influences the price that consumers pay for insurance. These are underwriting restrictions – rules that curtail the ability of insurers to assess and classify risk. The close relationship between insurance underwriting and pricing is evident from a standard definition of underwriting:

> [Underwriting is] the process of examining, accepting, or rejecting

insurance risks, and classifying those selected, in order to charge the proper premium for each. The purpose of underwriting is to spread the risk among a pool of insureds in a manner that is equitable for the insureds and profitable for the insurer.[1]

Since underwriting is necessary to determine the "proper premium" for each insured, regulation that affects the underwriting process necessarily affects premiums as well. Indeed, insurers' prices and underwriting criteria are closely intertwined – as they must be in a competitive market. Insurers often distinguish themselves through their underwriting standards: "Preferred" insurers have the most stringent underwriting standards and tend to offer the lowest rates, while "standard" and "non-standard" insurers have less stringent underwriting standards and charge higher rates. Thus, in addition to directly regulating prices, imposing constraints on underwriting selection is another way in which government officials may attempt to override market forces in order to socialize insurance costs.[2] As economist Scott Harrington observes, restrictions on underwriting and risk classification "materially affect the rates charged to different buyers, even if competition largely determines average year-to-year rate changes."[3]

This paper seeks to demonstrate the indispensability of an unfettered underwriting process. It provides a non-technical overview of underwriting, examining it as a process for assessing and classifying risk. It explains how competition drives insurers to improve the accuracy of their underwriting methods, and how greater accuracy benefits insurance consumers and society as a whole. The paper also examines the political and economic factors that lead to the enactment of underwriting restrictions, and identifies the negative consequences that typically follow.

Overview of the Underwriting Process

Underwriting may be understood as a three-step process that consists of:

1. assessing the risk exposures of things such as people, dwellings, vehicles, and businesses;

2. deciding whether to select or reject particular risks for insurance coverage; and

3. classifying the selected risks within groups that pose similar risks.

The grouping of people and things with similar risk characteristics for the purpose of setting prices is a fundamental precept of any private, voluntary insurance system. In order to function, insurance relies upon group rather than individual estimates of expected loss. It is virtually impossible to estimate the expected loss of an individual automobile or homeowners insurance policyholder, because an individual's previous loss experience is simply not credible enough statistically to warrant such an estimate. Indeed, no single individual can truly be said to have an expected loss probability; instead, underwriters use statistical analyses of groups to determine the average loss probability for each group member. Only when a person is treated as a member of a similarly situated group can insurers predict his expected loss. Without group probabilities, it would be impossible to set a price for insurance coverage at all.[4]

The grouping of people and things with similar risk characteristics for the purpose of setting prices is a fundamental precept of any private, voluntary insurance system.

The issue, then, is not whether insurers should be allowed to treat individuals as part of a group for risk assessment and rating purposes, but whether they should be allowed to classify individuals within a system of smaller groups constructed to reflect varying levels of average expected loss probability, or risk. In the absence of competition from other insurers, an insurance company could simply charge each individual a premium based on the average expected loss of all its insureds (plus a margin for profit and administrative expenses) without incurring the cost of assessing and classifying risk. Every policyholder would pay the same premium, regardless of his particular level of risk.

However, when many insurers vie for the dollars that people are willing to spend to protect themselves against risk, insurers compete by trying to assess individual risks more accurately than their rivals do, and by refining their systems of risk classification. This allows them to more precisely forecast the losses that any given individual is likely to experience. An insurer whose risk classifications are more refined than those of its competitors will be able to more closely align premiums with the actual level of risk that a policyholder presents. Low-risk individuals will be grouped together and offered premiums that are lower than those offered by insurers who lack accurate risk classification systems. High-risk individuals will be similarly isolated and charged higher premiums that reflect their higher loss costs. If other insurers do not respond by refining their own classification systems, they will lose their low-risk policyholders to their competitor's offer of lower premiums. Competitive risk classification is thus critical to insurers' ability to offer the lowest possible price to each insured based on the level of risk he presents.

Examples of Underwriting Criteria that Critics Have Sought to Restrict

Whether because they doubt that certain underwriting criteria are truly related to risk or simply because they regard them as politically or socially undesirable, policymakers and consumer activists have advocated – often successfully – that certain classification systems or rating factors be banned. Risk assessment and classification criteria that have encountered opposition include territorial rating, the age of a dwelling (in homeowners insurance), and consumer credit history. Laws that prevent consideration of these variables are detrimental to the underwriting process, because each is highly relevant to determining both the likelihood that a given individual will suffer a loss, and the probable magnitude of such losses:

Territorial Rating

Territorial rating is used by providers of automobile insurance to take account of geographic differences in the frequency and severity of auto insurance claims. Statistical analyses of the factors that contribute to accidents and claims consistently reveal stark differences among geographic territories.[5] Accidents are much more frequent in urban areas because of greater traffic density and more hazardous driving conditions. Likewise, the severity of bodily injury and physical damage claims tend to be greater in urban areas, as is the cost of medical and auto repair services. The incidence of vandalism and auto theft, which affects claims under auto comprehensive coverage, also is higher in urban areas. Finally, the tendency to litigate is greater in urban areas, which further adds to insurance costs.[6]

Territory is also an important risk factor for homeowners insurance. Homes located in geographic regions that are unusually prone to devastation by natural forces such as tornadoes, floods, earthquakes, and wildfires are more likely to suffer losses than homes located in areas that do not have a history of such calamities. Under a system of competitive risk classification, insurers would place homes located in areas with a history of natural devastation in higher risk classes for rating purposes. Conversely, homes located in areas that are relatively free of environmental hazards would be grouped together with other low-risk insureds – and their owners would be charged a premium commensurate with the pool's lower probability of loss. Indeed, if a particular territory was known to be extremely hazardous – for example, if devastating hurricanes occurred every year for the past 100 years – an insurer might refuse to offer homeowners insurance at any price.[7]

Competitive risk classification is thus critical to insurers' ability to offer the lowest possible price to each insured based on the level of risk he presents.

One of the biggest misconceptions about insurance is that its purpose is to spread risk among dissimilar insureds.

The quality of municipal services in a given territory can also affect the likelihood and magnitude of losses. For example, the equipment, training, and manpower of local fire fighting units – as well as the stringency of local building codes and inspections – can affect the frequency and severity of fires. Moreover, expected property losses due to criminal activity, such as burglary, vandalism, and arson, will vary across territories according to the efficacy of local law enforcement and criminal justice systems.[8]

Age of a Home

An insurer examining loss data could well conclude that older homes are more likely to have faulty wiring and heating systems, thereby increasing the risk of loss due to fire. Compared to newer homes, they may also be more susceptible to water-related damage caused by antiquated plumbing or a roof that is in poor condition. In older homes that are in good condition, the presence of uniquely crafted decorative features, such as carved wooden cornices and stained glass windows, can push repair or replacement costs significantly above a home's market value. Consequently, many insurers decline to offer owners of older homes the option of a full replacement-cost policy,[9] regardless of whether the home is a Victorian mansion in an exclusive suburb or a modest bungalow in the inner city.

Credit History

During the 1990s, a growing number of personal lines insurance companies began using consumer credit information to help them decide whether to issue or renew a policy, and to establish its price. Insurers use credit information to assess risk because an individual's experience managing credit is a strong predictor of whether he will file a claim for automobile or homeowners insurance and the potential size of losses.[10] Though no one knows for sure why credit history correlates with loss experience, the Insurance Information Institute has suggested that a person's experience handling credit may indicate certain behavioral characteristics that are directly related to risk:

> The character trait that leads to careful money management seems to show up in other daily situations in which people have to make decisions about how to act, such as driving. People who manage money carefully may be more likely to have their car serviced at appropriate times and may also more effectively manage the most important financial asset most Americans own – their house – making routine repairs before they become major insurance losses.[11]

Competitive Risk Classification vs. Indiscriminate Risk Spreading

One of the biggest misconceptions about insurance is that its purpose is to spread risk among dissimilar insureds. Insurance, according to this view, is a privately administered social welfare program, to which all policyholders contribute and from which those with relatively high levels of risk – those most prone to loss – benefit disproportionately.

Risk spreading occurs when the diverse risks presented by individuals within a heterogeneous risk population are combined and spread equally among all members of that population. An extreme example of risk spreading is "community rating," which has been tried in several states as a health insurance reform. Community rating essentially forbids insurers from assessing individual risk and utilizing risk classification systems. The inevitable result is substantial cross-subsidies among risk types. For example, in the early 1990s, New York instituted mandatory community rating for the state's individual and small-group health insurance markets. The law required that all insureds pay the same premium, regardless of age and other known risk factors. As a result, premium costs for young people doubled or tripled, nine health insurers abandoned the New York market, and more New Yorkers were without health insurance than before the reforms were instituted.[12]

The notion that insurance ought to operate as a mechanism for indiscriminate risk spreading is reminiscent of the Marxist slogan, "From each according to his ability, to each according to his need." As a theory of social justice, however, this conception of insurance is seriously flawed because underwriting restrictions that operate to spread risk indiscriminately typically are not "means-tested." Law and regulation that is intended to promote social justice usually aims to achieve greater equality of wealth and income. However, insurance regulation that redistributes risk may have the opposite effect, because the level of risk presented by a given individual will not necessarily be correlated with his level of wealth. In other words, risk-spreading schemes may operate to compel low-income consumers with low levels of risk to subsidize high-income consumers with high levels of risk. A fairer system is one in which insurers compete to offer coverage to each individual at a price that is commensurate with the benefits (i.e., the amount of risk protection) he receives from the coverage.

Social Benefits of Risk-Based Underwriting

In addition to providing the foundation for a rate structure in which the price consumers pay for insurance is commensurate with the benefits they receive, risk-based underwriting benefits society as a whole by influencing behavior and conveying important information. Through competitive underwriting, insurers are able to acquire useful information about risk and strategies for risk reduction that may not be readily apparent or available to individual insureds. Indeed, the knowledge that is generated from risk-based underwriting may actually deter people from unnecessarily purchasing high levels of insurance coverage when they can more cheaply protect against risk by investing in loss prevention. If, on the other hand, coverage is priced below expected cost because of government-imposed restrictions on underwriting, some people may not take safety precautions that would otherwise be worthwhile, because in the absence of risk-based underwriting and pricing, they may be able to more cheaply obtain protection against risk by purchasing insurance than by investing in measures to reduce their level of risk.[13]

How Competitive Underwriting Facilitates Risk-Sharing Among Insurers

For reasons noted earlier, a system of insurance based on indiscriminate risk spreading among a single group of individuals with widely varying levels of risk is unfair and probably unworkable. A competitive system of insurance, on the other hand, encourages insurers to rigorously assess and classify risk, which fosters the mutually beneficial practice of risk sharing among similar risk types. However, just as competitive underwriting facilitates risk sharing among insureds within particular risk classes, so does it also promote socially beneficial risk sharing practices *among insurers*. That is, by accurately assessing particular risks, insurers can avoid situations in which they absorb more risk than they are capable of insuring, a condition that can lead to financial instability and, in the worst case, insolvency. Instead, individual insurers use risk assessment techniques to refrain from acquiring more of a particular kind of risk than they are capable of indemnifying, effectively sharing such risk with other insurers. For example, competitive underwriting among property insurers has led to the development of sophisticated risk-assessment techniques such as catastrophe risk modeling, which allows individual property insurers to avoid over-concentration in geographic areas prone to natural disasters.[14]

Risk-spreading schemes may operate to compel low-income consumers with low levels of risk to subsidize high-income consumers with high levels of risk.

Historically, mutual companies have worked to develop innovative techniques and devices to assist their policyholders' efforts to reduce risk.

How Risk-Based Underwriting Creates Incentives for Risk Reduction

Competitive risk assessment and classification provide incentives for high-risk individuals to take actions to control losses, because doing so may result in lower premiums and fewer uninsured losses. Further, since risk classification involves the pooling of large numbers of similar risks, insurers are often better able than any individual insured to discover less risky courses of conduct than those its insureds currently follow. Thanks to their superior access to loss experience statistics and greater ability to finance research into loss prevention methods, insurers may be able to suggest specific changes in behavior that will reduce risk and lower premiums.

The rise of factory mutual insurance companies in New England during the early nineteenth century illustrates how risk-based underwriting operates to encourage risk reduction among insureds. One such mutual company, Boston Manufacturers, was among the first insurers to offer fire protection coverage to textile mills in the region. Following a mill inspection in 1865, the company's president, Edward Manton, gave the following instruction in a memo to subordinates: "Renew at same if an additional force pump is added. If not, renew for $10,000 at 1 ¼."[15] By this Manton meant that unless the mill owner took specific action to reduce the likelihood of fire, he would have to pay an additional 1 ¼ cents per $100 to renew coverage for the mill. Foreshadowing the role that property insurers would increasingly play as risk reduction consultants, Manton not only determined that the mill had a heightened risk of succumbing to fire, he also prescribed the means by which the risk could be reduced – investing in an "additional force pump."

Eventually the early factory mutual companies began requiring inspections of factories both prior to issuing a policy and after one was in force, which could lead either to the sudden cancellation of coverage for a high-risk facility, or to a reduced premium for a facility that instituted loss prevention measures. Risk-based underwriting thus provided a powerful ongoing incentive for textile mill and factory owners to reduce their levels of risk, often by acting on the specific recommendation of their insurers. The mutual companies, for their part, worked to develop innovative techniques and devices to assist their policyholders' efforts to reduce risk. Boston Manufacturers offered lower premiums to policyholders that purchased lanterns that met certain safety criteria, and then worked with lantern manufacturers to create the safer designs that would meet the specified criteria. Another factory mutual company, Manufacturers Mutual of Providence, Rhode Island, developed specifications for fire hoses and advised mills to purchase hoses only from companies that met those standards.[16] As underwriters learned more about the nature of industrial risk and how to reduce it, factory mutual companies routinely refused coverage to firms that failed to adopt specific loss prevention methods. For example, to be eligible for fire coverage, one company, the Spinners Mutual, required factories to install automatic sprinklers.[17]

How Risk-Based Underwriting Increases the Availability of Insurance

A society that relies primarily on private enterprise to distribute goods and services necessarily depends on companies and individuals to seek out potential customers and develop strategies for serving the needs of those customers. The companies that are most successful in serving consumers' needs will be rewarded with the largest share of the potential customers. Insurers doing business in the private, voluntary insurance market are no different. Their success as companies hinges on their ability to expand their markets, and to achieve a high level of penetration in the markets they serve. Accurate risk assessment and refined classification systems are essential to that task.

To market its products effectively, an insurer must devise a risk classification system that will allow it to offer insurance to as many potential customers as possible, while simultaneously ensuring that its prices will be adequate to cover its customers' potential losses. While competition is generally most intense for low-risk insureds, insurers seeking to improve their market penetration will also wish to compete for high-risk insureds within the same market. Increased market penetration provides economies of scale in the marketing and distribution of insurance, as it does for any product. Competitive risk classification therefore serves to increase the availability of insurance even for high-risk individuals, because the economic advantages of superior market penetration will accrue to those insurers whose refined risk classification systems permit them to price coverage in accordance with the expected costs of each identifiable class of risks within the markets they serve.[18]

Negative Consequences of Government Restrictions on Underwriting

Government restrictions on underwriting freedom ostensibly guard against unfair business practices and ensure that insurance will be available to meet market demand. In many instances, however, these regulatory interventions only create dysfunctional market conditions that are detrimental to insurance consumers. For example, a rigorous process of risk assessment might reveal that a certain risk is so great that it is "uninsurable." That is, the insurer will have discovered that the prospective insured's level of risk is so high, and the magnitude of the potential loss so great, that no premium would be sufficient to justify transferring that risk to the insurer. However, when risk selection freedom is curtailed, insurers can be forced to accept and maintain uninsurable risks, thus threatening their financial stability and possibly jeopardizing their solvency.

Of all the distortions to the competitive insurance system that are produced by underwriting restrictions, perhaps the most harmful are adverse selection, moral hazard, and cross-subsidies.

Adverse Selection

Adverse selection occurs when low-risk insureds purchase less coverage, and high-risk insureds purchase more coverage, than they would if the price of insurance more closely reflected the expected loss for each group. Thus, when an insurer is unable to distinguish between individuals who have a low probability of experiencing a loss – either because it lacks the ability to accurately assess and classify risk, or because it is prevented from doing so by regulation – adverse selection is the likely result.

To illustrate, suppose an insurer sets a premium based on the average probability of a loss, using the entire population as a basis for its estimate. All things being equal, those at the highest risk for a certain hazard will be the most likely to purchase coverage for that hazard. In an extreme case, the high-risk individuals will be the only purchasers of coverage, because low-risk individuals will regard an insurance premium based on the average expected losses of the entire population as too expensive. When low-risk individuals decline to purchase insurance, insurers are left with an increasing proportion of high-risk policyholders. As its loss exposure increases due to the predominance of high-risk policyholders, the insurer's costs rise accordingly.

When low-risk individuals decline to purchase insurance, insurers are left with an increasing proportion of high-risk policyholders. As its loss exposure increases due to the predominance of high-risk policyholders, the insurer's costs rise accordingly.

To avoid losing money, the insurer raises premiums – not just for its high-risk policyholders, but for everyone (because the insurer is not practicing risk classification). As the average price for insurance continues to rise, coverage remains a bargain for those with

Underwriting restrictions that prevent insurers from accurately assessing risk can create incentives for policyholders to conduct their affairs in a manner that is less risk averse than if they had no insurance.

the highest levels of risk, but becomes less valuable to those with lower levels of risk. A dynamic has been set in motion in which the ratio of high-risk to low-risk insureds grows ever larger, to the point where the only policyholders that remain are a small number of very high-risk individuals paying very high premiums.

The logic of adverse selection can be demonstrated further by a simple mathematical calculation. Suppose some homeowners have a low probability of suffering damage to their homes while others have a higher probability. The low-risk homeowners stand a 1 in 10 probability of loss; the high-risk homeowners, a 3 in 10 probability. Assume that there are 50 potentially insurable individuals in each group, and the combined loss for each group is $100. The expected loss for a member of the high-risk group will be $30 (.3 x $100), while for a member of the low-risk group, the expected loss will be just $10 (.1 X $100). For a random individual in the entire population, the expected loss will be $20 (calculated as follows: [50(.1 x $100) + 50(.3 x $100)] / 100 = $20).[19]

If the insurer charges a premium of $20 based on the average loss probability of the entire population, only members of the high-risk group would normally purchase coverage, since they would be delighted to pay only $20 for insurance that will compensate them for $30 in probable losses. On the other hand, it is unlikely that members of the low-risk group would be interested in paying $20 for coverage, given that their probable losses are only half that amount. If only the high-risk homeowners purchase coverage, the insurer will suffer an expected loss of $10 (i.e., $30 - $20) on every policy it sells.[20]

Moral Hazard

Underwriting restrictions that prevent insurers from accurately assessing risk can create incentives for policyholders to conduct their affairs in a manner that is less risk averse than if they had no insurance.

Insurers must contend with the fact that once an individual has purchased insurance, his or her incentive to control losses decreases. Moral hazard is the resulting tendency of an insured individual to underallocate resources to loss prevention after purchasing insurance.[21]

For example, when an individual purchases homeowners insurance, he has protected himself against loss due to hazards such as fire, and against liability for injuries suffered by visitors to his home. But thanks to the protection afforded by insurance, the policyholder has less incentive to be careful around the house than he did before he purchased coverage, because he no longer bears the full cost of his carelessness. Undoubtedly the policyholder will still take many safety precautions; after all, he will not want to see his home damaged or his guests injured, regardless of how much money these events might cost him. Still, there is no getting around the fact that insurance against loss reduces the policyholder's incentive to prevent the insured event from occurring.[22] Once the policyholder has paid a premium, he alone does not have to shoulder the cost of a loss. "In effect," explains insurance law expert Kenneth Abraham, "the loss is borne by the other holders of homeowners insurance, each of whom also has a reduced incentive to take loss prevention measures. In this broad sense, the problem of moral hazard plagues all forms of insurance and tends to produce an underallocation of resources to loss prevention."[23]

To some extent, the behavioral tendencies that are associated with moral hazard can be counteracted by contractual devices, such as coinsurance and deductible provisions, that are designed to give the insured a stake in loss prevention. But the insurer's most effective method of dealing with the problem of moral hazard is to accurately assess and classify risk, varying the price of coverage according to the expected loss of each class of insureds. By raising or lowering the price of coverage based on a policyholder's loss experience – "experience rating" – the insurer can create incentives for policyholders to minimize the likelihood that they will suffer a loss. When risk classification based on previous loss experience leads to an increase in the cost of coverage for a given policyholder, the message sent to that individual is that he could obtain insurance more cheaply by allocating more resources to loss prevention.

By making it more difficult for insurers to deal with the problem of moral hazard, restrictions on underwriting freedom increase overall claim costs, thereby driving up the price of coverage for all insureds. As Scott Harrington explains, "Higher-risk persons or businesses [...] will be more likely to engage in risky activity and less likely to take precautions. In the case of automobile insurance, for example, lowering rates for high-risk drivers will encourage them to buy more expensive cars, to buy policies with larger limits and lower deductibles, and to exercise fewer precautions to prevent accidents and theft losses than would be true if competition among insurers determined rates."[24] As noted earlier, effective rate competition can only occur when insurers are free to compete with respect to underwriting. Moral hazard – and the heavy cost it imposes on consumers – can be averted only if insurers are free to use the most accurate risk assessment techniques, together with the most homogeneous risk classifications, that they are capable of devising.

Cross-Subsidies

As the foregoing discussion suggests, underwriting restrictions serve to weaken the link between expected loss costs and premiums, creating cross-subsidies that flow from low-risk insureds to high-risk insureds. Applied to automobile insurance, for example, underwriting restrictions tend to force drivers in the voluntary market to subsidize drivers in the residual market. Apart from the injustice entailed by such compulsory wealth transfers, cross-subsidization of insurance rates has a number of adverse consequences. If high-cost drivers do not pay the full marginal costs they impose on the insurance system, they will have no incentive to drive less or to drive more carefully.[25] The net effect of misguided attempts to lower premiums for some drivers through cross-subsidies is likely to be an increase in accident rates and insurance loss costs, adding to the inflationary pressures on insurance premiums. While examples of regulatory cross-subsidies can be found in many states with respect to both automobile and homeowners insurance, the auto insurance regulatory regimes of Massachusetts and California offer particularly striking illustrations of how cross-subsidies are facilitated by underwriting restrictions.

If high-cost drivers do not pay the full marginal costs they impose on the insurance system, they will have no incentive to drive less or to drive more carefully.[25]

Massachusetts

According to the Automobile Insurers Bureau of Massachusetts, drivers in some Massachusetts rating classes and geographical territories receive cross-subsidies as high as 60 percent of the premium they would have paid if prices were strictly based on expected loss costs. Meanwhile, drivers in other rating class or territory combinations have seen their premiums increase by as much as 11 percent in order to subsidize higher-cost drivers. On average, territories outside of Boston pay a subsidy of two percent of premiums to support premium reductions averaging 20 percent for Boston drivers.[26]

In Massachusetts, cross-subsidies arise from a variety of sources. The capping and "tempering" of rates introduces cross-subsidies from low-risk classes and territories to high-risk classes and territories. Further, prohibitions on the use of risk-assessment variables such as age, gender, and marital status introduce cross-subsidization from low-risk to high-risk drivers *within* each of the various "rating cells" prescribed under state law.[27] Because insurers are prohibited from canceling policies based on loss or accident experience, those drivers who are most costly to insure remain in the system, driving up costs. The higher premiums charged due to the high accident costs of any one driver are shared across all members of the rating cell, dampening individual incentives to reduce

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costs. The result, according to economists Sharon Tennyson, Mary A. Weiss, and Laureen Regan, is that accident rates "will be higher, and expected accident losses higher, under the Massachusetts regulatory system than otherwise." [28]

Massachusetts' experience illustrates another familiar consequence of government restrictions on underwriting and pricing freedom: Few insurers will wish to enter or remain in a market governed by a set of rules that prevents them from competing. That axiom was confirmed by a report prepared for the Massachusetts Division of Insurance by Tillinghast Towers and Perrin, which found that between 1990 and 2004, the number of auto insurers in the state declined from 53 to 19 – a 64 percent decrease.[29] The report found that "certain urban risks, youthful operators, and youthful males" are charged premiums significantly below the costs associated with providing coverage, and that "the rating shortfall on these classes is made up by overcharges on other risks." Accordingly, "about 14 percent of the states' drivers are subsidized (i.e., their insurance premiums are less than the expected costs of providing the coverage), and 86 percent of the market pays more than the cost-based premium."[30] Vowing to "give our consumers more choice and the advantages that come with safe driving," Governor Mitt Romney responded to the report by appointing a task force "to form a consensus for a fair and smooth transition to a competitive marketplace."[31]

California

An important provision of California's Proposition 103, enacted by the state's voters in 1988, requires insurers to use a specific, hierarchical order of rating variables to determine the individual insured's premium. As interpreted by California Insurance Commissioner John Garamendi, this provision may essentially prohibit insurers from classifying risk based on the territory in which an insured's automobile is operated. In a March 2004 news release, Commissioner Garamendi announced his intention to determine "whether [postal] zip codes unfairly influence the price of insurance for California drivers." Noting that insurers' practice of considering zip codes "has drawn heavy criticism from cities and consumer groups," Mr. Garamendi promised to "provide a fair and equitable system for all."[32] As economist David Appel observes, if Proposition 103's underwriting provisions are interpreted to remove territory from the rate determination process, the effect will be to "impose significant cross-subsidies from rural to urban consumers" since "expected costs for urban drivers clearly exceed those for rural drivers."[33]

In April 2004, Commissioner Garamendi's apparent campaign to institute cross-subsidies by eliminating territorial rating received a significant boost from the California Supreme Court. Ruling on a case brought by consumer and civil rights activists against State Farm, the Court authorized the insurance commissioner to release documents submitted by insurers that break down policies sold by zip code.[34] Proposition 103 requires auto insurers to file that information with the commissioner's office, but State Farm and other insurers had expected the information to be held in confidence so as to protect their proprietary underwriting techniques and marketing strategies.

The Court's ruling will almost certainly harm competitive underwriting in California in two ways. First, it will undermine insurers' incentive to develop innovations in underwriting and marketing, because competitors can easily copy any innovations once they are publicly disclosed. And second, the ruling will give plaintiff attorneys access to statistical data that could be used to file class action lawsuits based on the dubious "disparate impact" theory of discrimination. While such lawsuits would probably lack legal merit, the prospect of defending against multiple class actions could force auto insurers in California to abandon territorial rating rather than endure costly litigation. If that occurs, opponents of competitive underwriting will have achieved through the courts what they could not accomplish legislatively: the imposition of insurance cross-subsidies from rural to urban drivers.

Competitive Risk Analysis vs. Social Regulation

Since they serve neither to correct market failure nor to advance public health and safety, measures that subsidize the insurance costs of high-risk groups by means of regulatory underwriting restrictions are best understood as "social regulation" – that is, as a form of regulation that is designed "to achieve social goals that are not fully valued in the market."[35] While traditional public interest regulation seeks to reduce or prevent harms confronting workers and consumers (e.g., from environmental pollution, dangerous products, and unsafe working conditions), social regulation aims to provide particular constituencies with benefits whose costs are borne by regulated business firms. As a previous NAMIC public policy paper observes, "the end result of social regulation is that it corrupts markets and shifts unjustified costs to businesses. It is purely political. Its goal is not to prohibit illegal conduct, nor is it intended to strengthen competition. Rather, it is a way for government to mandate socially engineered outcomes with no impact on budgets or tax levels."[36]

The persistence of social regulation in property/casualty insurance markets is perhaps best explained by the *political entrepreneurship theory* of regulation.[37] This theory holds that certain regulatory policies can be engineered by political entrepreneurs such as candidates for public office or consumer advocates. The theory suggests that under some circumstances, political entrepreneurs can exploit public dissatisfaction over market outcomes in specific industries and motivate consumers to express their frustration through the political process. For example, in states such as New Jersey and Massachusetts, auto insurance prices have been a prominent issue in legislative and gubernatorial elections for decades. California's Proposition 103, although it was framed as a ballot initiative and characterized by the media as the product of a grassroots movement, may also be regarded as the result of opportunistic behavior by electoral candidates and consumer activists.[38]

Moreover, though they are praised by some as the purest form of democracy, ballot initiatives tend to attract the interest of those voters who have the most to gain from a particular electoral result.[39] This is especially so when, as in the case of Proposition 103, the voters who will bear the cost of a benefit provided to others are unaware of the negative consequences that the initiative holds for them. Thus, when an initiative promises to reduce the insurance premiums of high-risk insureds through a system of hidden cross-subsidies, voters who stand to benefit from such "relief" will participate in greater numbers than those who will eventually be harmed by cross-subsidization. This happened in California, where the electoral outcome of Proposition 103 was disproportionately influenced by voters in predominantly urban counties where the cost of providing coverage is highest.

Social Regulation and the Politicization of Insurance Underwriting

The predominance of social regulation in insurance, especially where underwriting and pricing are concerned, reflects the degree to which insurance has become politicized in many states. The politicization of insurance is fueled in part by the belief that insurance is an entitlement, and that social regulation is needed to ensure that everyone shares equally in the benefits that insurance provides.

Those who regard insurance as an entitlement seem especially troubled by underwriting and rating systems that classify people as especially risky because of factors they cannot control, such as age, gender, geographic residence, or credit score. In these circumstances, well-intentioned policymakers

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who believe that government should help the less fortunate are confronted with a private insurance market that sometimes seems to "blame the victim." Their inclination often is to eliminate the perceived unfairness of risk-based underwriting and pricing by imposing restrictions on underwriting practices.

Consider the inner city resident who cannot afford the high premiums for auto or homeowners insurance that prevail in his congested, crime-ridden neighborhood. Suppose that a woman files frequent property-damage and medical insurance claims because of violent acts perpetrated against her by an abusive husband or boyfriend. Should insurers be allowed to isolate these people and others like them in high-risk classes, charging them more for insurance than other policyholders who are not beset by these misfortunes? If insurance is to preserve its risk-sharing function and avoid becoming a mechanism for indiscriminate risk spreading, the answer must be "yes."

Allowing insurers to accurately assess and classify risk does not mean, however, that government policy must be indifferent to the plight of high-risk individuals. For example, it would not be difficult – from a technical standpoint, at least – for governments to use taxpayer dollars to directly subsidize members of high-risk classes. Direct subsidies of this sort have long been employed to provide an array of social goods (e.g., food stamps, Medicaid, and housing subsidies) to particular subgroups within the population. Targeted insurance subsidies that operated like food stamps would not interfere with the ability of insurers to engage in competitive underwriting and pricing, nor would they deter insurers from continuing to search for ways to more closely align the price of coverage with the particular benefits that individual insureds derive from coverage.

Unfortunately, policymakers usually avoid direct methods of risk redistribution in favor of ad hoc regulatory adjustments to the system of risk classification. Rather than raise taxes to subsidize the insurance costs of high-risk groups, politicians and regulators prefer to attack risk-based underwriting practices as "unfair." The reasons are not hard to fathom. Like other government-administered social welfare programs, direct methods of risk redistribution – and the costs they entail – would be more transparent to the public than is the hidden system of cross-subsidies that result from underwriting restrictions. Politically, it is far easier to pretend that insurers are to blame for the cost disparities that exist among different risk classes. As former South Carolina Insurance Commissioner Ernst N. Csiszar explains, the tendency toward political expedience often leads to "bold" regulatory intervention in the competitive insurance system:

> State regulators [are] restless as their careers and futures often hinge on the boldness of their regulatory actions. Consumers, dissatisfied with ever-increasing premiums and ever-decreasing coverage, only encourage such boldness. Moreover, politicians love a populist cause, as it is easy to raise the specter of corporate greed and regulatory incompetence. So the pressure is on to do something – and that something often turns out to be ever more of the trivial and intrusive regulation of the past.[40]

Conclusion

The tendency of underwriting restrictions to produce adverse selection, moral hazard, and cross-subsidies makes clear that as a strategy for improving the availability and affordability of insurance, curtailing underwriting freedom is irrational and counterproductive. The main effect of underwriting restrictions is to require some policyholders to pay more for coverage so that others can pay less. Moreover, by distorting incentives for loss control, underwriting restrictions lead to increased claim costs, thereby causing premiums to rise for all insureds and reducing the availability of insurance, especially for those with higher levels of risk.

In the absence of government-imposed restrictions, competitive underwriting forces insurers to strive continuously to improve the accuracy of their risk assessment techniques, and to make their risk classifications narrower and more homogeneous. The efficiencies that result from this process lead to increased price competition, and make possible the development of new coverage options tailored to the specific needs of particular consumers.

By eschewing underwriting restrictions and allowing competitive insurance markets to flourish, state regulators would realize their common goal of ensuring that property insurance rates are "adequate, not excessive, and not unfairly discriminatory." Insurance rates that are determined by market-driven efforts to assess risk with the greatest possible rigor, and to group similarly situated insureds into precisely constructed risk classes, cannot, by definition, be unfairly discriminatory. Nor could rates established through competitive, risk-based underwriting be considered "excessive," because the same competitive forces that promote underwriting accuracy also conspire to drive down prices. Far from improving the lot of property insurance consumers, government-imposed underwriting restrictions prevent consumers from enjoying the full range of benefits that come from unfettered competition.

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[22] Interestingly, this observation also applies to insurers, whose risk of insolvency is reduced by the presence of state guaranty funds. Depending on how they are financed and administered, state guaranty funds can have the effect of discouraging prudent behavior on the part of insurers with respect to pricing and overall risk management. For this reason, some analysts have urged policymakers to consider changes to the manner in which government guaranty systems are financed and operated. See, e.g., Elijah Brewer III, Thomas S. Mondschean, and Philip E. Strahan, "The Role of Monitoring in Reducing the Moral Hazard Problem Associated with Government Guarantees: Evidence from the Life Insurance Industry," Wharton Financial Institutions Center, University of Pennsylvania, May 1996. Available at http://fic.wharton.upenn.edu/fic/papers/96/9615.pdf.

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ATTACHMENT 2

New Jersey Citizen Action Report
Risky and Wrong: New Jersey Auto Insurance Rates for Lower Income and Minority Drivers
March 2, 2007 (revised)

NEW JERSEY CITIZENACTION

Risky & Wrong:

New Jersey Auto Insurance Rates for Lower Income & Minority Drivers

An Analysis of the Impact of GEICO's Use of Education and Occupation on the Price of Auto Insurance

A Report by New Jersey Citizen Action
February 28, 2007
[Revised March 2, 2007]

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Conclusion: New Jersey Should Ban the Use of Occupation and Education as Factors in Determining Auto Insurance Rates..........11

New Jersey Citizen Action (NJCA) is the state's largest citizen watchdog organization, representing over 60,000 family members and more than 100 senior, labor, faith-based, environmental, tenant and women's organizations. For 24 years NJCA has worked to protect and expand the rights of individuals and families and to ensure that government officials respond to the needs of people rather than the interests of those with money and power. NJCA's issue-based campaigns promote economic, social, racial and political justice and encourage the active involvement of New Jersey residents in challenging the public and private institutions and agencies that impact our lives. NJCA has engaged tirelessly in organizing campaigns focused on issues relating to banking, insurance and community reinvestment.[1] *We are dedicated to ensuring that New Jersey residents are not subjected to discriminatory market practices, engaged in time after time by financial institutions, often to the detriment of lower income people and minorities.*

Executive Summary

New Jersey consumers have faced exceptionally high auto insurance rates since the mid-1970s. Improving the state's auto insurance industry and lowering rates has been a major priority for government law makers and regulators. However, prohibitively high auto insurance rates are only part of the dilemma facing New Jersey drivers. A number of auto insurance companies writing policies in New Jersey, such as GEICO, use education and occupation to determine the rates paid by consumers. This practice results in higher rates for lower income and minority drivers in comparison to those who are more affluent and Caucasian. In essence the use of education and occupation as auto insurance pricing factors serve as proxies for race and class.

Using GEICO's well-publicized website, New Jersey Citizen Action (NJCA) performed a study to obtain and compare GECIO rate quotes for consumers with different educational background and occupational status. Contrary to GEICO's public representation, NJCA discovered that education and occupation are used as independent and determinative factors in setting rates and have a considerable impact on the rates consumers receive.

> A 51 year-old woman who lives in Camden, NJ, drives a 2000 Buick Century Custom, Sedan 4 Door, purchased in the last 30 days, works for a private company or organization as a vice president and has a PhD, receives a rate quote of $1,063.10 from GEICO's website. However, if the same woman, living in the same location and driving the same car, has only a high school diploma, her GEICO rate quote is $1,712.30 – **an increase of $649.20 *or* 61%**.

NJCA compiled over 400 rate quotes from GEICO's website and used this data to calculate average rate quotes for groups of consumers based on their education and occupational status.

- ***The average rate quote for consumers without a Bachelors degree (consumers having a high school or vocational degree) is 19% higher than the average rate quote for consumers with a Bachelors degree (or higher educational degree).***

- ***The average rate quote for consumers with a nonprofessional job is 27% higher than the average rate quote for consumers with a professional job.***

Fair, transparent, non-discriminatory business practices are a fundamental component of a thriving market. GEICO's use of education and occupation in setting auto insurance prices has a deleterious impact on people who do not have higher educational degrees and professional jobs – individuals who tend to be of lower income and minorities. By basing rates, in whole or in part, on education and occupation, *regardless of an individual's driving record*, GEICO provides higher rates to lower income people and minorities. New Jersey should ban the use of education and occupation in auto insurance rating and underwriting by passing ***S-1714/A-2819***.

Introduction

A number of auto insurance companies selling policies in New Jersey, most notably, Government Employees Insurance Company (GEICO) Group of companies, use educational attainment and occupation to determine the eligibility and rates paid by consumers. This practice results in higher rates for drivers who do not have a four-year college degree or do not work in a professional occupation, which disproportionately effects lower income individuals and minorities because education and occupation, used in this fashion, are simply serving as proxies for race and class.[2]

This report demonstrates that GEICO uses education and occupation as independent and determinative factors in setting auto insurance rates and eligibility. **The recently approved use of education and occupation as rate-making factors in New Jersey must be prohibited in order to protect New Jersey drivers from discriminatory market practices.**

GEICO's ratemaking and underwriting practices are threaded through its use of four separate GEICO insurance companies – GEICO, GEICO General, GEICO Indemnity and GEICO Casualty. By creating four different companies using the same trademark name, GEICO gives the *illusion* that they are only one insurance company. Yet, each company charges different base rates. Drivers qualifying for GEICO's *preferred* insurance company receive the best (lowest) rates, while drivers who do not quality for GEICO's preferred company receive rates from one of GEICO's *substandard* insurance companies and pay substantially higher rates. Having four separate companies and four separate base rates enables GEICO to increase rates for one group, without affecting the rates of others.

Contrary to GEICO's public representation, both a driver's education and occupation alone can determine eligibility for one of GEICO's preferred companies, regardless of driving record. Thus, education and occupation will, by themselves, significantly impact a consumer's rate. Factors such as driving record, geographic location and car type are taken into account only after a consumer is placed in one of GEICO's four companies. Remarkably, individuals are not even informed when they are rejected by the preferred GEICO Company based solely on their education and/or occupation. While GEICO asserts that drivers are not rejected from its *group of companies*, GEICO fails to mention that drivers with lower education and nonprofessional jobs are denied access to the preferred company without notice and hence denied the lowest available rates.

New Jersey: A History of High Insurance Rates

New Jersey is famous for being home to some of the highest auto insurance rates in the country. As a result, auto insurance has been unattainable for thousands of state residents because they simply cannot afford to pay for it.

Compounding the problem, between 1993 and 2003 over 30 auto insurance companies left New Jersey due to, what they and some policy makers asserted, was an over-regulated and unpredictable market. Insurance companies contended that regulation in New Jersey hampered their ability to turn a profit. When State Farm Indemnity, once New Jersey's largest auto insurer, announced its intention to withdraw in 2001, concern escalated over the deteriorating condition of the state's auto insurance market.

On June 9, 2003, then-Governor James E. McGreevey signed into law a series of reforms, encompassed in the New Jersey Auto Insurance Competition and Choice Act (NJAICCA), aimed at making New Jersey's auto insurance market a more attractive place for the industry to do business. By bringing auto insurance companies back to the state, lawmakers hoped to restore competition, lower auto insurance prices and enhance consumer choice. NJAICCA was "designed to simplify the regulatory process... creating a friendly climate for insurers..."[3] Since 2003, numerous auto insurance companies have entered and/or returned to the state, including five of the country's largest – Mercury Indemnity, GEICO, Esurance, AMEX and Progressive.

Since the law's enactment, the New Jersey Department of Banking and Insurance (NJ DOBI) has issued dozens of press releases and reports highlighting "the positive impact" the reforms have had on New Jersey's auto insurance market.[4] NJ DOBI lauded the reforms for attracting new carriers to invest in New Jersey, reversing the course of insurers that had threatened to leave the state, bringing in hundreds of new agents, providing access to affordable auto insurance for thousands of previously uninsured drivers, creating the dollar-a-day program through which low-income drivers can purchase auto insurance for $360 per year, placing downward pressure on rates and generating industry competition and consumer choice.[5]

However, despite countless press releases, DOBI and lawmakers have curiously failed to mention several key facts to the public regarding the condition of New Jersey's auto insurance market post-NJAICCA. First, despite more nationally recognizable insurance companies entering New Jersey, the actual number of insurers writing auto insurance has decreased since 2003.[6] Second, New Jersey continues to maintain the title for having the highest auto insurance rates in the country as of 2004.[7] Third, the country-wide private passenger auto insurance marketplace has reported record profit levels since 2003, discrediting claims that NJAICCA was primarily responsible for the improved profits by auto insurers in New Jersey.[8] Most importantly, the concerted effort to lure national auto insurers into New Jersey went beyond the scope of NJAICCA's original reforms and ultimately resulted in accommodations to the auto insurance industry at the price of consumer protections, in particular, protection for lower income individuals and racial minorities in New Jersey.

Furthermore, while NJAICCA is commonly credited as the legislation that permitted new rating and underwriting factors to be approved for use by auto insurance companies, it should be noted that the Act never examined nor expressly addressed underwriting methods used by car insurers, particularly those that are influenced by socio-economic factors such as education and occupation. Both of these new discriminatory methods have been approved for use in New Jersey without any public hearings or comprehensive studies.

Socio-economic rating factors differ significantly from previously accepted rating factors such as age, gender, driving experience, driving record, annual mileage and use of the vehicle because they are affected by socio-economic influences in our society. A driver's ability to become older, be male or female, get married, become more experienced as a driver, operate a vehicle safely and use their vehicle differently is not affected by socio-economic influences.

Missing in Action: Consumer Protection

While lowering rates through increased competition may have been the primary objective of the 2003 reforms, this was not the only intention. Section 2 of the law states, "**[t]he promotion of a competitive marketplace should not diminish the ability of the State to protect policyholders and the public generally from unfair insurance practices**..."[9] (*Emphasis added.*) The law requires the Commissioner of DOBI to "**[protect] policyholders and the public from unfair market practices of insurers**."[10] (*Emphasis added.*) Unfortunately the interests of New Jersey consumers and residents have been relegated to the back burner.

Lawmakers were especially pleased when GEICO, the nation's fifth largest auto insurer, re-entered the New Jersey marketplace in the fall of 2004. However, and unbeknownst to consumers, GEICO returned to New Jersey using education and occupation as rate-making factors. In February 2006, the *Star Ledger* exposed the insurance company's explicit use of education and occupation as rating factors, referencing GEICO's Automobile Group Guide to Company Placement.[11] This document reveals that based on education and occupation alone, drivers are rejected from GEICO's preferred companies and charged higher rates, regardless of driving record, age, residential location and vehicle type.

The GEICO Guide designates accountants, administrators, architects, dentists, engineers, judges, lawyers, pharmacists, pilots, scientists, teachers, physicians, actuaries, executive secretaries with college degrees and college educated sales representatives among the most highly favored occupations while "minimally-skilled clerks, assistants, postal clerks and stock clerks... long haul drivers, route men, unskilled and semiskilled blue and gray collar workers" are put in the least favorable group.[12] The Guide also states that "[r]isks who have achieved at least a high school diploma or its equivalent are more favorable than those without a high school education. Bachelors, masters, and other advanced degrees are considered most favorable."[13] Prior to GEICO's re-entry into New Jersey's auto insurance market, education and occupation were never used by an insurance carrier to determine rates and eligibility. As of February 2007, 16 auto insurance companies writing policies in New Jersey use education, occupation or both as rate-making factors.[14]

Investigation of GEICO Rate Quotes

GEICO claims that education and occupation are just two of the many factors it uses to calculate rates. To better understand the financial impact of GEICO's use of education and occupation in rate-making, NJCA carried out the following study.

Using GECIO's own well-publicized website, where company rate quotes are free and accessible to the public, NJCA researchers obtained and compared rates for consumers with different education and occupational status. Using GEICO's online rate quote application, information was input that reasonably resembles a typical New Jersey driver and a rate quote was received. Then, NJCA went back through GEICO's questionnaire and left *all the information* the same, but altered the education and, in a separate trial, the occupation of the consumer. The results demonstrate great disparity.

Between July 31, 2006 and August 15, 2006 NJCA collected 449 rate quotes from GEICO's website.[15] GEICO rate quotes can be obtained by going to *www.GEICO.com*, and following the prompts for purchasing auto insurance or receiving a rate quote. After filling in a zip code, the user must answer approximately 60 questions ranging from personal information such as address, phone number, marital status, birth date and gender to vehicle information including year, make, model, miles driven and safety features to coverage information such as the monetary amount of bodily injury liability (BI), property damage liability (PD), comprehensive (COMP) and collision (COLL) one wishes to purchase. The applicant must also fill in categories pertaining to the highest education level he/she has completed, employment status, industry and occupation.

NJCA varied those characteristics that we believe are more likely to impact auto insurance rates and held factors constant that we believe either could apply to many New Jersey drivers or would have little effect on rates. In NJCA's study there were 21 factors held constant in every single rate quote elicited from GEICO's website.[16] The pre-selected coverage limits suggested by GEICO were also consistently used.[17] Personal information such as first and last name, street address, phone number, social security number, email address and password could not be held constant.[18]

NJCA varied answers for ten of the questions on GEICO's website – gender; whether or not the car was purchased in the last 30 days; the year, make and model of the car[19]; the area in which one lives[20] (one urban and two suburban locations were used covering the north, south and central regions of the State); employer/employment status (both private and government jobs were used); line of work (a wide assortment of job fields were included such as education, accounting, real estate, advertising, law enforcement, management, machine operators, science, counseling, manufacturing, construction, medicine and agriculture); occupation (a wide variety were included from factory worker to college dean to mechanic to journalist to physician to carpenter); and education (vocational, high school, Associate, Bachelors, Masters and PhD).

The study produced, in many instances, considerably different rate quotes when the exact same information was provided (relating to the consumer, vehicle, and coverage options) but education and/or occupation was altered.[21]

Example of the impact of GEICO's practice of using education alone: A 51 year-old woman who lives in Camden, NJ, drives a 2000 Buick Century Custom, Sedan 4 Door, purchased in the last 30 days, works for a private company or organization as a vice president and has a PhD, receives a rate quote of $1,063.10 from GEICO's website. However, if the same woman, living in the same location and driving the same car, has only a high school diploma, her GEICO rate quote is $1,712.30 – **an increase of $649.20 *or* 61%.**

Example of the impact of GEICO's practice of using occupation alone: A 51 year-old man who lives in Highland Park, NJ, drives a 2004 Ford Taurus, SE Sedan 4 Door, purchased within the last 30 days, works for a private company or organization as an architect and has a Masters degree, he receives a GEICO rate quote of $644.80. However, if the same man, with the same degree, works as a repairman, he receives a GEICO rate quote of $993.30 – **an increase of $348.5 or 54%.**

Example of the impact of GEICO's practice of using education and occupation: A 51 year-old man who lives in Camden, NJ, drives a 2002 Subaru Forester, Wagon 4 Door, purchased within the last 30 days, works for a private company or organization as a white collar developer and has a PhD, he receives a GEICO rate quote of $1,060.10. However, if the same man is a construction worker and has only a high school degree, he receives a GEICO rate quote of $1,663.90 – **an increase of $603.80 or 57%.**

Results of Study and Analysis

NJCA generated 449 rate quotes from GEICO's website, calculated the average rate quotes for eight groups of consumers and compared the results.

Group Comparisons:

- Rate quotes derived with lower education (high school and vocational) were compared to rate quotes derived with higher education (Bachelors degree or higher educational degree);
- Rate quotes derived with nonprofessional jobs were compared to rate quotes derived with professional jobs;[22]
- Rate quotes derived with higher education (Bachelors degree or higher educational degree) **and** professional jobs were compared to all other rate quotes;
- And rate quotes derived with lower education (high school and vocational) **and** nonprofessional jobs were compared to all other rate quotes.

Results:

- *The average rate quote for consumers without a Bachelors degree (consumers having a high school or vocational degree) is 19% higher than the average rate quote for consumers with a Bachelors degree (or higher educational degree);*
- *The average rate quote for consumers with a nonprofessional job is 27% higher than the average rate quote for consumers with a professional job;*
- *The average rate quote for consumers with a Bachelors degree (or higher educational degree)* ***and*** *a professional job is 38% lower than the average rate quote for all other consumers;*
- *And the average rate quote for consumers without a Bachelors degree* ***and*** *with a nonprofessional job is 22% higher than the average rate quote for all other consumers.*

The average rate quote comparisons presented here represent the data collected for this study by NJCA.[23] While broader conclusions regarding New Jersey's population at large may be drawn from this data, there is a need for more comprehensive research, involving a random and more robust set of data. Such research should be undertaken by the DOBI so that the effect of GEICO's use of education and occupation on rate quotes can be more fully understood and applied to the state's population at large.[24]

Summary

GEICO's use of education and occupation in rate-making and underwriting is discriminatory and should be banned in New Jersey. The results of NJCA's research clearly illustrate that GEICO provides people with higher rates due to lower educational attainment and nonprofessional job status. This study demonstrates that GEICO's use of education and occupation as rating and underwriting factors results in discrimination against lower income people and minorities, as education and occupation serve simply as proxies for race and income class.

Why do multi-state, multi-billion dollar insurance companies use education and occupation to determine premiums? The answer is simple.

These companies want to insure more affluent drivers. Higher income consumers have more profit potential for multi-line insurance companies. Private passenger automobile insurance typically yields small profit margins in comparison to homeowners', boat, life and umbrella insurance. With higher income households, a multi-line insurance company has the opportunity to reap larger profits because higher income households possess more assets to insure. Auto insurance in this fashion is being used as simply a "foot in the door" to sell other types of insurance. The practice of artificially lowering rates for higher income households has an unjustified impact on lower income households, because auto insurance is mandated by law and is a necessary tool for those who are striving to earn a living.

It is clear from simply a cursory glance at GEICO's occupational class categorizations that the purpose of segregating occupations into these groups is to provide preferred status eligibility to individuals with higher incomes. The only homogeneous characteristic trait among these occupational groupings is their traditional salary levels, not their driving records. Although GEICO will contend that its rating and underwriting methods must be beneficial to the market as a whole because they have rapidly become the state's fourth largest auto insurer in less than four years, this growth should be examined closely, as recent statistics indicate that most of their growth has been in GEICO's preferred companies, while only a small portion of drivers have joined their substandard company, GEICO Casualty.[25] This is further proof that GEICO is reaching its underlying objective, to attract higher income drivers, by providing them significantly lower rates than GEICO charges those with only high school diplomas and nonprofessional jobs.

Despite the desire to attract higher income households, the use of race and income as rating and underwriting factors is off-limits to auto insurance companies. The Civil Rights Act of 1964 prohibits basing insurance rates upon a person's race. Several life insurance companies, such as People's Life Insurance Company and Home Security Life Insurance Company began using occupation as a proxy for race when the practice of basing premiums on race was prohibited.[26] They accomplished this by determining which occupations were primarily performed by undesirable racial minorities and charging higher rates to individuals who purchased insurance with those occupations. This is a discouraging but factual history of how some large insurance companies under competitive pressures to make profits have gone to great lengths and even employed unconscionable underwriting and rating practices to reach their objectives. Furthermore, income has been expressly prohibited as a method to base rates for auto insurance due to its obvious disparate impact on racial minorities.

The use of education and occupation violates NJ DOBI regulatory requirements. N.J.A.C. 11:3-19A.5 (b) 2 states, "Underwriting rules shall be based on a reasonable and demonstrable relationship between the **risk characteristics** of the driver(s) and vehicle(s) insured and the hazards insured against".[27] (*Emphasis added.*) Thus, in order for a group of drivers to be separated, categorized and given different rates, the group must demonstrate more than simply a correlation to loss. It must be shown that **the characteristic trait of the drivers** being isolated is correlated to the risk of loss for which the insurance is purchased to protect against. There is no evidence that education or occupation – characteristic traits being used by GEICO to class drivers – correlate to risk.

Despite loss data commonly cited by NJ DOBI and auto insurance companies that adopt this practice, demonstrating a correlation between education and occupation and corresponding loss ratios, this does not constitute sound "actuarial loss data." Mere data that shows a correlation to loss ratios by group fails to meet such a standard of review, as GEICO would be compelled to demonstrate that education and occupation as characteristic traits by drivers are the *principal* factors responsible for the loss ratio correlation.

The industry fails to mention that the reason for this correlation is that education and occupation are simply proxies for income. The primary reason education and occupation correlate to lower loss ratios is that lower income drivers will likely produce higher reported losses to insurance companies. A person with higher disposable income is more likely to settle an accident without the insurance company than a person who earns less and has less disposable income. A 2000 National Highway Traffic Safety Association (NHTSA) report shows that nearly 50% of auto accidents involving only property damage are not reported.[28] The importance of this data is that only individuals with a certain level of income have the luxury of not reporting accidents and can instead pay for the damage themselves.

In summary, insurance companies use education and occupation as rating and underwriting factors because these factors are *proxies* for income. With this in mind, insurance actuaries could take *any* group characteristic trait that is aligned to income and demonstrate corresponding loss ratios. For example, if auto insurance companies provided loss ratios correlated to ownership of television sets, and classed drivers who have "large plasma TV's", "conventional TV sets" and "those who do not own a TV" in separate groups, we would likely see nearly identical correlations to loss ratios that are based upon income alone. Why? Lower income individuals do not typically have the disposable income to afford more costly TV's. Would such data justify the use of this factor in determining auto insurance rates? Of course not. Any grouping that correlates strongly with income will produce nearly identical results in loss ratios. It would be hard to argue with historical U.S. Census reports that show the strong correlation between educational attainment and income.[29]

Auto insurance companies' practice of classing groups through the use of factors such as historically high-paying occupations enables them to isolate high income drivers with relative ease. However, N.J.A.C. 11:3-19A.3 (f) states, "The placement of applicants and insureds at or within a tier and the movement of insureds between tiers shall be based on underwriting rules that...are mutually exclusive per tier, objective and not applied so as to violate any statute or regulation of the United States or the State of New Jersey."[30] Based on NJCA's study, GEICO is using education and occupation in a manner that is not objective and in a manner that violates regulations of the United States and the state of New Jersey.

Conclusion: New Jersey Should Ban the Use of Occupation and Education as Factors in Determining Auto Insurance Rates

GEICO's use of education and occupation in rate-making should be banned in New Jersey. The results of NJCA's research illustrate that GEICO provides people with higher rates due to lower educational attainment and nonprofessional job status. This study clearly reveals that GEICO's use of education and occupation as rate-making factors results in discrimination against lower income people and minorities, because education and occupation are serving as proxies for race and class.

This heightened level of scrutiny regarding auto insurance companies' use of education and occupation in rating and underwriting is not limited to New Jersey. Florida Insurance Commissioner Kevin McCarty publicly stated he is, "concerned that the use of such information, primarily by automobile insurance companies, discriminates against minority policyholders who end up paying higher premiums regardless of their driving records."[31] **NJCA believes New Jersey, the state in which this practice by GEICO was first discovered, should lead the nation in protecting consumers from such discriminatory practices by banning the use of education and occupation in auto insurance rating and underwriting now.**

NJCA supports legislation introduced in the New Jersey State Legislature on March 20, 2006 by Senators Nia Gill (D-34) and Joseph Vitale (D-19) that would outlaw the use of these underwriting factors. NJCA urges the Legislature to move forward and pass ***S-1714/A-2819*** to ensure that New Jersey consumers are not subject to the discriminatory use of education and occupation in determining rates. The Bill states, "No underwriting rule shall operate in such a manner as to assign a risk to a rating plan on the basis of an insured's: (1) educational level; or (2) employment, trade, business, occupation or profession."[32]

Fair, transparent, non-discriminatory business practices are fundamental components of a thriving market. NJAICCA, which promised an auto insurance market characterized by fair and transparent practices, has not delivered on this commitment. GEICO's use of education and occupation in rate-making has a deleterious impact on those who do not have higher educational degrees and professional jobs – people who tend to be of lower economic status and from minority groups. New Jersey's auto insurance market must be both accessible *and* affordable and consumers must be treated fairly and equally. The implementation of NJAICCA, legislation designed to generate competition, choice and lower rates, has *not* produced an auto insurance market that upholds fair and nondiscriminatory practices for all.

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[1] See Appendix A. *Overview of NJCA's Advocacy Work on Issues Relating to Banking, Insurance and Community Reinvestment.*

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[2] See Appendix B. *Education and Occupation Serve as Proxies for Race and Class.*

[3] News Release. State of New Jersey, Office of the Governor. 9 June 2003. *McGreevey Signs Groundbreaking Auto Insurance Reforms.*

[4] News Release. State of New Jersey, Office of the Governor. 9 January 2004. *Governor Reports to NJ Drivers on Auto Insurance Reform: Promise Made, Promise Kept.*

[5] News Release. State of New Jersey, Office of the Governor. 9 January 2004. *Governor Reports to NJ Drivers on Auto Insurance Reform: Promise Made, Promise Kept.*

News Release. New Jersey Department of Banking and Insurance (NJ DOBI). 4 March 2004. *Banking and Insurance Commissioner Announces New Tool to Help New Jersey Drivers Purchase Auto Insurance.*

[6] See Appendix C. *Private Passenger Auto Insurance Companies in New Jersey by Year.*

[7] National Association of Insurance Commissioners (NAIC). *2003/2004 Auto Insurance Database Report.* USA: NAIC, 2006. Pg. 34, Table 4: "Average Premiums and Expenditures 2000-2004".

[8] "The Best of all Worlds: Both Liability and Physical Damage Rise," *Auto Insurance Report*, 13 (20 February 2006).

[9] State of New Jersey, 210th Legislature. *Assembly No. 2625, New Jersey Automobile Insurance Competition and Choice Act*, Introduced 28 June 2002. Page 3, Section 2, lines 11-13.

[10] State of New Jersey, 210th Legislature. *Assembly No. 2625, New Jersey Automobile Insurance Competition and Choice Act*, Introduced 28 June 2002. Page4, Section 4, lines 39-40.

[11] "Geico's Two Rates: White-Collar And Blue-Collar" *The Star Ledger*, 27 February 2006. <http://www.njcitizenaction.org/news/cra016.html>

[12] Government Employee Companies. *GEICO Automobile Group Guide to Company Placement.* Revised 07/06/04. Pages 3-5.

[13] Government Employee Companies. *GEICO Automobile Group Guide to Company Placement.* Revised 07/06/04. Pages 4.

[14] See Appendix D. *New Jersey Auto Insurance Companies Using Education, Occupation or Both as Rating and Underwriting Factors.*

[15] Subsequent to August 15, 2006, the date on which NJCA completed data collection of rate quotes from GEICO's website, GEICO's website was visibly modified and with the approval of NJ DOBI, GEICO adjusted its rate/rule filing procedures. The appearance and format of the website, the order and arrangement of questions and some of the question content was changed as was the formula with which GEICO rates are calculated. When identical information is supplied, GEICO's website now yields different rates than those provided during NJCA's data collection period.

The data presented in the study reflect rates obtained between July 31, 2006 and August 15, 2006. However, specific **examples** documenting disparate rate quotes reflect information generated by NJCA researchers on GEICO's website in February 2007.

[16] See Appendix E. *Characteristics Held Constant When GEICO Rate Quotes Were Obtained Between July 31, 2006 and August 15, 2006.*

[17] See Appendix F. *Coverage Options Pre-Selected on GEICO's Website and Used by NJCA when GEICO Rate Quotes were Obtained Between July 31, 2006 and August 15, 2006.*

[18] GEICO's website does not allow an unlimited number of rate quotes to be obtained under one name. After approximately 10 to 15 rate quotes are elicited, GEICO's website requests that the consumer call a customer service line for further assistance. Therefore, it was necessary for NJCA to create multiple names, addresses, phone numbers, social security numbers, emails and passwords in order to elicit a large number of rate quotes from GEICO's website.

[19] The following cars were used in the study: 2007 Acura RL, Sedan 4 Door; 2004 Ford Taurus SE, Sedan 4 Door; 2002 Subaru Forester L Wagon; and 2000 Buick Century Custom, Sedan 4 Door.

[20] The following cities and zip codes were used in the study: Mahwah 07495; Highland Park 08904; and Camden 08103.

[21] The following are rate quotes for six-month policies.

[22] Professional and nonprofessional jobs were classified based on the definition of learned professional employees provided in the Federal Labor Standards Act (FLSA), 15574.

[23] As previously stated, subsequent to NJCA's data collection, GEICO's website and rate/rule filing procedures were altered so that GEICO's website now yields different rate quotes than those provided during the data collection period when identical information is supplied.

[24] See Appendix G. *Study Results – Average GEICO Rate Quotes Generated by NJCA According to Education and Occupation.*

[25] See Appendix H. *Number of Vehicles Insured, Total Written Premiums and Average Policy Premiums for GEICO Group Companies Operating in New Jersey.*

[26] State of Maryland Insurance Administration; State of Florida Office of Insurance Regulation; Commonwealth of Pennsylvania Insurance Department; and Virginia State Corporation Commission, Bureau of Insurance. *Multi-State Target Market Conduct Examination Report of the Life of Business of Monumental Life Insurance Company.* Baltimore: NAIC, June 2003. Pgs. 23-24.

[27] N.J.A.C. 11:3-19A.5 (b) 2

[28] US Department of Transportation, National Highway Traffic Safety Association (NHTSA). *The Economic Impact of Motor Vehicle Crashes, 2000.* Washington, D.C.,, May 2002. Pg. 28.

[29] See Appendix B. *Education and Occupation Serve as Proxies for Race and Class.*

[30] N.J.A.C. 11:3-19.A.3 (f)

[31] Media Release. Florida Office of Insurance Regulation. 12 January 2006. *Public Hearing Scheduled on Use of Occupational and Educational Information by Insurance Companies to Set Rates.* *<http://www.floir.com/PressReleases/ViewMediaRelease.asp?ID=2529>*

[32] State of New Jersey, 212th Legislature. *Senate No. 1714*, Introduced 20 March 2006. Page 2, lines 23-26.

Appendix A

Overview of New Jersey Citizen Action's (NJCA) Advocacy Work on Issues Relating to Banking, Insurance and Community Reinvestment

NJCA works to ensure that financial institutions doing business in the State uphold their obligations established under the federal Community Reinvestment Act (CRA), a 1977 law requiring that banks and savings and loan associations reinvest in cities where they take deposits. CRA guarantees that financial institutions make loans to residents of lower income and minority communities and offer credit throughout their entire market area. CRA facilitates ownership opportunities for underserved populations by prohibiting banks from targeting only wealthier neighborhoods with their services.

Working with other community leaders, NJCA has negotiated and/or renewed 30 Community Reinvestment Agreements with New Jersey banks, committing more than $15 billion to low and moderate income families and neighborhoods. In July 2006, NJCA brokered an $8 billion contract with Wachovia Bank, dwarfing all previous Community Reinvestment Act agreements in size.

NJCA also works to educate people about their rights under the federal Fair Housing Act and to increase access to affordable housing through fair and equal access to credit, capital and banking services for traditionally underserved populations, specifically low and moderate income minorities and non-English or limited English speaking adults, seniors and people with disabilities living in New Jersey's urban areas. NJCA works closely with over 300 organizations, including grassroots, faith-based and neighborhood groups that have direct access to the underserved populations which are at high risk for predatory abuse.

On February 27, 2003, New Jersey's first Anti-Predatory Lending Legislation (A.75 NJ Homeownership Security Act) was passed in the State Senate. NJCA worked for over a year with the Coalition for Fair Lending to introduce and strengthen the momentum for this legislation, which helps protect New Jersey families from unscrupulous predatory lenders and provides recourse for families who do fall prey to these lenders. Although the lending industry attempted to weaken the bill for consumers, the Coalition was successful in getting the strongest possible bill passed in the Senate.

NJCA has successfully developed various pilot programs to ensure low and moderate income individuals access to affordable insurance. One such program facilitated by NJCA provides discounted homeowners' insurance to first time home buyers who go through NJCA's HUD certified loan counseling program. Another recently coordinated pilot program, called *Wheels in Motion*, provides discounted auto insurance to low and moderate income young adults in apprenticeship programs, thereby removing a major barrier to accessing vocational training. Wheels in Motion provides these young adults with access to below market-rate auto loans and discounted insurance and offers them admission to financial education workshops that facilitate informed financial decisions.

NJCA is a HUD designated Fair Housing Agency and provides a number of direct services to New Jersey residents such as free, one-on-one Mortgage and Credit Counseling and Home Improvement Counseling with HUD certified counselors. These services assist low and moderate income first time homebuyers deal with budgeting and credit repair and help homeowners review contracts, research contractors and obtain affordable financing for home improvement projects. NJCA also holds Women's Housing Initiatives statewide to encourage women to use loan counseling to achieve the dream of homeownership. Additionally, NJCA provides marketing and outreach services to increase communities' awareness of bank loans available through Community Reinvestment Agreements.

Appendix B

Education and Occupation Serve as Proxies for Race and Class

- According to the U.S. Census Bureau, in 2005, 30.6 percent of Caucasians, 25 years and over, held a Bachelors or higher educational degree, while only 17.6 percent of African Americans and 12 percent of Hispanics held comparable degrees.[i]

- African Americans and Hispanics hold proportionally more jobs than Caucasians in the service sector, where there is "the highest proportion of workers earning at or below the Federal minimum wage."[ii] In 2005, 13 percent of Caucasians, between the ages of 18 and 64 years, worked in the service industry as compared to 23 percent of African Americans and 24 percent of Hispanics.[iii]

- African Americans and Hispanics are less likely to hold jobs "in management, professional, and related occupations and natural resources, construction, and maintenance occupations" where there is the *lowest proportion* of minimum wage workers.[iv] In 2005, 49 percent of Caucasians held jobs in "management, business, and financial occupations; professional and related occupations; construction and extraction occupations; and installation, maintenance, and repair occupations" as compared to 33 percent of both African Americans and Hispanics respectively.[v]

- U.S. Mean Annual Earnings by Education[vi]

Education	**Annual Income**
No High School	$26,593
High School	$36,700
Some College	$43,275
Bachelor's Degree	$65,442

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[i] U.S. Census Bureau. Current Population Survey. 2005 Annual Social and Economic Supplement.

[ii] U.S. Department of Labor. Bureau of Labor Statistics. Labor Force Statistics from the Current Population Survey. <www.bls.gov>.

[iii] U.S. Census Bureau. Current Population Survey. Table 6. Educational Attainment of Employed Civilians 18 to 64 Years, by Occupation, Age, Sex, Race, and Hispanic Origin: 2005.

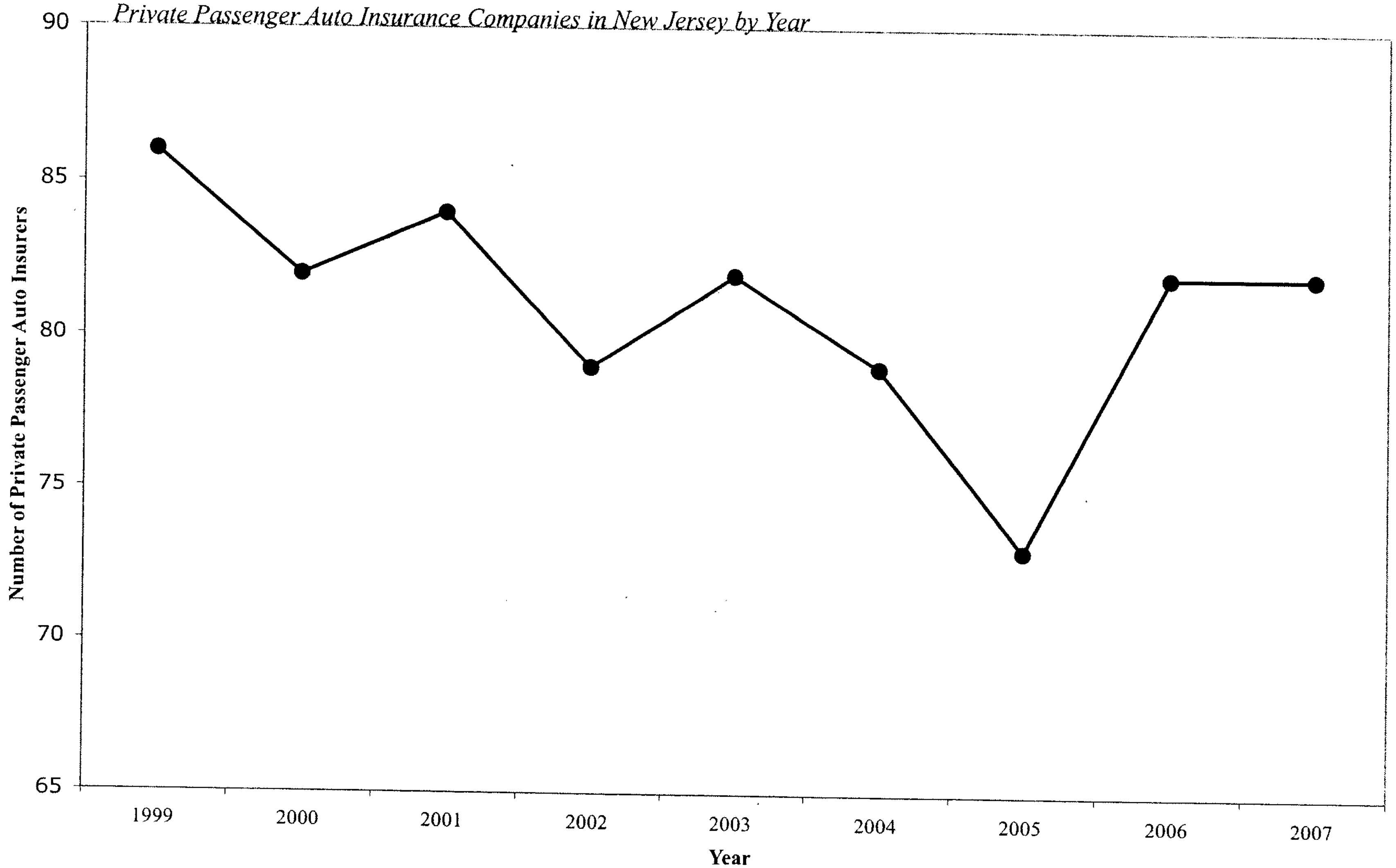
[iv] U.S. Department of Labor. Bureau of Labor Statistics. Labor Force Statistics from the Current Population Survey. <www.bls.gov>

[v] U.S. Census Bureau. Current Population Survey. Table 6. Educational Attainment of Employed Civilians 18 to 64 Years, by Occupation, Age, Sex, Race, and Hispanic Origin: 2005.

[vi] Money Income in the United States 2004, U.S. Department of Commerce.

Appendix C

Private Passenger Auto Insurance Companies in New Jersey by Year



Appendix D

New Jersey Auto Insurance Companies Using Education, Occupation or Both as Rating and Underwriting Factors[i]

Auto Insurance Company	Education	Occupation	Education and Occupation
AIG Premier Insurance Company		X	
AMEX Assurance Company	X		
Electric Insurance Company	X	X	X
Esurance Insurance Company	X		
GEICO – Government Employees Insurance Company	X	X	X
GEICO Casualty Company	X	X	X
GEICO General Insurance Company	X	X	X
GEICO Indemnity Company	X	X	X
Homeland Central Insurance Company	X		
Liberty Insurance Corporation	X		
Liberty Mutual Fire Insurance Company	X		
Liberty Mutual Midatlantic Insurance Company	X		
Merastar Insurance Company	Pending		
New Jersey Skylands Insurance Association	X		
New Jersey Skylands Insurance Company	X		
Selective Auto Insurance Company of New Jersey		X	

[i] Information obtained through Open Public Records Request, New Jersey Department of Banking and Insurance. February 2005.

Appendix E

Characteristics Held Constant When GEICO Rate Quotes Were Obtained Between July 31, 2006 and August 15, 2006

GEICO's Questions	**NJCA's Answers**
Read consumer disclosure?	Yes
Number of vehicles?	One
Number of drivers?	One
Marital status?	Single
Currently insured?	No, I haven't needed insurance
GEICO auto insurances in the last 6 months?	No
Vehicle vandalized or stolen; ticket; license suspended?[i]	No
DUI?[ii]	No
Vehicles kept at same address?	Yes
Years lived at current address?[iii]	Five or more
Full-time student?	No
Days driven to work?	Five
Days driven to school?	Zero
Use (vehicle) for business other than driving to work?	No
Anti-lock breaks?	Yes
Anti-theft device?	None
Total odometer mileage (only applies to Acura)?	0-99
Expected mileage in the next 12 months?	9,001-12,000[iv]
Miles driven to work one way?	25
Age first obtained U.S. license?	17
National guard, military reserves, or military retiree?	Does not apply
Defensive driving last three years?	No
Member of any of these groups which have a GEICO Partnership?	No

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[i] This question currently reads:

> Accidents (regardless of fault) in the last 5 years
> Violations in the last 5 years
> Thefts or Vandalisms in the last 5 years
> Suspensions in the last 5 years
>
> **Do you have an incident?** **Yes** **No**

[ii] This question is no longer asked on GEICO's website.

[iii] This question is no longer asked on GEICO's website.

[iv] As of February 1, 2007, the date on which NJCA completed cross-checking of rate quote data obtained from GEICO's website between July 31, 2006 and August 15, 2006, GEICO's website no longer accepted 9,001-12,000 mi. as the *annual mileage* when all other identical information regarding driving and mileage is input. Consequently, NJCA had two options in cross-checking the rate quote data and both were applied. In one trail, *annual mileage* was changed to 12,001-15,000 mi. (instead of 9,001-12,000 mi.) in order to satisfy GEICO's website. In another trial, *miles driven to work one way* was changed to 20 mi. (instead of 25 mi.) and *annual mileage* was kept at 9,001-12,000 mi. Each trial produced identical rate quotes. However these rate quotes are not consistent with the rate quotes obtained from the original data collected between July 31, 2006 and August 15, 2006.

Appendix F

Coverage Options Pre-Selected on GEICO's Website and Used by NJCA when GEICO Rate Quotes were Obtained Between July 31, 2006 and August 15, 2006

Coverage Option	**NJCA Answer**
Basic Personal Injury Protection Coverage	PIP Full PIP Primary
Additional Personal Injury Protection Coverage	I decline this coverage
New Jersey Tort Options	Limited Tort[i]
Bodily Injury Liability (BI)	$15,000/$30,000 (New Jersey State Minimum)
Property Damage Liability (PD)	$10,000
PIP Full PIP Primary	$15,00 limit medical/$250 deductible
Uninsured & Underinsured Motorist	$15,000/$30,000
UM & Underinsured Motorist PD	$10,000
Medical Payments (MED)	$1,000 (included at no additional charge)
Comprehensive (COMP)	$500 deductible
Collision (COLL)	$500 deductible
Emergency Road Service (ERS)	I decline this coverage
Rental Reimbursement (RR)[ii]	I decline this coverage

[i] In January 2007, when NJCA cross-checked the rate quote data obtained from GEICO's website between July 31, 2006 and August 15, 2006, this coverage option was no longer pre-selected on GEICO's website (while all other coverage options were pre-selected as they had been during the data collection time period.) NJCA manually selected the Limited Tort coverage option when cross-checking the data in January 2007.

[ii] In January 2007, when NJCA cross-checked the rate quote data obtained from GEICO's website between July 31, 2006 and August 15, 2006, an additional coverage option was presented on GEICO's website: Mechanical Breakdown Insurance. NJCA used GEICO's pre-selected answer: decline this coverage.

Appendix G

Study Results - Average GEICO Rate Quotes Generated by NJCA According to Education and Occupation

	Observations	Average Rate Quote
Occupation:[1]		
Non-Professional	175	$ 1,618
Professional	274	$ 1,276
Edicational Attainment:		
With College Degree[2]	198	$ 1,299
Without College[3]	251	$ 1,548
Combined Groupings:		
Professional With College Degree	157	$ 1,129
All Others	292	$ 1,559
Non-Professional Without College Degree	81	$ 1,658
All Others	368	$ 1,354

[1]Professional and nonprofessional jobs were classified based on the definition of learned professional employees provided in the Federal Labor Standards Act (FLSA), 15574.
[2]Bachelors or Higher Educational Degree
[3]High School or Vocational Degree

Appendix H

Number of Vehicles Insured, Total Written Premiums and Average Policy Premiums for GEICO Group Companies Operating in New Jersey[i]

GEICO Company	Total Vehicles Insured	Total Written Premium	Average Policy Premium
GEICO preferred (educated, professional)	348,578	$353,259,647	$1,013.43
GEICO Indemnity	168,074	$240,677,570	$1,431.97
GEICO Casualty (blue collar-high school)	40,790	$ 83,942,198	$2,057.91

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[i] New Jersey Department of Banking and Insurance Semiannual Private Passenger Automobile Reports as of June 30, 2006. Voluntary Market – All Territories Combined – Total Written Premium by Company.

ATTACHMENT 3

S-1714 (Gill/Vitale)
Prohibits use of education and occupation as rating factors
in automobile insurance underwriting
March 5, 2007

SENATE, No. 1714
STATE OF NEW JERSEY
212th LEGISLATURE

INTRODUCED MARCH 20, 2006

Sponsored by:
Senator NIA H. GILL
District 34 (Essex and Passaic)
Senator JOSEPH F. VITALE
District 19 (Middlesex)

Co-Sponsored by:
Senator Doria

SYNOPSIS

Prohibits use of education and occupation as rating factors in automobile insurance underwriting.

CURRENT VERSION OF TEXT

As introduced.

AN ACT concerning certain automobile insurance underwriting rules, amending P.L.1997, c.151 and supplementing P.L.1972, c.70 (C.39:6A-1 et seq.).

BE IT ENACTED *by the Senate and General Assembly of the State of New Jersey:*

1. Section 15 of P.L.1997, c.151 (C.17:29A-46.2) is amended to read as follows:

15. a. Insurers shall put in writing all underwriting rules applicable to each rate level utilized pursuant to section 14 of P.L.1997, c.151 (C.17:29A-46.1). An insurer may take into account factors, including, but not limited to, driving record characteristics appropriate for underwriting and classification in formulating its underwriting rules; provided that no underwriting rule based on motor vehicle violations shall be formulated in such a manner as to assign any named insured to a rating tier other than the standard rating tier applicable to the insured's territory solely on the basis of accumulating four motor vehicle points or less. No underwriting rule shall operate in such a manner as to assign a risk to a rating plan on the basis of the territory in which the insured resides or any other factor which the commissioner finds is a surrogate for territory. No underwriting rule shall operate in such a manner as to assign a risk to a rating plan on the basis of an insured's: (1) educational level; or (2) employment, trade, business, occupation or profession. An insurer which knowingly fails to transact automobile insurance consistently with its underwriting rules shall be subject to a fine of not less than $1,000 for each violation.

b. All underwriting rules applicable to each rate level as provided for in section 14 of P.L.1997, c.151 (C.17:29A-46.1) shall be filed with the commissioner and shall be subject to his prior approval. All underwriting rules shall be subject to public inspection. Except as provided in subsection d. of section 27 of P.L.1990, c.8 (C.17:33B-15), insurers shall apply their underwriting rules uniformly and without exception throughout the State, so that every applicant or insured conforming with the underwriting rules will be insured or renewed, and so that every applicant not conforming with the underwriting rules will be refused insurance.

c. An insurer with more than one rating plan for private passenger automobile insurance policies providing identical coverages shall not adopt underwriting rules which would permit a person to be insured for private passenger automobile insurance under more than one of the rating plans.

d. An insurer that revises its underwriting rules with respect to the assignment of insureds to rating tiers based on the number of accumulated motor vehicle points, as provided by subsection a. of this section, as amended by P.L.2003, c.89, shall certify to the commissioner that the revised rule will produce rates that are revenue neutral based upon the insurer's current coverages and book of business.

(cf: P.L.2003, c.89, s.40)

2. (New section) No insurer shall require as to any application or selection of coverage for an automobile insurance policy issued or renewed in this State, any information from an insured or applicant as to the insured's or applicant's: (1) educational level; or (2) employment, trade, business, occupation or profession.

3. This act shall take effect on the 90th day following enactment.

STATEMENT

This bill prohibits automobile insurers from assigning an insured to a rating tier based upon an insured's: (1) educational level; or (2) employment, trade, business, occupation or profession. The bill also prohibits automobile insurers from requiring, as to any application or selection of coverage, any information from an insured or applicant as to these factors.

ATTACHMENT 4

Testimony of the Department of Banking and Insurance
Regarding
S-1714 (Gill/Vitale)
Prohibits use of education and occupation as rating factors
in automobile insurance underwriting
March 5, 2007

State of New Jersey
DEPARTMENT OF BANKING AND INSURANCE
PO BOX 325
TRENTON, NJ 08625-0325

JON S. CORZINE
Governor

TEL (609) 292-5360

STEVEN M. GOLDMAN
Commissioner

NJ Dept. of Banking and Insurance Testimony Before the Senate Commerce Committee – 3/5/07

S-1714 (Gill/Vitale) – Prohibits use of education and occupation as rating factors in automobile insurance underwriting

Thank you, Madam Chair, and members of the Committee. I am Sheila Kenny with the Department of Banking and Insurance and I am joined by Don Bryan, Director of Insurance and Assistant Commissioner of Property and Casualty Bill Rader.

At the outset, it is important to state that we are not here to testify on the recently issued Citizen Action report, as the Department has not yet had the opportunity to review that report in depth. We do want to let the committee know that we have begun and intend to continue to reach out in an effort to work with the interested parties to better understand their concerns and explain our processes. To that end, the Department will undertake its own review of the present status of availability and affordability of auto insurance in urban markets.

We are here to testify on S-1714 because we are concerned that a bill such as the one before the Committee could begin a process of rolling back the auto insurance market reforms which by any objective measure have greatly benefited the overall availability and affordability of auto insurance in New Jersey. The New Jersey auto insurance market has improved dramatically and the Department is in the midst of implementing the remaining reforms needed to finish the job of improving the market. The Department believes that the citizens of New Jersey are best served by completing the reforms and then gathering meaningful data before making adjustments.

Specifically, we would like to clarify some information that has been circulating regarding the Department's regulations on the issue of education and occupation. Contrary to recent statements, the Department's action permitting use of these rating factors is consistent with its regulations. The regulation repeatedly cited (N.J.A.C. 11:3-35.3 (c) 2) while still on the books, by its terms only applies to private passenger auto rating systems filed before 3/1/98. After this, an auto insurance reform package was enacted "AICRA" and the Department promulgated N.J.A.C. 11:3-19A which instituted Tier Rating Systems. The regulation in question remains in our regs because those rating systems filed before March 1, 1998 continued to be on file and effective for a period of time.

The essence of the Department's regulatory responsibility is reflected in N.J.S.A. 17:29A-4 which requires that rates be neither unreasonably high, nor inadequate for the safety and soundness of the insurer, nor unfairly discriminatory between customers presenting essentially the same level of risk and expense. This standard, which is also the standard used across the country, is important not only for assuring that companies remain financially strong enough to pay claims, but to assure that each customer is charged rates that are fair with respect to the risk of loss they present.

Therefore, since the use of education and occupation is not prohibited by either our tier rating statute or our regulations, we allowed these factors as part of the larger reform plan to improve the market by making New Jersey look more like the rest of the country, where these factors are overwhelmingly permitted. Specifically regarding GEICO, the Department did review their data and we are comfortable that the use of these factors is actuarially justified.

On the legislation being considered this afternoon, it is important to recognize that this bill does far more than prohibit the use of education and occupation as rating factors in the manner criticized by the Citizen Action report and has many potential unintended consequences. As written, the bill would end good-student discounts and it would require companies that now limit their writing to certain occupational or business groups from doing business as they have done historically, and prohibit many group marketing discounts. Prohibition of these practices would be a significant shift from the current practices of many companies in New Jersey and might severely affect New Jersey's auto insurance market to the detriment of New Jersey consumers.

In addition, the continued presentation of this issue creates uncertainty in the minds of the insurance industry of New Jersey's commitment to reform, and will make it more difficult to attract additional companies to the state, including those whose specialty is writing in urban markets and who would directly affect the consumers whose interests are addressed in the proposed bill.

New Jersey's past auto insurance problems were not created in one fell swoop, but rather were an amalgamation of incremental statutory mandate upon statutory mandate. To date, the effect of the 2003 reforms has been dramatic. Auto coverage is readily available and a large number of consumers have saved significant money. However, there should be no mistaking that this is a critical time in a transitional market. The Department wants to continue this success and is concerned that this bill could be the first step in unraveling our progress based in great measure on a report whose findings have not been widely disseminated and examined.

Therefore, we ask members of the committee to not support S-1714 in order to permit the 2003 reforms to move forward. Thank you.

ATTACHMENT 5

New Jersey Citizen Action Letter to
Commissioner Steven Goldman
June 6, 2007

NEW JERSEY

CITIZENACTION

Phyllis Salowe-Kaye, Executive Director

RECEIVED
2007 JUN -8 P 3: 04
NJ DOBI
OFFICE OF THE
COMMISSIONER

June 6, 2007

Commissioner Steven M. Goldman
Department of Banking and Insurance
P. O. Box 325
Trenton, NJ 08625-0325

Dear Commissioner Goldman:

On behalf of New Jersey Citizen Action (NJCA), the state's largest citizen watchdog coalition representing over 60,000 individuals and over 100 member and affiliate organizations, we are writing to request that the New Jersey Department of Banking and Insurance (DOBI) properly enforce N.J.A.C. 11:3-35, which among other criteria, set forth that "no underwriting rule shall be based on the lawful occupation or profession of an insured…" We believe the current use by GEICO Group of Companies to set rates and eligibility upon a driver's lawful occupation, and a growing number of other private passenger automobile insurance carriers, is an unlawful discriminatory practice that must be stopped by your regulatory body. We are deeply concerned about this growing practice, and by this letter respectfully request your prompt enforcement of this consumer protection regulation.

Furthermore, we believe the use of educational attainment by auto insurers such as GEICO is serving as a surrogate for race and class[1] and violates existing DOBI regulations and request your agency insure that this practice cease as well. See N.J.A.C. 11:3-35.3 (4).

As you are aware, GEICO Group of Companies categorizes drivers based upon their lawful occupations to determine which of the four GEICO companies a driver will qualify for. Drivers who possess "white collar" traditionally high paying occupations are eligible for the lowest rates through GEICO's preferred companies, while those drivers who are employed in traditionally lower-paying occupations are put in GEICO's sub-standard company and charged higher rates. This discriminatory underwriting practice rejects these drivers based upon their lawful occupation and charges them higher rates without even informing them of the basis of their rejection. Consumers victimized by this practice cannot file formal complaints with your department about this practice because they are unaware of its existence.

NJCA is an affiliate of USAction, a national progressive coalition

www.njcitizenaction.org

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The statute authorizing the Department of Banking and Insurance to promulgate regulations addressing underwriting is N.J.S.A. 17:29A-46 et seq. Enacted in 1988 (effective date Nov. 14, 1989), N.J.S.A. 17:29A-46 placed into law the obligation that insurers of private passenger automobiles put all underwriting rules applicable to each rate level in writing to the Commissioner of Insurance, and required that no underwriting rule should operate to assign risk on the basis of the territory in which the insured resides. The statute gave rise to N.J.A.C. 11:3-35, which among other criteria, set forth that "no underwriting rule shall be based on the lawful occupation or profession of an insured, except that this provision shall not apply to any insurer which limits all its insureds to one lawful occupation or profession, or to several related lawful occupations or professions." See N.J.A.C. 11:3-35.3 (c) (7). Note that this regulation is included in the same subsection which protects citizens against insurance underwriting rules that are set forth on the basis of race, creed, and religion. See N.J.A.C. 11:3-35.3 (c) (4).[2]

Throughout the historical notes surrounding enactment of these various laws and code provisions, there is the repeated refrain that the laws and rules are intended to expand the marketplace, make insurance broadly available, and lower prices for consumers, all while assuring that underwriting rules are not imposed in an arbitrary, capricious or unreasonable fashion.

Despite the enactment of the Auto Insurance Consumer Reform Act (AICRA) in 1998, which among other new regulations allowed insurers to create rating tiers to qualify and place drivers within its business model, the regulations prohibiting lawful occupation, race, creed and religion **continued to remain**.

With an eye toward maintaining the public trust and prohibiting discriminatory practices from invading the insurance marketplace, New Jersey has always maintained these proscriptions on underwriting guidelines. Recently, with the promulgation of rules pertaining the Use of Alternative Underwriting Rules, N.J.A.C. 11:3-35A et seq., the Department of Banking and Insurance reiterated its stance against insurers utilizing discriminatory criteria within underwriting guidelines, citing the existing proscription against using "lawful occupation" to assign risk.

The Department was both vocal and unequivocal in its position, with the following public exchange contained within the April 2004 edition of the New Jersey Register:

> "**COMMENT:** Several commenters expressed concern with N.J.A.C. 11:3-35A.5(a)(3), which provides that no underwriting rules shall be based on the lawful occupation or profession of an insured. The commenters believed that insurers should have the right to evaluate a person's occupation as one of the factors in its underwriting rules, for example, in cases where people have occupations that pose greater exposure to risk. This commenter suggested that the rule be revised to read (additions in boldface): 'No underwriting rule shall be based **solely** on the lawful occupation or profession of an insured."
>
> **RESPONSE:** [Given by Department of Insurance] "Upon review of the commenter's concern, the Department has determined that no change is required. N.J.A.C. 11:3-

35A.5(a)(3) tracks verbatim **the existing standards for private passenger automobile insurance underwriting rules set forth at N.J.A.C.11:3-35.3(c)(7). Accordingly, the Department believes that these rules are appropriate and that they reflect standards for underwriting rules currently in place with respect to private passenger automobile insurers."** See 36 N.J.R. 1929 (a).

Thus, New Jersey has long recognized that "lawful occupation" as an underwriting criterion could well serve as a surrogate for race or creed, and has maintained that use of that criterion is prohibited as a discriminatory practice. Given the clarity of this position, and the importance of keeping discriminatory practices out of the marketplace for insurance, we are stunned to witness the advent of certain New Jersey insurance carriers, most notably GEICO, using "lawful occupation" as an underwriting criterion and the unjust result it produces.

Despite the fact that the Department of Banking and Insurance has repeatedly deemed this a proscribed practice, and despite the fact that the practice violates N.J.S.A. 17:29A-46, the use of "lawful occupation" as an underwriting criterion appears to be growing in an unchecked, expansive manner. **Seven auto insurance companies operating in New Jersey use lawful occupation as a rating or underwriting criterion, as of February 2005.**

We would also note that to the extent other unlawful criteria are being utilized, criteria which also serve as a surrogate for race, creed or territory, their usage must be eliminated if the Department is to stay within established law. Most notable in this regard is consideration of an applicant's level of education, the use of which, just as with "lawful profession," carries the unavoidable and unassailable conclusion that socio-economic status is fast becoming the benchmark by which insurers such as GEICO are rating risks in New Jersey. Clearly, such an offensive, discriminatory practice runs contrary to, and indeed violates, the express intent of the New Jersey Legislature as embodied in N.J.S.A. 29A-46, as well as the Department's own rulemaking which derives from that statutory authority. **Thirteen auto insurance companies operating in New Jersey use education as a rating or underwriting factor, as of February 2005.**

As an organization devoted to promoting fairness and social equality as well as protecting low income and minority groups from discriminatory business practices, we are deeply troubled by the failure of your department to properly protect unsuspecting citizens from these practices.

By operation of law, there is extensive scrutiny of an insurer's underwriting criteria prior to acceptance by the Department of Banking and Insurance. Yet despite the formidable regulatory oversight which necessarily accompanies acceptance of underwriting guidelines, it has been made clear that auto insurers can and will use a consumer's "lawful occupation" to rate an automobile insurance risk. Simply put, this is inconsistent with New Jersey state law and a regulatory system that expressly precludes discriminatory practice.

The New Jersey Supreme Court has clearly indicated its view of a governmental agency's obligation to adhere to its own regulations when it stated, "absent a statute or regulation authorizing the waiver of otherwise valid an enforceable administrative regulations, an agency generally should not waive its own duly enacted regulations by disregarding them." In re CAFRA Permit No. 97-0959-5 Issued to Gateway Associates, 152 N.J. 287 (1997) (citing

County of Hudson v. Department of Corrections, 152 N.J. 60 (1997). The Court further favorably commented upon the following principles governing administrative agencies:

- An agency is bound by express terms of its regulations until it amends or revokes them.
- Administrative agencies must follow their own rules as written, without making *ad hoc* exceptions or departures there from in adjudicating.
- A government agency must respect is own regulations as long as they exist "on the books."
- Once promulgated, rules may not be violated or waived by the agency that issued them.

On behalf of our member groups and the tens of thousands of members we represent, we hereby formally request that the Department of Banking and Insurance order GEICO Group of Companies and other private passenger automobile insurance carriers to immediately cease from using lawful occupation and education as underwriting and/or rating factors. Furthermore, we request the Department provide a formal explanation as to how certain insurance carriers have been allowed to bypass or flatly ignore existing law proscribing the use of "lawful occupation" as an underwriting criterion, and how consumers in New Jersey have become subjected to a marketplace which, allows this discriminatory underwriting practice as well as the use of educational attainment of a driver which serve as a surrogate for race. Clearly these regulations were meant to protect consumers from discrimination, and your duty as our state regulatory body is to ensure these protections are properly enforced. Finally, we request the Department investigate whether and how much of a refund may be due any and all auto insurance consumers who have been paying discriminatory rates.

Thank you for your prompt consideration of, and attention to, this most serious matter. We look forward to receiving the Department's response.

Sincerely,

Phyllis Salowe-Kaye

Phyllis Salowe-Kaye
NJCA Executive Director

Cc: David Weiner, NJCA Board Co-Chair
Paulette Eberle, NJCA Board Co-Chair
James Harris, President, NJ-NAACP
Richard Barber, Treasurer, NJ-NAACP
Bob Regan, CWA 1037

Rex Reid, AFSCME Council 1
David McCann, SEIU-NJ State Council
Ray Ocasio, La Casa de Don Pedro
Reverend Bruce Davidson, Lutheran Office of Governmental Ministries
Daniel Santo Pietro, Hispanic Directors Association
Pete Guzzo, Consumers for Civil Justice
Larry Hamm, Chair, People's Organization for Progress
Marretta Short, President, NJ-NOW
Reverend Reginald Jackson, Black Ministers Council
Jeremiah Grace, Racial Justice Organizer, ACLU
Eve Weissman, NJCA
Ev Liebman, NJCA
The Honorable State Senator Nia Gill
Governor Jon Corzine
The Honorable Ken Zimmerman, Counsel to the Governor
The Honorable Heather Howard, Policy Council to the Governor

---

[1] According to the U.S. Census Bureau, in 2005, 30.6 percent of Caucasians, 25 years and over held a Bachelors or higher educational degree, while only 17.6 percent of African Americans and 12 percent of Hispanics held comparable degrees. (U.S. Census Bureau, Current Population Survey, 2005 Annual Social and Economic Supplement.)

[2] Although N.J.A.C. 11:3-35.1 (c) states that "No private passenger automobile insurer shall make any filing pursuant to this subchapter after March 1, 1998." this represents nothing more than a procedural switch to N.J.S.A. 17:29-46.1, as of March 1, 1998, as the authority which requires rate filings with the Commissioner. The remaining language contained in 11:3-35.1 regarding underwriting criteria, such as the ban of lawful occupation found in the same subchapter, remains good law.

The language banning lawful occupation was never repealed and is formally on the books as an in-force regulation. Furthermore, the New Jersey Department of Banking and Insurance reconfirms in 36 N.J.R. 1929 (a), the current proscriptions against using "lawful occupation" as an underwriting criterion, as enumerated in N.J.A.C. 11:3-35.3 (c) (7) are part of the "existing standards," and that they "reflect standards for underwriting rules currently in place with respect to private passenger automobile insurers."

ATTACHMENT 6

Maryland Insurance Administration Market Conduct Examination of GEICO
June 8, 2006

MARYLAND INSURANCE ADMINISTRATION
R. STEVEN ORR, COMMISSIONER

MARKET CONDUCT EXAMINATION REPORT

OF THE PROPERTY & CASUALTY BUSINESS

OF

GOVERNMENT EMPLOYEES INSURANCE COMPANY (NAIC #22063)
GEICO CASUALTY COMPANY (NAIC #41491)
GEICO GENERAL INSURANCE COMPANY (NAIC #35882)
GEICO INDEMNITY COMPANY (NAIC #22055)

ONE GEICO PLAZA
WASHINGTON, DC 20076-0001

Report No. MCPC-1-2006-E

R. STEVEN ORR
COMMISSIONER

ROBERT L. EHRLICH, JR.
GOVERNOR

JAMES V. MCMAHAN, III
DEPUTY COMMISSIONER

MICHAEL S. STEELE
LIEUTENANT GOVERNOR

P. TODD CIONI
ASSOCIATE COMMISSIONER

State of Maryland
MARYLAND INSURANCE ADMINISTRATION
525 ST. PAUL PLACE, BALTIMORE, MARYLAND 21202-2272
Writer's Direct Dial: 410-468-2235
Facsimile Number: 410-468-2289
e-mail : tcioni@mdinsurance.state.md.us

June 8, 2006

The Honorable R. Steven Orr
Commissioner of Insurance
State of Maryland
525 St. Paul Place
Baltimore, Maryland 21202

Dear Commissioner Orr:

Pursuant to your instructions and authorization, a target examination has been made of the market conduct affairs of

GOVERNMENT EMPLOYEES INSURANCE COMPANY
GEICO CASUALTY COMPANY
GEICO GENERAL INSURANCE COMPANY
GEICO INDEMNITY COMPANY

whose home office is located at One GEICO Plaza; Washington, DC 20076. The report of such Examination is respectfully submitted.

Sincerely,

Signature on file with original

P. Todd Cioni, Associate Commissioner
Compliance and Enforcement Unit

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I. EXECUTIVE SUMMARY

The Maryland Insurance Administration (hereinafter referred to as "MIA") conducted a target market conduct examination of Government Employees Insurance Company; GEICO General Insurance Company; GEICO Indemnity Company and GEICO Casualty Company, (hereinafter collectively referred to as “GEICO” or "Companies").

The examination focused on whether the Companies’ practice of using education and occupation as underwriting factors is prohibited by Section 27-501(a) of the Insurance Article. To assist with the actuarial review and analysis, the MIA utilized the services of Merlinos & Associates (M&A) with whom the MIA has a contract to provide actuarial services. The examination report represents the collaborative work of the Maryland Insurance Administration and M&A (hereinafter referred to as “examiners”).

In general, the MIA found:

- GEICO’s use of education and occupation as underwriting factors is reasonably objective;
- GEICO has demonstrated that education and occupation are predictors of loss;
- GEICO’s use of education and occupation as risk characteristics meets actuarial standards of practice and principles related to risk classification;
- From an actuarial perspective, GEICO’s use of education and occupation is reasonable;
- GEICO notified the Administration that it does not use education or occupation to solely underwrite a risk, the examiners identified a certain sub-class within an occupational group that was not eligible at initial underwriting for the most preferred company based solely on occupation. This occupation sub-class, however, was eligible for the preferred company at renewal. GEICO has corrected this underwriting rule to ensure no applicant is denied access to the preferred company based solely on occupation at the time of initial underwriting.
- The Companies’ use of education and occupation as underwriting factors is not in violation of Section 27-501(a) of the Insurance Article.

II. SCOPE OF EXAMINATION

The MIA conducted a target market conduct examination of the Companies. The examination was conducted at the Companies' offices located in Chevy Chase, MD. The examination focused on whether the Companies' practice of using occupation and education as underwriting factors is prohibited by Section 27-501(a) of the Insurance Article. The MIA recently concluded a comprehensive market conduct examination of the Companies and those findings are reported in MIA Examination Report #3866-03 issued April 29, 2005. A copy of the Market Conduct Examination Report is available on the MIA's website at www.mdinsurance.state.md.us.

The Examination was conducted pursuant to Sections 2-205, 2-207, 2-208 and 2-209 of the Insurance Article.

Because the examination required actuarial review of various underwriting and rating manuals, the MIA utilized the services of M&A with whom the MIA has a contract to provide actuarial services to assist in the examination. M&A is an independently owned property and casualty consulting firm that employs 15 actuarial professionals; of which eight are members of the Casualty Actuarial Society. As part of the contractual agreement with the MIA, M&A maintains a Conflict of Interest Policy to ensure neutrality, objectivity and professionalism in performing its duties.

In addition, the MIA's in-house actuarial staff also assisted the examiners with their review.

All unacceptable or non-compliant practices may not have been discovered or noted in the Report. Failure to identify or criticize improper or non-compliant business practices in Maryland or in other jurisdictions does not constitute acceptance of such practices. Examination report findings that do not reference specific insurance laws, regulations, or bulletins are presented to improve the Companies' practices and ensure consumer protection. When applicable, corrective action for other jurisdictions should be addressed.

The examination and testing methodologies follow the standards established by the National Association of Insurance Commissioners ("NAIC") and procedures developed by the Maryland Insurance Administration. Testing performed during the review provides a credible basis for the findings and recommendations contained in the report.

III. COMPANY PROFILE

The Government Employees Insurance Company was reincorporated and redomesticated on January 3, 1986 under the laws of Maryland to effect a change in corporate domicile from the District of Columbia to Maryland. The original Government Employees Insurance Company was formed August 1936 in Texas, and was reincorporated in the District of Columbia in 1937 and 1979.

The GEICO General Insurance Company was incorporated on March 27, 1978 under the temporary title “Equi - Gen Insurance Company” under the laws of Iowa. The present name was adopted on September 29, 1982.

The GEICO Indemnity Company was incorporated on March 22, 1961 and reincorporated in 1980 in the District of Columbia under the name of Criterion Insurance Company. On June 25, 1986 the Company was redomiciled to Maryland and changed its name to the present title.

The GEICO Casualty Company was incorporated on August 31, 1982 under the laws of Maryland as the Guardian Casualty Company and the present title was adopted on January 6, 1994.

A.M. Best assigns each company a Financial Size Category. Best's Financial Size Category is based on reported policyholders' surplus plus conditional or technical reserve funds, such as mandatory securities valuation reserve, other investment and operating contingency funds and miscellaneous voluntary reserves reported as liabilities. The Financial Size Category is represented by roman numerals ranging from Class I (the smallest) to Class XV (the largest). The Companies’ Financial Size Category is XV.

IV. CERTIFICATE OF AUTHORITY

The Companies' Certificates of Authority to write business in the State of Maryland were last issued on July 1, 2005 and are currently in good standing.

The Government Employees Insurance Company is licensed in DC and all States.

GEICO General Insurance Company is licensed in DC and all States.

GEICO Casualty Company is licensed in DC and all States except MA, MI, NC, TX, VT and WV.

GEICO Indemnity Company is licensed in all States except MA.

V. UNDERWRITING

Issue 1 - Is the Companies use of education and occupation as underwriting factors in violation of Section 27-501(a)?

Section 27-501(a) provides:

> (a) In general. - (1) An insurer or insurance producer may not cancel or refuse to underwrite or renew a particular insurance risk or class of risk for a reason based wholly or partly on race, color, creed, sex, or blindness of an applicant or policyholder or for any arbitrary, capricious, or unfairly discriminatory reason.
>
> (2) Except as provided in this section, an insurer or insurance producer may not cancel or refuse to underwrite or renew a particular insurance risk or class of risk except by the application of standards that are reasonably related to the insurer's economic and business purposes.[1]

Background

In Maryland, the GEICO Group underwrites private passenger automobile policies through four companies. Government Employees Insurance Company and GEICO General Insurance Company are the preferred companies, using identical rates and underwriting rules. The former is reserved for active and retired government employees (State and Federal Employees) while the latter writes all other preferred policies. GEICO Indemnity Company is the standard company and GEICO Casualty Company writes non-standard risks.

Generally, an applicant may obtain an insurance quote either through an internet application or by calling a toll free number and completing a telephonic application. Placement of an applicant within a specific company is an automated process. The process identifies, from the information submitted with the application, a number of risk characteristics that correlate with potential loss experience. Each characteristic, including education and occupation, is assigned a point value and then all values are totaled. This total score is used to determine whether the applicant is eligible for

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[1] Subsection (a) of § 27-501 requires that an insurer's decision to cancel or to refuse to underwrite or renew a policy of insurance be based on underwriting standards that exist, that are clearly stated, that are uniformly and objectively applied, and that can be demonstrated objectively to be related to the insurer's economic and business purposes. §27-501(a)(2). In addition, an underwriting decision cannot be based on those specific characteristics identified in paragraph (a)(1) or any characteristics similar to those specifically enumerated. *St. Paul Fire & Mar. Ins. Co. v. Ins. Comm'r*, 275 Md. 130, 136 (1975)(recognizing that §27-501(a)(1) is "directed only at the historic prejudices enumerated in the first sentence" or "any arbitrary, capricious or unfairly discriminatory reason like those specifically mentioned"); *see also Ins. Comm'r v. Allstate Ins. Co.*, 268 Md. 428, 441 (1973)(same).

GEICO's preferred companies, and then to determine the tier within the preferred company for which the applicant is eligible. If the applicant is not eligible for the preferred companies, then the score is utilized to determine the company (standard or non-standard) for which the applicant is eligible and then which specific tier within the specific company for which the applicant is eligible.

Upon renewal, the policyholder will not be moved based on occupation or education to a different tier. However, if at renewal, a policyholder is eligible for a lower rate with one of the preferred Companies, education and occupation will be considered in determining the appropriate tier within the new company. In no case, will a policyholder ever receive a higher rate at renewal as a result of a change in education or occupation.[2]

Education and occupation are two of the many risk characteristics identified by the Companies as predictors of risk and loss experience and are used in determining the initial placement of an applicant within a particular company. It is important to note for multi-driver policies, the driver with the most favorable Occupation Group will dictate the Occupation Score for that policy.

Education and Occupation in Underwriting

The Companies, like numerous other private passenger auto insurers, utilize education and/or occupation as underwriting variables. As noted above, education and occupation are two of the many underwriting factors used to determine the company for which an applicant is eligible and the specific tier for which an applicant is eligible.

By reviewing the Companies' underwriting manuals, the examiners determined that while GEICO's underwriting model is not static and is based on a multi-variate minimum bias approach, the maximum impact that education, as utilized in GEICO's scoring model can have is to move an applicant up or down one tier. The maximum impact occupation can have is to move an applicant up or down four tiers within a company.

At renewal, a policyholder will not be penalized based on a change in education or occupation that reduces a policyholder's score. However, if a change in education or occupation would result in the policyholder being eligible for a more preferred company, the policyholder will be re-scored, education and occupation being two of the factors utilized, to determine appropriate tier placement within that company.

[2] This was tested and confirmed in MIA Examination Report 3866-03 issued April 29, 2005.

Propriety of Education and Occupation as Class Factors

M&A was asked to assist in reviewing whether it is appropriate to use education and occupation as class factors for underwriting. The actuarial profession provides guidance as to whether or not a characteristic can or should be used as a class factor (ASOP #12 – Risk Classification – CAS Statement of Principles Regarding P&C Insurance Ratemaking). Those guidelines include, but are not limited to, the following pertinent issues:

1. Homogeneity
2. Objectivity
3. Credibility

Education

The examiners determined that the use of education as an underwriting factor provides an objective classification system as the qualifications can be proven. Additionally, the classes are homogenous with similar education levels grouped together and there is sufficient credibility in the individual classes. There is not an adverse selection due to the size of the classes.

GEICO has provided sufficient evidence, based on a multi-variate analysis, minimum bias approach, to show education is an accurate predictor of loss. Furthermore, GEICO has met the threshold for supporting its use of education as an underwriting factor. Therefore, the examiners have determined that education meets the actuarial standards of practice related to a classification to be used as an underwriting standard and is reasonably related to the Companies' economic and business purpose as being an accurate predictor of loss. Consequently, its use is not in violation of Section 27-501(a).

Occupation

The examiners determined that the use of occupation as an underwriting factor provides an objective classification system, the classes are homogenous and there is sufficient credibility in the Occupation Groups.

GEICO divides different occupations into seven different groups, with each group receiving a different score. The seven Occupation Groups are of sufficient size to be fully credible.

While the Occupation Groups are fully credible, this is not true for each and every job that makes up each Occupation Group. However, the Examiners have gained comfort that this is not a material issue. This is not unique to the occupation class or to scoring models in general. Accurate occupation classification is an issue that also exists within the workers' compensation insurance line of business. This is reasonable from an actuarial perspective. Additionally, GEICO reviews the reasonability of the allocation of sub-class to Occupational Group approximately every two years and makes adjustments accordingly.

In determining an applicant's occupation, the Companies provide guidance to select an applicant's occupation. The number of applicants whose occupation may be unclear appears very small. The Companies provide their customer service representatives with guidance on how to deal with those situations when occupation may be unclear; however, the Examiners noted this guidance is not available on the website. There are, however several help panels available to help guide the applicant to the occupation that best describes what they do.

Given the precedence of using occupation in workers compensation insurance and the available support for determining occupation, the Examiners concluded that GEICO's use of occupation reaches the objectivity threshold.

Therefore, the examiners have determined that occupation meets the actuarial standards of practice related to a classification to be used as an underwriting standard and is reasonably related to the Companies' economic and business purpose as being an accurate predictor of loss. Consequently, its use is not in violation of Section 27-501(a).

Testing

GEICO provided several examples to support their use of education and occupation as valid classifications.

It is important to understand that the GEICO underwriting model is not static. Many of the tests performed assume that one can "eliminate" education and occupation as an underwriting classification and then see what the results would have been. This is not entirely accurate as GEICO sets the rating values based on a multi-variate, minimum bias approach. In this approach, the values of all variables are affected by each of the other variables.

For example, deleting occupation as a classification may significantly increase the scores for education, in addition to other potential material changes in other factors. In addition, changing the weights or eliminating various rating variables will potentially increase the premiums for certain insureds that will leave. It may also lower the premiums for other potential policyholders who will now choose GEICO, and who may increase the GEICO loss ratios.

While GEICO notified the Administration that it does not use education and occupation to solely underwrite a risk, during the testing process, it was discovered that a sub-class within an Occupational Group was not eligible for the most preferred company based solely on occupation. This occupation sub-class, however, was eligible for the preferred company at renewal. The affected sub-class represents approximately less than .1% of GEICO's total book of business.

GEICO has corrected this underwriting rule to ensure no applicant is denied access to the preferred company based solely on occupation at the time of initial underwriting.

VI. CONCLUSION

The use of education and occupation as underwriting variables meets the actuarial standards of practice related to classification. Furthermore, education and occupation have been shown to be valid predictors of loss and the Companies have provided documentation to support their scoring for education and occupation.

Consequently, the Companies have objectively demonstrated that their use of education and occupation as factors in underwriting is reasonably related to their economic and business purpose and is not in violation of Section 27-501(a) of the Insurance Article.

VII. EXAMINATION REPORT SUBMISSION

The courtesy and cooperation extended by the Officers and Employees of the Companies during the course of the Examination is hereby acknowledged.

Signature on file with original

____
Dudley B. Ewen, A.I.E., Chief Examiner
Compliance and Enforcement

In addition, the following individuals participated in this examination and in the preparation of this Report.

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ATTACHMENT 7

DOBI Press Release:
Commissioner Bakke Extends "Last Chance" Because of Availability Crisis
February 28, 2003

News Release

Commissioner Holly C. Bakke

For Immediate Release: February 28, 2003

For Further Information:: Mary Caffrey - **(609) 292-5064**
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COMMISSIONER BAKKE EXTENDS "LAST CHANCE" BECAUSE OF AVAILABILITY CRISIS

TRENTON, N.J. - Banking and Insurance Commissioner Holly C. Bakke today formally extended and modified the "Last Chance" program for uninsured drivers, giving them until March 31, 2003, to take advantage of this opportunity to drive legally. The program was scheduled to expire today, February 28.

"Last Chance," which began in mid-September, waives certain underwriting surcharges for drivers who can only be insured through the residual market, formally known as the New Jersey Personal Automobile Insurance Plan. These drivers, who face the greatest financial hurdles to becoming insured, can save between $115 and $1,035 through the program.

"During this marketplace crisis, we want to do everything we can to help as many people as possible become and remain insured,' Commissioner Bakke said.

Although the Commissioner said the extension will allow more uninsured drivers to become legal, she also noted that the measure addresses only a limited number of drivers. Commissioner Bakke stressed that the comprehensive auto insurance reform plan proposed by Governor James E. McGreevey is necessary to correct the current availability crisis that is plaguing the marketplace and making it difficult for drivers to get policies. Under the current regulatory system, the ability to extend "Last Chance" is one of the few tools available to the Commissioner to address this unprecedented crisis in the marketplace.

"We stand ready to work with the Legislature to get the auto insurance plan passed," Commissioner Bakke said. "The situation gets worse every day."

"Many drivers have taken advantage of 'Last Chance,' but more can and should," Commissioner Bakke said. "For many, the biggest obstacle to getting insured is cost. We have taken steps to make sure that low-cost insurance options are available and want to give those still interested in 'Last Chance' a few more weeks to get insured."

In late December, Commissioner Bakke made an initial decision to extend "Last Chance" due to the resistance some drivers have faced when considering the Basic Policy. This low-cost option offers minimum coverage at a price that can be hundreds of dollars below the cost of the Standard coverage most drivers buy.

Originally, only drivers who had been uninsured since September 16, 2002 were eligible for the "Last Chance" program.

Today, Commissioner Bakke modified the program to allow people who were uninsured up until today to also be eligible.

The Commissioner attributed the modification to the fact that drivers whose policies were cancelled since September for failure to pay premiums have probably had a particularly difficult time finding new policies in the current marketplace.

Through February 21, 2003, the number of vehicles that became insured through "Last Chance" was over 31,600.

"We are pleased that thousands of uninsured drivers are now legal," Commissioner Bakke said.

"We hope that our actions will allow thousands more to become legal before March ends."

"Last Chance" waives underwriting surcharges for those who have a conviction for driving uninsured or failed to pay their premium, causing their policy to be canceled. The program waives underwriting surcharges only; all court costs and surcharges to the Division of Motor Vehicles must be paid.

ATTACHMENT 8

DOBI Press Releases:
First Major Insurer Enters Market
August 07, 2003
First Major Insurer to Expand Agent Base in New Jersey
August 26, 2003
NJ Drivers will benefit from State Farm Decision
October 9, 2003

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News Releases

RELEASE: August 07, 2003

Previous Screen

Benefits of McGreevey's Auto Insurance Reforms Materialize

First Major Insurer Enters Market

(TRENTON)— Keeping his promise to change the way New Jersey regulates the auto insurance industry, Governor James E. McGreevey today welcomed the first new auto insurer to enter the New Jersey market since 1996. The Governor was joined by Banking and Insurance Commissioner Holly C. Bakke.

The announcement comes just two months after the Governor signed an auto insurance reform package that overhauls the State's auto insurance system. Beginning today, the new insurer--Mercury General--will be hiring as many as 50 agents and plans to offer policies to drivers not renewed by State Farm Indemnity.

"There is no doubt that our reforms are making New Jersey an attractive place to do business again," said Governor McGreevey, "and the result means more choices for New Jersey drivers."

Commissioner Bakke credits Mercury's entrance into the New Jersey marketplace to the Governor's auto insurance reform package, which was signed in June. The reforms have been endorsed by consumer and anti-fraud groups, as well as the insurance industry and AAA Mid-Atlantic. It now imposes some of the Nation's toughest penalties for auto insurance fraud, while strengthening consumer protections and cutting down on the number of uninsured drivers on the road. Innovations include stricter categorization of high-risk drivers, a dollar-a-day insurance plan for low-income drivers and phases out the "Take All Comers" law that forces companies to insure drivers with bad records.

"We are on the right road toward a healthier, more stable auto insurance market," Commissioner Bakke said. "Mercury is a sure sign that the market is improving, and that we are getting closer to our goal of giving consumers the choices they deserve."

"This is a huge first step in welcoming the insurers that for so long used the disclaimer *not available* in New Jersey," said McGreevey. "Insurance is *now available* in New Jersey. The word is getting out that New Jersey has established a new playing field."

Mercury General is a Los Angeles based company with a reputation for low cost and careful assessment of driver risk. The company presently has $2 billion in assets and offers auto insurance in eight other states including California, Texas and Florida.

"We are excited about joining the market. We're here not only because of the reform legislation itself, but also because of the clear commitment that Governor McGreevey and Commissioner Bakke have made to making auto insurance work in New Jersey," said Jack Dougherty, Vice President, Mercury General.

"The Professional Insurance Agents of New Jersey is excited to have Mercury Insurance Group enter

New Jersey's auto insurance market. We welcome efforts to restore competition to the market for the ultimate benefit of consumers and hope this will encourage further regulatory reform, stabilization and competition in the industry," said PIANJ President John D'Agostino Jr., CIC, whose agency is based in Hammonton.

Mercury General is the leading independent broker and agency writer of automobile insurance in California and has been one of the fastest-growing automobile insurers in the Nation. It is ranked as the sixth-largest among all insurers in California, with total assets more than $2 billion.

Since its formation in 1961, Mercury has focused on careful underwriting, strict cost control and efficient claims management that support affordable, competitive automobile insurance rates. Its most recent rating by A.M. Best is A-plus, putting the company in the ranks of the most financially stable insurers.

Mercury will offer auto insurance policies to 4,000 drivers that State Farm Indemnity is not renewing each month under a June 2002 Market Stabilization Order. Through a revamped Department's Market Assistance Procedure, which was established to help State Farm Indemnity motorists find auto insurance coverage, policyholders who are non-renewed by State Farm will get an offer from Mercury within 30 days. These motorists have the right to opt out of receiving a Mercury quote, and, as before, they have the right to look elsewhere for coverage. Over the next 14 months 50,000 State Farm Policy holders will have the option to go to Mercury General.

Eligible drivers will be placed into one of seven tiers, depending on a number of factors, including driving history, the levels of coverage they choose, and a variety of discounts that may apply, including good student, driver education, senior citizen and good credit discounts, which will be offered in New Jersey for the first time. Good credit discounts are used in most states to evaluate driver risk and will be assessed by the Department of Banking and Insurance with Mercury's entry into the State.

New Jersey has had more than 20 insurers leave the State in the last 10 years. With enactment of the regulatory reforms laid out in the Governor's reform plan, New Jersey drivers can expect more companies and more competition over time. The law is specifically designed to reward companies that operate efficiently and increase their investment in the State. Those companies that provide additional coverage or increase their capital beyond what is mandated for the level of risk that they carry would receive economic incentives.

Companies also benefit from the commonsense approach taken in re-writing the "excess-profit rule." In years past, levels of profitability were determined over a three-year period. Excess profit will now be evaluated over seven years in an attempt to even out the effects of good and bad years. In 1998 the excess-profit rule forced State Farm Indemnity to return $38 million to its customers only to find itself in dire straits in the years to follow.

Bringing in new carriers has been a primary goal of the McGreevey Administration's efforts to reform the State's auto insurance system to operate with minimum red tape and maximum market competition. It requires redressing more than 30 years of damage to the way New Jersey's auto insurance industry operates.

"Whether it is auto insurance, EZPass or DMV reform, we are delivering real change for New Jersey drivers," said McGreevey.

Photos and audio and video clips from Governor McGreevey's press conferences are available on the Governor's web page at http://www.state.nj.us/governor/. Links are located in the Governor's Newsroom section of the page.

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News Releases

Previous Screen

RELEASE: August 26, 2003

Benefits of McGreevey's Auto Insurance Reforms Materialize

First Major Insurer to Expand Agent Base in New Jersey

(BRIDGEWATER)— Marking the continued progress made to reform auto insurance, Governor James E. McGreevey today welcomed the decision by Allstate New Jersey to expand the number of agents writing auto insurance. Joined by Banking and Insurance Commissioner Holly C. Bakke, the Governor noted that the move serves as a confirmation that recently signed auto insurance reforms are working to the benefit of consumers.

"More agents translates into more places for drivers to find auto policies," Governor McGreevey said. "It's expected that over the next year, at least 20,000 more drivers will have easier access to auto insurance than they have today."

Allstate New Jersey, the state's second-largest auto insurance carrier, today announced the appointment of five new Exclusive Agents and one Independent Agent to write auto, property and financial services products. These are the first new increases in sales offices since 1975, according to the Department of Banking and Insurance.

This fall, Allstate New Jersey also plans to open four more Exclusive Agent offices as well as grant auto-writing authority to a group of independent agents who currently write life-insurance only for Allstate New Jersey. This will expand the number of sales offices for auto insurance, marking a shift from the business strategy that Allstate New Jersey and many other New Jersey insurance companies

Less than three months ago, on June 9, 2003, Governor McGreevey signed into law a landmark reform package that aimed to boost competition and consumer choice in the auto insurance market. The new law, passed in response to a crisis that forced drivers to hunt for up to a month for auto insurance, takes aim at uninsured motorists and fraud, stops making good drivers pay for bad drivers, and gives consumers new rights and tools for finding the best policy for their needs.

Earlier this month, the reform package attracted major national carrier, Mercury General, to New Jersey. The company is in the process of appointing 50 new agents. Commissioner Bakke also credits the reform package for persuading the AIG companies to choose defer their option to leave the state at the end of 2003.

Banking and Insurance Commissioner Holly C. Bakke noted that Allstate's decision to expand its agent force reverses a decades-long business plan of reducing the number of neighborhood agencies. "Other than a limited, national experiment with independent agents in 1999, Allstate had not expanded the number of auto agents in a generation," Bakke noted.

"We are making auto insurance more available to New Jersey consumers -- and they will be able to see that change in their neighborhoods."

Allstate's expansion will bring auto insurance offices to areas where population shifts have made policies especially hard to find. Appointments in Marmora and Mays Landing, for example, bring distribution points to counties that have generated a disproportionate number of phone calls to the Department from drivers who cannot find auto insurance.

Commissioner Bakke has talked to some of these callers during a session in the DOBI call center. "In an hour, I talked to two consumers who were moving permanently from Pennsylvania to their summer homes in Cape May County. They couldn't understand why it was so difficult to find auto insurance in New Jersey, when across the river they could walk into an agent's office and walk out with a policy."

Allstate's decision shows that companies are viewing New Jersey differently, Governor McGreevey said. "We promised that our reforms would make companies reach out to consumers, not run from them. It's working. We promised that we would put consumers in the driver's seat, and we are."

Richard C. Crist, Jr., President of Allstate New Jersey, said, "The New Jersey Auto Insurance Competition and Choice Act is energizing the company. It ensures strong consumer protection while encouraging and generating more competition and choice for New Jersey drivers. Reform is a big win for consumers." Crist continued, "Our agents and sales force are looking ahead with focus and optimism; we're upbeat about the possible opportunities resulting from the reform," he said. "This attitude is also shared by the new Exclusive Agents - customer-oriented, dedicated and forward-thinking professionals - who are bringing new energy into Allstate New Jersey."

Crist concluded, "I applaud the vision, fortitude and perseverance of the Governor, the New Jersey Legislature, Commissioner Holly Bakke and all the bill sponsors."

Bringing in new carriers and expanding availability has been a primary goal of the McGreevey Administration's efforts to reform the State's auto insurance system to operate with minimum red tape and maximum market competition. It requires redressing more than 30 years of damage to the way New Jersey's auto insurance industry operates.

"Whether it is auto insurance, EZPass or DMV reform, we are delivering real change for New Jersey drivers," said McGreevey.

Photos and audio and video clips from Governor McGreevey's press conferences are available on the Governor's web page at http://www.state.nj.us/governor/. Links are located in the Governor's Newsroom section of the page.

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News Releases

RELEASE: October 09, 2003

Previous Screen

Governor's Auto Insurance Reform Continues to Produce Results

NJ drivers will benefit from State Farm decision

(TRENTON) – In another action demonstrating the success of the Governor's landmark auto insurance reform, State Farm Indemnity has suspended its practice of dropping coverage for 4,000 New Jersey drivers each month.

"In just a few months, we've seen historic changes for New Jersey drivers," said Governor James E. McGreevey. "There are real results and tangible signs that progress is being achieved.

The Governor said New Jersey motorists are benefiting from a series of recent accomplishments, including Mercury Insurance's decision to move to New Jersey (the first new auto insurance company to do so in seven years); Allstate's plans to add 15 to 20 new agents, and State Farm's voluntary rate reduction, which will save 500,000 drivers an average of $70.

The Governor said State Farm's decision to suspend its practice of dropping coverage for 4,000 New Jersey drivers each month will prevent thousands of drivers from being forced to look for new coverage. He also noted that the company is taking this action a full year ahead of schedule.

Since September 2002, State Farm Indemnity has been non-renewing policies that cover about 4,000 cars per month. Regulators in Illinois and New Jersey required this action to bring financial stability to the company. The suspension of non-renewals, approved by Illinois regulators, helps drivers of 94,000 cars who were notified a year ago that they might be non-renewed under the orders.

"Today is a great day for New Jersey drivers," McGreevey said. "Every State Farm Indemnity policy that stays in force brings stability to an improving auto insurance market, which benefits all consumers. When fewer drivers are forced to hunt for new coverage, those who must shop will find it in less time."

State Farm Indemnity's condition was emblematic of the auto insurance crisis that Governor McGreevey faced upon taking office in January 2002. At its peak, State Farm Indemnity insured 20 percent of the New Jersey market but had asked to leave due to its poor financial condition. A rapid departure would have flooded a fragile auto insurance market, one that had suffered the departure of 20 companies over the previous decade.

The Governor and Banking and Insurance Commissioner Holly C. Bakke set to work immediately to stabilize State Farm Indemnity and limit the impact on consumers. "Auto insurance has bedeviled New Jersey lawmakers for 30 years, but for the first time we faced a crisis in which drivers could not find coverage at any price," Bakke said.

On June 25, 2002, State Farm Indemnity was placed under a Corrective Order by regulators in Illinois, its home state. This order required the company to shrink in size to reflect capital levels. The same day, New Jersey issued a Market Stabilization Order that specified the non-renewal schedule of approximately 4,000 cars per month. New Jersey's order also granted the company the right to leave after December 2005 and outlined financial benchmarks the Department would use to gauge progress.

If State Farm Indemnity meets the benchmarks in 2005, New Jersey has the right to make a case why the company should stay in New Jersey. "State Farm remains on track to meet these targets," Commissioner Bakke said.

The Market Stabilization Order also called for New Jersey to take steps to change its regulatory environment. Governor McGreevey advanced that cause by signing landmark auto insurance reform legislation on June 9, 2003.

The new law, still being implemented, will overhaul a 30-year-old regulatory structure in an effort to attract new companies and capital. It also features the nation's toughest provisions to fight insurance fraud, offers new consumer protection and education measures, and takes steps to reduce the ranks of the uninsured.

"Today's action by State Farm Indemnity does not alter its right to leave after 2005, but it does show, beyond a doubt, that the Market Stabilization Order was the right step for consumers," Bakke said. "Instead of pointing fingers and laying blame, this Administration stepped in and made the tough choices that have allowed the company to successfully manage its business. Consumers have benefited from these actions."

Mercury General, which entered the New Jersey market in August, has been offering binding quotes to all State Farm Indemnity non-renewals. Mercury may now have the ability to offer replacement coverage to drivers covered by several small carriers that had petitioned to leave the state, Bakke said.

"The Department is working with Mercury to explore how they can continue to provide New Jersey drivers with options," she said.

Commissioner Bakke noted that State Farm Indemnity policyholders who have received non-renewal notices must get replacement coverage, either through Mercury General, which will still offer quotes, or from a company of their choosing. "A State Farm Indemnity non-renewal notice that has arrived in the last month is still valid. Drivers should take care to not be caught without coverage," Bakke said.

Like all other auto carriers, State Farm Indemnity can still non-renew drivers for other reasons, such as failure to pay premium or accumulation of too many insurance points.

ATTACHMENT 9

Average Premiums and Expenditures
2001-2005
National Association of Insurance Commissioners

Table 4

Average Premiums and Expenditures 2001-2005

	Average Expenditure				
STATE	2005	2004	2003	2002	2001
Alabama	678.01	677.36	656.94	627.31	605.32
Alaska	961.72	973.61	937.83	883.97	826.10
Arizona	926.33	930.58	921.35	886.95	822.35
Arkansas	693.31	707.74	698.48	672.35	620.90
California	844.50	846.87	837.30	778.14	722.79
Colorado	827.47	849.84	923.16	921.45	807.51
Connecticut	990.52	990.75	987.66	970.06	912.19
Delaware	1,027.65	1,022.19	977.34	899.55	850.56
District of Columbia	1,181.77	1,184.63	1,134.67	1,044.30	1,011.76
Florida	1,063.36	1,062.31	1,017.96	933.99	850.25
Georgia	783.69	778.63	759.49	738.89	703.07
Hawaii	842.78	817.45	776.18	738.63	705.10
Idaho	582.99	589.82	585.90	562.81	523.38
Illinois	742.65	760.00	762.27	729.09	682.59
Indiana	657.35	670.88	670.97	648.13	614.86
Iowa	555.04	579.95	580.54	547.75	512.66
Kansas	590.29	603.47	610.81	587.40	555.90
Kentucky	749.62	758.00	738.58	688.12	645.21
Louisiana	1,076.09	1,062.33	1,014.88	927.53	838.96
Maine	643.50	649.63	632.60	586.51	546.01
Maryland	944.73	947.15	892.60	840.01	783.77
Massachusetts	1,112.73	1,112.87	1,051.60	983.59	936.01
Michigan	930.79	980.32	949.76	886.55	735.12
Minnesota	791.47	829.33	836.69	801.08	735.20
Mississippi	744.84	749.03	710.42	680.82	637.62
Missouri	685.49	702.39	702.33	669.38	633.52
Montana	685.01	683.18	674.65	628.42	572.06
Nebraska	620.60	637.44	623.97	589.58	553.83
Nevada	982.56	938.69	913.82	895.70	851.15
New Hampshire	791.71	798.34	779.14	732.85	685.62
New Jersey	1,183.54	1,221.08	1,193.17	1,125.21	1,027.71
New Mexico	727.35	727.60	732.47	706.23	662.27
New York	1,122.45	1,171.62	1,167.91	1,099.67	1,014.96
North Carolina	602.20	597.02	604.61	587.90	564.76
North Dakota	554.30	562.45	536.70	504.61	497.79
Ohio	668.93	680.14	672.07	642.23	613.75
Oklahoma	677.53	689.89	689.37	653.65	610.33
Oregon	736.67	753.38	735.80	682.40	642.52
Pennsylvania	849.14	842.66	812.67	777.23	726.41
Rhode Island	1,059.13	1,033.84	996.51	939.11	880.06
South Carolina	752.56	763.35	745.42	702.88	636.26
South Dakota	565.23	586.96	563.65	542.06	510.42
Tennessee	658.60	666.22	650.44	632.42	610.65
Texas	844.87	846.93	837.40	791.39	735.46
Utah	705.56	722.27	733.45	702.63	640.12
Vermont	698.74	692.72	683.11	650.34	602.52
Virginia	697.86	702.23	658.22	625.50	610.14
Washington	840.17	838.61	825.05	790.91	749.74
West Virginia	856.53	874.96	844.41	778.44	706.90
Wisconsin	615.33	635.59	620.90	611.30	573.46
Wyoming	639.05	628.77	617.90	585.44	527.63
Countrywide	**829.17**	**839.55**	**824.49**	**780.77**	**725.57**

ATTACHMENT 10

Median Family Income by State, 2006
2006 American Community Survey
U.S. Census

Median Family Income (In 2006 Inflation-Adjusted Dollars): 2006
Universe: Families
Data Set: 2006 American Community Survey
Survey: 2006 American Community Survey, 2006 Puerto Rico Community Survey
Geographic Area: United States and States

NOTE. For information on confidentiality protection, sampling error, nonsampling error, and definitions, see Survey Methodology.

Rank	State	Median	Margin of Error
1	Connecticut	78,154	+/-951
2	New Jersey	77,875	+/-649
3	Maryland	77,839	+/-851
4	Massachusetts	74,463	+/-753
5	New Hampshire	71,176	+/-1,111
6	Hawaii	70,277	+/-1,454
7	Alaska	69,872	+/-2,371
8	Virginia	66,886	+/-623
9	Minnesota	66,809	+/-485
10	Rhode Island	64,733	+/-1,971
11	Colorado	64,614	+/-975
12	California	64,563	+/-413
13	Washington	63,705	+/-650
14	Illinois	63,121	+/-529
15	Delaware	62,623	+/-2,217
16	New York	62,138	+/-364
17	Nevada	61,466	+/-837
18	District of Columbia	61,105	+/-4,029
19	Wisconsin	60,634	+/-462

	United States	58,526	+/-100
20	Vermont	58,163	+/-1,411
21	Pennsylvania	58,148	+/-361
22	Utah	58,141	+/-835
23	Michigan	57,996	+/-535
24	Wyoming	57,505	+/-1,708
25	Nebraska	56,940	+/-649
26	Kansas	56,857	+/-698
27	Ohio	56,148	+/-388
28	Georgia	56,112	+/-609
29	Oregon	55,923	+/-757
30	Indiana	55,781	+/-459
31	Iowa	55,735	+/-577
32	Arizona	55,709	+/-646
33	North Dakota	55,385	+/-1,467
34	Florida	54,445	+/-402
35	South Dakota	53,806	+/-936
36	Missouri	53,026	+/-561
37	Maine	52,793	+/-973
38	Texas	52,355	+/-275
39	North Carolina	52,336	+/-481
40	Idaho	51,640	+/-1,028
41	Montana	51,006	+/-829
42	South Carolina	50,334	+/-657
43	Tennessee	49,804	+/-564
44	Alabama	49,207	+/-747
45	Kentucky	48,726	+/-682
46	Louisiana	48,261	+/-794
47	New Mexico	48,199	+/-1,352
48	Oklahoma	47,955	+/-776
49	Arkansas	45,093	+/-813

50	West Virginia	44,012	+/-823
51	Mississippi	42,805	+/-1,008
	Puerto Rico	20,425	+/-414

ATTACHMENT 11

Profitability Report
2003-2005
National Association of Insurance Commissioners

2005 NAIC Profitability Report PPA TOTAL		
State	Return on Net Worth	Rank
AL	7.7	46
AK	9.3	43
AZ	13.6	29
AR	13.9	26
CA	14.2	20
CO	19.1	6
CT	13.7	28
DE	8.4	45
DC	18.9	8
FL	2.6	47
GA	9.7	41
HI	19.6	3
ID	16.9	14
IL	13.9	27
IN	14.2	21
IA	19.2	5
KS	19.0	7
KY	13.0	31
LA	-22.7	50
ME	17.6	10
MD	14.2	23
MA	14.1	24
MI	-2.2	49
MN	17.9	9
MS	-22.9	51
MO	13.9	25
MT	9.5	42
NE	15.9	17
NV	1.4	48
NH	17.0	12
NJ	11.0	37
NM	11.1	36
NY	19.8	2
NC	10.8	38
ND	11.7	35
OH	16.6	15
OK	14.2	22
OR	15.5	18
PA	8.9	44
RI	17.4	11
SC	12.6	33
SD	19.2	4
TN	12.2	34
TX	12.7	32
UT	13.4	30
VT	16.9	13
VA	16.0	16
WA	9.8	40
WV	15.2	19
WI	10.1	39
WY	19.8	1
Countrywide	11.0	

2004 NAIC Profitability Report PPA TOTAL		
State	Return on Net Worth	Rank
AL	12.2	36
AK	9.8	44
AZ	16.4	17
AR	12.8	31
CA	16.0	19
CO	13.3	30
CT	14.0	26
DE	7.1	47
DC	19.4	8
FL	6.1	48
GA	10.1	43
HI	17.4	14
ID	19.6	7
IL	12.8	32
IN	16.6	15
IA	18.3	13
KS	22.9	1
KY	11.7	38
LA	12.6	33
ME	18.4	12
MD	14.6	23
MA	11.0	41
MI	6.1	49
MN	20.7	6
MS	13.4	29
MO	11.5	40
MT	10.3	42
NE	19.3	9
NV	0.5	51
NH	13.8	28
NJ	12.4	35
NM	8.7	45
NY	18.6	11
NC	5.5	50
ND	20.9	5
OH	15.4	21
OK	14.1	25
OR	16.1	18
PA	8.7	46
RI	14.0	27
SC	15.9	20
SD	22.0	2
TN	11.7	39
TX	18.7	10
UT	15.2	22
VT	21.6	3
VA	16.5	16
WA	12.5	34
WV	12.1	37
WI	14.5	24
WY	21.0	4
Countrywide	13.2	

2003 NAIC Profitability Report PPA TOTAL		
State	Return on Net Worth	Rank
AL	9.8	30
AK	9.8	30
AZ	14.1	10
AR	12.0	20
CA	10.6	27
CO	8.7	35
CT	13.3	15
DE	4.2	48
DC	12.0	20
FL	10.3	28
GA	7.5	38
HI	15.9	7
ID	14.1	10
IL	8.9	34
IN	13.7	13
IA	13.6	14
KS	16.5	5
KY	6.8	42
LA	4.5	47
ME	15.2	8
MD	7.5	38
MA	3.3	49
MI	3.5	51
MN	18.8	3
MS	7.3	41
MO	10.2	29
MT	7.4	40
NE	12.2	19
NV	2.1	50
NH	12.0	20
NJ	13.0	17
NM	16.5	5
NY	12.9	18
NC	6.8	42
ND	19.2	2
OH	13.1	16
OK	11.2	25
OR	13.9	12
PA	5.6	44
RI	9.4	32
SC	11.5	24
SD	14.7	9
TN	4.9	46
TX	8.2	36
UT	35.5	1
VT	17.3	4
VA	8.1	37
WA	11.2	25
WV	5.3	45
WI	11.9	23
WY	9.0	33
Countrywide	9.4	

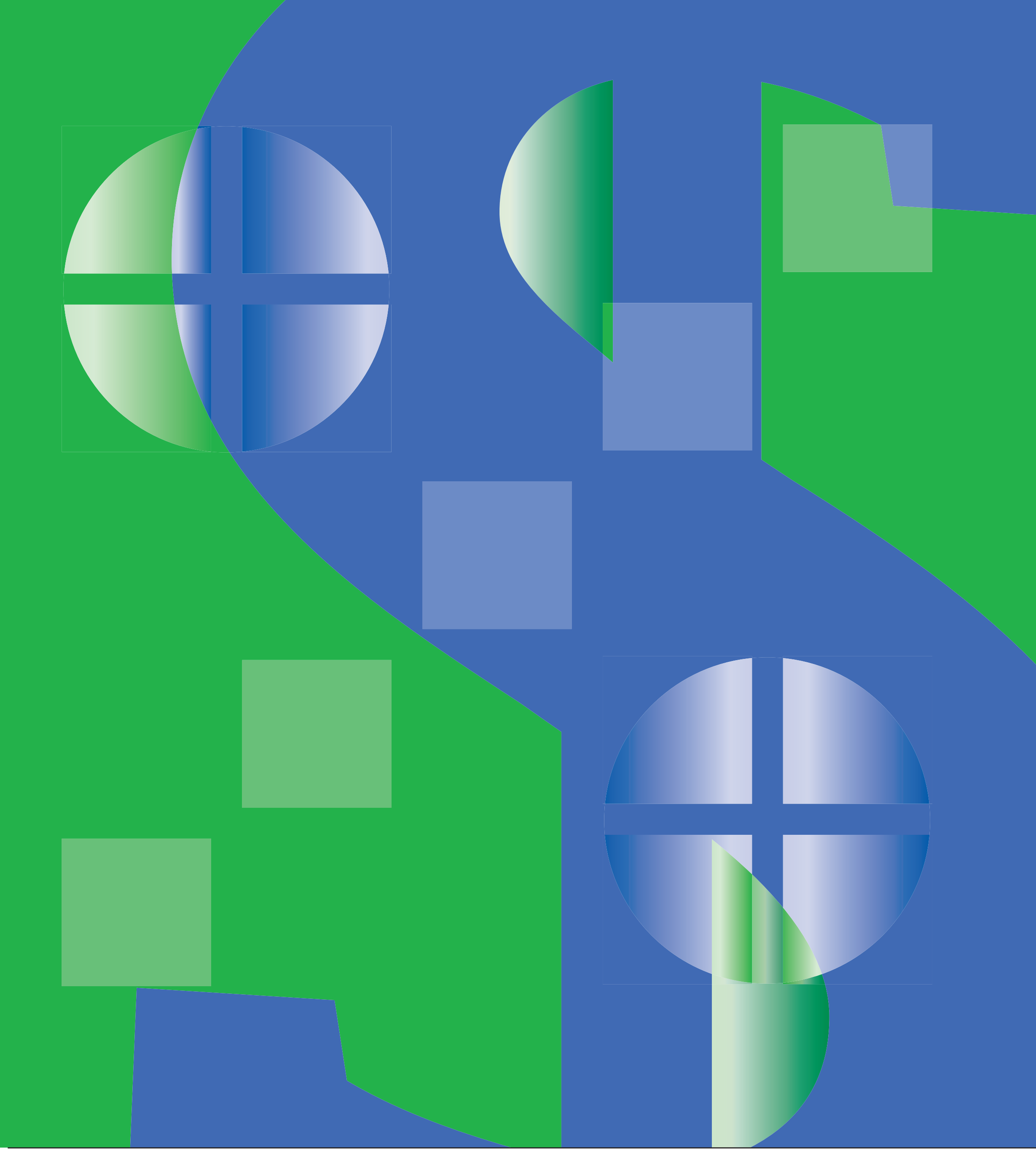
ATTACHMENT 12

Income in the United States: 2002
Current Population Reports
U.S. Census
September, 2003

Income in the United States: 2002

Issued September 2003

P60-221



Current Population Reports

Consumer Income

By
Carmen DeNavas-Walt
Robert W. Cleveland
Bruce H. Webster, Jr.

Demographic Programs

USCENSUSBUREAU

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U.S. Department of Commerce
Economics and Statistics Administration
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Income in the United States: 2002

Issued September 2003

P60-221

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HISTORICAL INCOME

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Income in the United States: 2002

INTRODUCTION

The 2002 median household money income in the United States was $42,409, representing a 1.1 percent real decline from its 2001 level of $42,900.[1] By type of residence, the decline in median household money income was experienced mainly by households in metropolitan areas. Both family and nonfamily households also experienced declines in money income. In contrast, both men and women who were full-time, year-round workers in 2002 experienced increases in their median earnings. Income inequality as measured by money income did not change.

Traditionally, income data in Census Bureau reports have been based on the amount of money people or households receive during a calendar year. This income concept is limited and does not provide a completely satisfactory measure of economic well-being. For example, it does not include the effect of taxes and, therefore, does not reflect the effect of tax law changes on economic well-being. Similarly, this concept excludes the effect of noncash benefits (such as employer-provided group health insurance, food stamps, school lunches, and housing assistance), which certainly enhance economic well-being.

This report features four alternative income measures that deduct payroll, federal, and state income taxes and includes the value of various noncash benefits — food stamps, school lunches, housing subsidies, health programs, and return on home equity. Of these four alternative income definitions, only one showed a real decline in median household income between 2001 and 2002 — money income less taxes declined 0.8 percent from $37,376 to $37,066. The other three were unchanged.

HIGHLIGHTS

Most of the estimates described in this section are shown in Table 1, Table 3, Table 7, and Appendix Table A-1; the estimates for states are shown in Table 5.

- Real median household money income declined by 1.1 percent between 2001 and 2002 to a level of $42,409. This is the second consecutive annual decline in median household money income.
- Real median household income was unchanged between 2001 and 2002 for three of the four alternative income definitions highlighted in this report. The fourth, real median household income less taxes, declined 0.8 percent.
- Real median household money income declined for all race groups except those with a White or Asian (and no other race) householder. However, under the alternative income definitions, most groups experienced no change. Only households with householders who were Asian or Native Hawaiian and Other Pacific Islander experienced a real decline in median household income.

[1] All income values are in 2002 dollars. Changes in real income refer to comparisons after adjusting for inflation. The percentage changes in prices between earlier years and 2002 were computed by dividing the annual average Consumer Price Index for 2002 by the annual average for earlier years. The CPI-U values for 1947 to 2002 are available on the Internet at: *www.census.gov/hhes/income/income02/cpiurs.html*; click on "Annual Average Consumer Price Index (CPI-U-RS): 1947 to 2002." Inflation between 2001 and 2002 was 1.6 percent.

Source of Estimates; Statistical Accuracy

The estimates in this report are based on data collected by the 2003 Current Population Survey Annual Social and Economic Supplement (ASEC was formerly called the Annual Demographic Supplement or the March Income Supplement) conducted by the U.S. Census Bureau. As with all surveys, the estimates may differ from the actual values because of sampling variation or other factors. All statements in this report have undergone statistical testing, and all comparisons are significant at the 90-percent confidence level unless otherwise noted. For further information about the source and accuracy of the estimates, go to *www.census.gov/hhes/income/income02.sa.pdf*.

- The real median money income of both family and nonfamily households declined between 2001 and 2002. Overall, family household income dropped 0.8 percent to $52,704. Nonfamily households experienced a decline of 2.4 percent to $25,406.

- The real median money income of households in the Midwest declined, for the second consecutive year, to $43,622. The incomes of households in the other regions remained unchanged.

- For the second consecutive year, real median money income declined for households inside metropolitan areas, by 1.5 percent, to $45,257.

- Per capita money income declined by 1.8 percent, in real terms, between 2001 and 2002 to $22,794. This is the first annual decline in per capita income since 1991.

- Based on comparisons of 2-year-average medians (comparing 2000-2001 with 2001-2002), real median household income rose for one state (Oklahoma), and declined for ten states and the District of Columbia. Four of the states that experienced declines were in the Midwest (Illinois, Michigan, Missouri, and Ohio), three in the South (Florida, Mississippi, and North Carolina), and three in the West (Hawaii, Nevada, and Oregon).

- Both the Gini index of income inequality and the quintile shares of aggregate income indicated no change in household money income inequality between 2001 and 2002, but income inequality declined between 2001 and 2002 under each of the four alternative income definitions.

What are. . . definitions of income?

Money Income (**MI**) is collected for all people in the sample 15 years old and over. Money income includes earnings, unemployment compensation, workers' compensation, social security, supplemental security income, public assistance, veterans' payments, survivor benefits, pension or retirement income, interest, dividends, rents, royalties, income from estates, trusts, educational assistance, alimony, child support, assistance from outside the household, and other miscellaneous sources. It is income before deductions for taxes or other expenses and does not include lump-sum payments or capital gains.

MI - Tx is money income plus realized capital gains (losses), less federal and state income taxes, and less payroll taxes.

MI - Tx + NC - MM is money income, plus realized capital gains (losses), less federal and state income taxes, less payroll taxes, plus the value of employer-provided health benefits and the value of all noncash transfers except medicare and medicaid. Noncash transfers include food stamps, rent subsidies, and free and reduced-price school lunches.

MI - Tx + NC is money income plus realized capital gains (losses), less federal and state income taxes, less payroll taxes, plus the value of employer-provided health benefits and all noncash transfers.

MI - Tx + NC + HE is money income plus realized capital gains (losses), less federal and state income taxes, less payroll taxes, plus the value of employer-provided health benefits and all noncash transfers, plus the annual benefits of converting one's home equity into an annuity, net of property taxes.

INCOME IN THE UNITED STATES

Real median money income declined 1.1 percent between 2001 and 2002 to $42,409. Under alternative income definition MI-Tx, median household income was $37,066, 0.8 percent lower in real terms than its 2001 level (see, "What are . . . definitions of income?"). None of the other alternative income definitions showed a statistically significant change from 2001. For income definition MI-Tx+NC-MM, 2002 median household income was $39,426, for definition MI-Tx+NC, it was $42,061, and for definition MI-Tx+NC+HE, it was $43,760.

Race and Hispanic Origin

The money income definition shows that real median income did not change between 2001 and 2002 for households with a non-Hispanic householder who reported White as his or her only race category and households with householders who reported Asian as his or her only race category. Real median household income

Table 1.
Household Income by Race and Hispanic Origin and Income Definition: 2001 and 2002

(See text for comparability issues regarding 2001 and 2002 race data using single and multiple race reporting methods. Households as of March of the following year)

Race and Hispanic origin	2001			Race and Hispanic origin	2002			Percent change in real income 2002 less 2001	90-percent confidence interval[1] (±) of percent change
	Number (thousands)	Median income (in 2002 dollars) Value (dollars)	Median income (in 2002 dollars) 90-percent confidence interval[1] (± dollars)		Number (thousands)	Median income Value (dollars)	Median income 90-percent confidence interval[1] (± dollars)		
MONEY INCOME (MI)									
All races	**109,297**	**42,900**	**215**	**All races**	**111,278**	**42,409**	**229**	***–1.1**	**0.6**
White	90,682	45,225	349	White alone or in combination	92,740	44,964	319	–0.6	0.8
				White alone[2]	91,645	45,086	301	–0.3	0.8
White, not Hispanic	80,818	47,041	321	White alone, not Hispanic	81,166	46,900	303	–0.3	0.8
Black	13,315	29,939	581	Black alone or in combination	13,778	29,177	632	*–2.5	2.3
				Black alone[3]	13,465	29,026	643	*–3.0	2.3
Asian and Pacific Islander	4,071	54,488	2,139	Asian alone or in combination	4,079	52,285	1,301	*–4.0	3.7
				Asian alone[4]	3,917	52,626	1,515	–3.4	3.8
				Asian, Native Hawaiian and Other Pacific Islander, alone or in combination	4,371	52,018	1,091	*–4.5	3.6
				Asian and/or Native Hawaiian and Other Pacific Islander[5]	4,164	52,291	1,288	*–4.0	3.7
Hispanic origin (of any race)	10,499	34,099	712	Hispanic origin (of any race)	11,339	33,103	793	*–2.9	2.1
MI - Tx (MONEY INCOME PLUS REALIZED CAPITAL GAINS (LOSSES), LESS INCOME AND PAYROLL TAXES)									
All races	**109,297**	**37,376**	**201**	**All races**	**111,278**	**37,066**	**199**	***–0.8**	**0.6**
White	90,682	38,991	232	White alone or in combination	92,740	38,764	224	–0.6	0.7
				White alone[2]	91,645	38,857	227	–0.3	0.7
White, not Hispanic	80,818	40,254	247	White alone, not Hispanic	81,166	40,212	253	–0.1	0.7
Black	13,315	26,613	447	Black alone or in combination	13,778	26,288	400	–1.2	1.8
				Black alone[3]	13,465	26,168	405	–1.7	1.8
Asian and Pacific Islander	4,071	45,360	1,328	Asian alone or in combination	4,079	43,803	1,270	*–3.4	3.2
				Asian alone[4]	3,917	44,080	1,286	–2.8	3.2
				Asian, Native Hawaiian and Other Pacific Islander, alone or in combination	4,371	43,482	1,194	*–4.1	3.1
				Asian and/or Native Hawaiian and Other Pacific Islander[5]	4,164	43,779	1,221	*–3.5	3.1
Hispanic origin (of any race)	10,499	30,607	507	Hispanic origin (of any race)	11,339	30,291	479	–1.0	1.5

See footnotes at end of table.

declined for each of the remaining race groups and for households of Hispanic origin.[2]

The money income definition shows that real median income declined by 2.5 percent for households with householders who reported his or her race was Black (and may or may not have reported another race) and by 3.0 percent for households with householders who reported Black as his or her only race. Real median income declined by 4.0 percent for households with householders who reported only Asian or Asian and another race and by 4.5 percent for households with householders who reported his or her race as either

[2] Because Hispanics may be of any race, data in this report for Hispanics overlap with data for racial groups. Hispanic origin was reported by 11.4 percent of White householders who reported only one race; 3.5 percent for Black householders who reported only one race; 27.3 percent for American Indian or Alaska Native householders who reported only one race; 1.4 percent for Asian householders who reported only one race; and 19.0 percent for Native Hawaiian and Other Pacific Islander householders who reported only one race. Data users should exercise caution when interpreting aggregate results for the Hispanic population or for race groups because these populations consist of many distinct groups that differ in socio-economic characteristics, culture, and recency of immigration. Data were first collected for Hispanics in 1972 and Asians and Pacific Islanders in 1987.

Table 1.
Household Income by Race and Hispanic Origin and Income Definition: 2001 and 2002—Con.

(See text for comparability issues regarding 2001 and 2002 race data using single and multiple race reporting methods. Households as of March of the following year)

Race and Hispanic origin	2001			Race and Hispanic origin	2002			Percent change in real income 2002 less 2001	90-percent confidence interval[1] (±) of percent change
	Number (thousands)	Median income (in 2002 dollars) Value (dollars)	Median income (in 2002 dollars) 90-percent confidence interval[1] (± dollars)		Number (thousands)	Median income Value (dollars)	Median income 90-percent confidence interval[1] (± dollars)		
MI - Tx + NC - MM (MONEY INCOME PLUS REALIZED CAPITAL GAINS (LOSSES), LESS INCOME AND PAYROLL TAXES, PLUS VALUE OF EMPLOYER-PROVIDED HEALTH BENEFITS AND ALL NONCASH TRANSFERS EXCEPT MEDICARE AND MEDICAID)									
All races	**109,297**	**39,553**	**217**	**All races**	**111,278**	**39,426**	**219**	**–0.3**	**0.6**
White	90,682	41,218	247	White alone or in combination	92,740	41,173	237	–0.1	0.7
				White alone[2]	91,645	41,272	239	0.1	0.7
White, not Hispanic	80,818	42,521	266	White alone, not Hispanic	81,166	42,623	276	0.2	0.7
Black	13,315	28,748	462	Black alone or in combination	13,778	28,467	434	–1.0	1.8
				Black alone[3]	13,465	28,338	443	–1.4	1.8
Asian and Pacific Islander	4,071	48,287	1,219	Asian alone or in combination	4,079	47,252	1,209	–2.1	2.8
				Asian alone[4]	3,917	47,501	1,260	–1.6	2.9
				Asian, Native Hawaiian and Other Pacific Islander, alone or in combination	4,371	46,829	1,124	*–3.0	2.7
				Asian and/or Native Hawaiian and Other Pacific Islander[5]	4,164	47,109	1,183	–2.4	2.8
Hispanic origin (of any race)	10,499	32,678	497	Hispanic origin (of any race)	11,339	32,651	485	–0.1	1.4
MI - Tx + NC (MONEY INCOME PLUS REALIZED CAPITAL GAINS (LOSSES), LESS INCOME AND PAYROLL TAXES, PLUS VALUE OF EMPLOYER-PROVIDED HEALTH BENEFITS AND ALL NONCASH TRANSFERS)									
All races	**109,297**	**42,194**	**212**	**All races**	**111,278**	**42,061**	**201**	**–0.3**	**0.6**
White	90,682	43,860	240	White alone or in combination	92,740	43,767	229	–0.2	0.6
				White alone[2]	91,645	43,871	232	–	0.6
White, not Hispanic	80,818	45,171	253	White alone, not Hispanic	81,166	45,203	255	0.1	0.6
Black	13,315	31,002	457	Black alone or in combination	13,778	30,698	475	–1.0	1.7
				Black alone[3]	13,465	30,576	477	–1.4	1.7
Asian and Pacific Islander	4,071	49,913	1,265	Asian alone or in combination	4,079	48,698	1,163	–2.4	2.7
				Asian alone[4]	3,917	48,954	1,189	–1.9	2.8
				Asian, Native Hawaiian and Other Pacific Islander, alone or in combination	4,371	48,303	1,156	*–3.2	2.7
				Asian and/or Native Hawaiian and Other Pacific Islander[5]	4,164	48,596	1,181	–2.6	2.8
Hispanic origin (of any race)	10,499	34,939	546	Hispanic origin (of any race)	11,339	34,633	475	–0.9	1.4

See footnotes at end of table.

Asian or Native Hawaiian and Other Pacific Islander (and may or may not have reported any other race). Real median income also declined by 4.0 percent for households with householders who reported his or her race as being only Asian or only Native Hawaiian and Other Pacific Islander or as Asian and Native Hawaiian and Other Pacific Islander. Median income declined 2.9 percent for households with householders who were of Hispanic origin (see Table 1).[3]

[3] The differences between the percentage declines in household income by race and Hispanic origin are not statistically significant.

Table 1.
Household Income by Race and Hispanic Origin and Income Definition: 2001 and 2002–Con.

(See text for comparability issues regarding 2001 and 2002 race data using single and multiple race reporting methods. Households as of March of the following year)

Race and Hispanic origin	2001 Number (thousands)	2001 Median income (in 2002 dollars) Value (dollars)	2001 Median income 90-percent confidence interval[1] (± dollars)	Race and Hispanic origin	2002 Number (thousands)	2002 Median income Value (dollars)	2002 Median income 90-percent confidence interval[1] (± dollars)	Percent change in real income 2002 less 2001	90-percent confidence interval[1] (±) of percent change
MI - Tx + NC + HE (MONEY INCOME PLUS REALIZED CAPITAL GAINS (LOSSES), LESS INCOME AND PAYROLL TAXES, PLUS VALUE OF EMPLOYER-PROVIDED HEALTH BENEFITS AND ALL NONCASH TRANSFERS, PLUS IMPUTED RETURN TO HOME EQUITY)									
All races	**109,297**	**43,925**	**214**	**All races**	**111,278**	**43,760**	**220**	**–0.4**	**0.6**
White	90,682	45,631	234	White alone or in combination	92,740	45,635	232	–	0.6
				White alone[2]	91,645	45,743	234	0.2	0.6
White, not Hispanic	80,818	47,033	265	White alone, not Hispanic	81,166	47,199	252	0.4	0.6
Black	13,315	31,891	477	Black alone or in combination	13,778	31,523	474	–1.2	1.7
				Black alone[3]	13,465	31,408	479	–1.5	1.7
Asian and Pacific Islander	4,071	51,624	1,152	Asian alone or in combination	4,079	50,312	1,207	–2.5	2.6
				Asian alone[4]	3,917	50,604	1,252	–2.0	2.6
				Asian, Native Hawaiian and Other Pacific Islander, alone or in combination	4,371	49,920	1,158	*–3.3	2.5
				Asian and/or Native Hawaiian and Other Pacific Islander[5]	4,164	50,242	1,199	*–2.7	2.6
Hispanic origin (of any race)	10,499	35,882	543	Hispanic origin (of any race)	11,339	35,447	610	–1.2	1.5

– Represents zero or rounds to zero. *Significantly different from zero at the 90-percent confidence level.

[1]For an explanation of confidence intervals, see "Standard errors and their use" at *www.census.gov/hhes/income/income02/sa.pdf*.

[2]The 2003 Current Population Survey allowed respondents to choose more than one race. White alone refers to people who reported White and did not report any other race category. The use of this single-race population does not imply that it is the preferred method of presenting or analyzing data. The Census Bureau uses a variety of approaches. Information on people who reported more than one race, such as "White and American Indian and Alaska Native" or "Asian and Black or African American," in Census 2000 is forthcoming and will be available through American FactFinder in 2003. About 2.6 percent of people reported more than one race.

[3]Black alone refers to people who reported Black and did not report any other race category.

[4]Asian alone refers to people who reported Asian and did not report any other race category.

[5]Asian and/or Native Hawaiian and Other Pacific Islander refers to people who reported either or both of these categories, but did not report any other category.

Source: U.S. Census Bureau, Current Population Survey, 2002 and 2003 Annual Social and Economic Supplements.

Under the four alternative income measures, none of the race or Hispanic groups showed a decline in real household income between 2001 and 2002 except for households with householders who were Asian or Native Hawaiian and Other Pacific Islander (and may or may not have reported any other race). These households experienced declines of 4.1 percent under income definition MI-Tx; 3.0 percent under income definition MI-Tx+NC-MM; 3.2 percent under income definition MI-Tx+NC; and 3.3 percent under income definition MI-Tx+NC+HE (see Table 1).[4]

Households with householders who indicated they were Black and did not report any other race had the lowest median income for each of the income definitions (see Figure 1).[5]

Their 2002 median money income was $29,026, which was 62 percent of the median for households with non-Hispanic householders who reported a single race category of White; $26,168 under definition MI-Tx, 65 percent of the non-Hispanic White median; $28,338 under definition MI-Tx+NC-MM, 66 percent of the non-Hispanic White median; $30,576 under definition MI-Tx+NC, 68 percent of the non-Hispanic White median; and $31,048 or 67 percent of the non-Hispanic White median under

[4] The differences among the percentage declines in median household income by income definitions were not statistically significant.

[5] The differences among the median incomes for households with householders who reported Black are not statistically significant. The levels of household income for different groups are influenced by many different variables such as number of earners and household size.

the most comprehensive income definition, MI-Tx+NC+HE.[6]

Median money income for households with an Hispanic origin householder was $33,103 in 2002 which was 71 percent of the median for households with non-Hispanic householders who reported a single race category of White and 14 percent higher than households with householders who reported a single race category of Black. The Hispanic-to-non-Hispanic White median income relationships under the alternative income definitions were 75 percent for definitions MI-Tx and MI-Tx+NC+HE and 77 percent for definitions MI-Tx+NC-MM and MI-Tx+NC. The Hispanic-to-Black median income relationships were 116 percent for definitions MI-Tx; 115 percent for MI-Tx+NC-MM; and 113 percent for MI-Tx+NC and MI-Tx+NC+HE.[7]

Households with householders who reported Asian as his or her only race category had the highest median income under all definitions of income.[8] Their 2002 median money income was $52,626, 112 percent of the median for households with non-Hispanic householders who reported a single race category of White; $44,080 under definition MI-Tx, 110 percent of the non-Hispanic White median; $47,501 under definition MI-Tx+NC-MM, 111 percent of the non-Hispanic White median; $48,954 under definition MI-Tx+NC, 108 percent of the non-Hispanic White median; and $50,604 or 107 percent of the non-Hispanic White median under

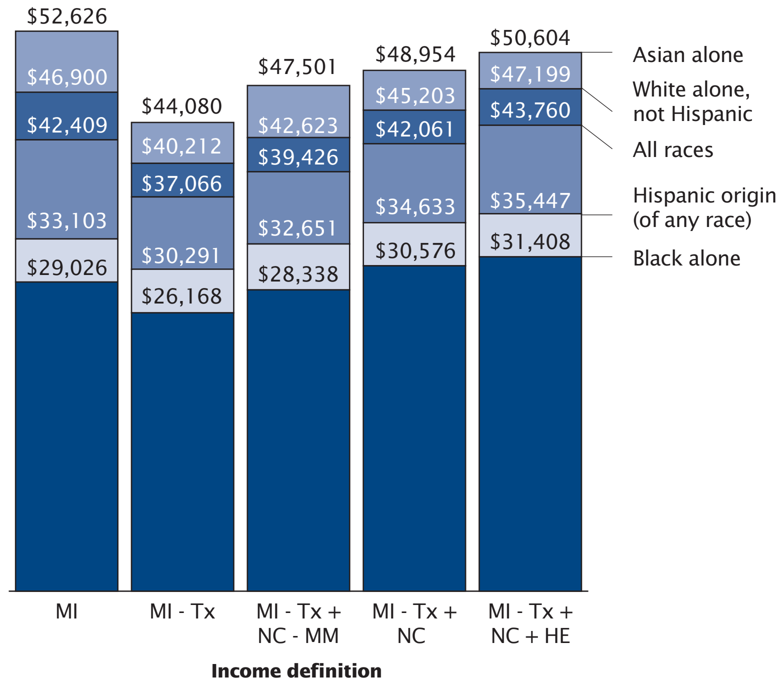
[6] The income ratios for MI-Tx+NC-MM and MI-Tx+NC+HE were not different from one another.

[7] The income ratio for MI-Tx+NC-MM was not different from MI-Tx+NC and MI-Tx+NC+HE.

[8] The differences among the median incomes for households with householders who reported Asian are not statistically significant.

Figure 1.

Median Household Income by Race and Hispanic Origin of Householder and Income Definition: 2002



Source: U.S. Census Bureau, Current Population Survey, 2003 Annual Social and Economic Supplement.

Racial Group Comparisons in the 2003 Current Population Survey

For the first time in 2003, CPS respondents could identify themselves in more than one racial group; previously they had to choose one.[9] This may complicate year-to-year comparisons. We do not know how people who reported more than one race in 2003 previously reported their race; there is no single way to compare changes in income by race. This report compares 2001 single-race data with two different sets of race data for 2002: one comparison based on those who reported only one race and another comparison based on those who reported more than one race. For example, this report compares the 2001 income figures for Blacks with 2002 income figures for two groups:

1. Those who reported Black and did not report any other race (alone).
2. Those who reported Black and did not report any other race or Black who reported some other race (alone or in combination).

This report provides year-to-year comparisons for each racial group except American Indians and Alaska Natives, and Native Hawaiians and Other Pacific Islanders, because the sample was not sufficiently large.

[9] The Office of Management and Budget (OMB) establishes the guidelines for the collection and classification of data for race (including the option for respondents to mark more than one race) and Hispanic origin. Race and Hispanic origin are treated as separate and distinct concepts in accordance with OMB guidelines. For further information, see *www.whitehouse.gov/omb/ombdir15.html.*

Table 2.
Change in Real Median Household Income During Recessions by Income Definition

Recessions[1]	Income years	Percent change in real median income[2]				
		MI	MI-Tx	MI-Tx+NC-MM	MI-Tx+NC	MI-Tx+NC+HE
March 2001 to November 2001	1999 to 2002	*–3.4	*–2.4	*–1.6	*–0.7	*–1.3
July 1990 to March 1991	1989 to 1992	*–4.7	(NA)	(NA)	*–2.1	*–3.9
January 1980 to July 1980 and July 1981 to November 1982	1978 to 1983	*–4.8	(NA)	(NA)	(NA)	(NA)
November 1973 to March 1975	1973 to 1975	*–5.7	(NA)	(NA)	(NA)	(NA)
December 1969 to November 1970	1969 to 1971	*–1.7	(NA)	(NA)	(NA)	(NA)

NA Not available.
*Significantly different from zero at the 90-percent confidence level.

[1]Recessions are determined by the National Bureau of Economic Research, a private research organization.
[2]Median household income adjusted to 2002 dollars using the CPI-U-RS price deflator.

Note: Income years are based on peak income year prior to the start of the recession, unless the recession started after June, and the year after the end of the recession, unless the recession ended before June.

Source: U.S. Census Bureau, Current Population Survey, 1970 to 2003 Annual Social and Economic Supplements.

the most comprehensive income definition, MI-Tx+NC+HE.[10]

Income During Recessions

Before the most recent recession, which began in March 2001 and ended in November 2001, median household money income peaked in 1999 at $43,915 (in 2002 adjusted dollars).[11] The decline in household income between 1999 and 2002 was 3.4 percent, not statistically different from the 4.7 percent decline in income which occurred between 1989 and 1992, the income years surrounding the July 1990 to March 1991 recession, but lower than the 4.8 percent decline between 1978 and 1983, the income years surrounding the combined recessions spanning January 1980 to July 1980 and July 1981 to November 1982, and the 5.7 percent decline between 1973 and 1975, the income years surrounding the November 1973 to March 1975 recession. However, the current decline in household money income is significantly larger than the decline in money income for the years surrounding the recession spanning from December 1969 to November 1970 (see Table 2 and Figure 2).[12]

The most recent recession resulted in less severe declines in real median household income under the alternative income definitions. Between 1999 and 2002, income declined 2.4 percent under definition MI-Tx; 1.6 percent under definition MI-TX+NC-MM; and 1.3 percent under the most comprehensive income definition, MI-TX+NC+HE (see Table 2 and Figure 2).[13]

Detailed Tabulations

Detailed tabulations that provide income estimates for households, families, and people 15 years of age and older for 2002 and earlier years are available on the Internet at: *www.census.gov/hhes/www/income.html.*

Income data are cross-tabulated by various demographic characteristics such as age, sex, race, Hispanic origin, presence of children, marital status, educational attainment, work experience, occupation, type of worker, and source of income.

OTHER FINDINGS

This section examines changes in income between 2001 and 2002 for several demographic groups using only the money income (MI) definition. Income tabulations for these additional demographic groups are not currently available for the alternative income definitions. An expanded set of tabulations for the alternative income definitions will be made available on the Internet when completed and will be a part of next year's report.

Household Composition

The real median money income of family households declined 0.8 percent between 2001 and 2002 to $52,704 (see Table 3). For nonfamily households, income dropped by 2.4 percent to $25,406. The apparent changes in income by type of family households and for

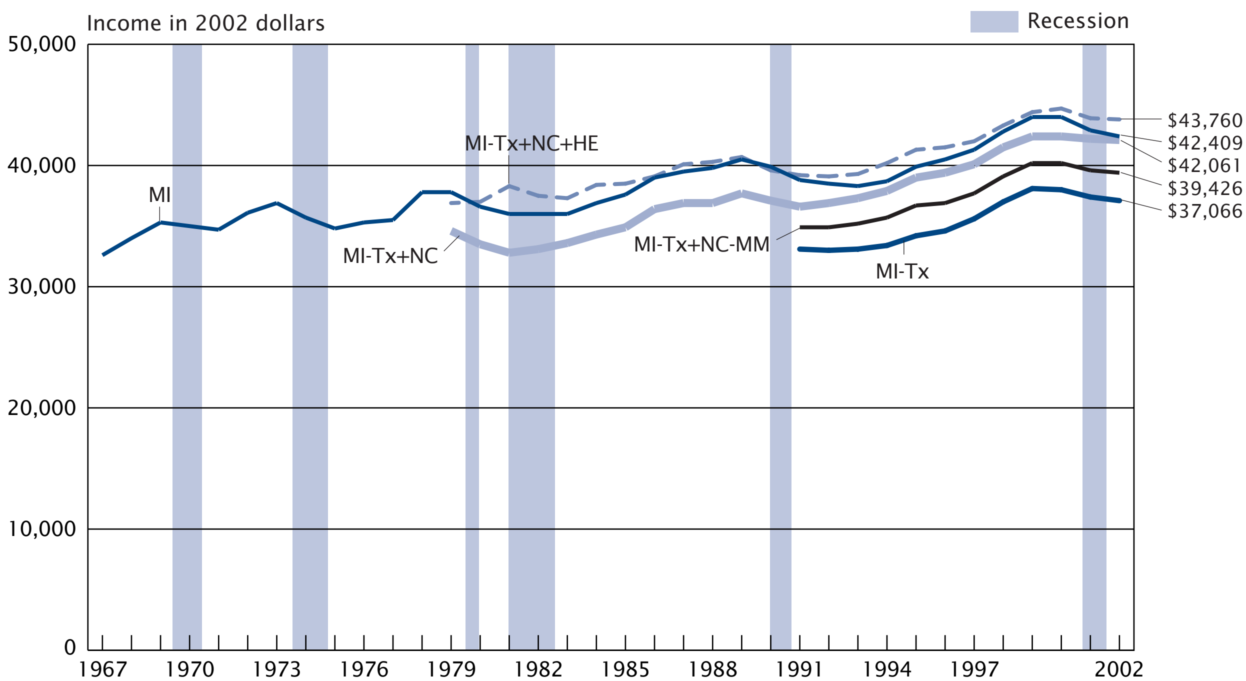
[10] The ratios for the following income definitions were not different from one another: MI and MI-Tx+NC-MM; MI-Tx and MI-Tx+NC-MM; MI-Tx and MI-Tx+NC; and MI-Tx+NC and MI-Tx+NC+HE.

[11] Recessions are determined by the National Bureau of Economic Research, a private research organization.

[12] The differences between the declines in median household income for the following years are not statistically different: 1989 to 1992 compared with 1978 to 1983 and 1973 to 1975; and 1978 to 1983 compared with 1973 to 1975.

[13] None of the declines for the alternative income definitions were different from one another.

Figure 2.
Median Household Income by Income Definition: 1967 to 2002



Source: U.S. Census Bureau, Current Population Survey, 1968 to 2003 Annual Social and Economic Supplements.

nonfamily households maintained by a woman were not statistically significant. For nonfamily households maintained by a man, median income dropped 4.3 percent, to $31,404.

Nativity

Native households and foreign-born households each had real median money incomes in 2002 that were not different from 2001, but were very different from each other (see Table 3).[14] The real median income of households maintained by a foreign-born person who was not a citizen of the United States, however, declined by 3.9 percent. This is the second consecutive annual decline for these households.

Median money income was $43,222 for native households, 14 percent higher than the median for foreign-born households ($37,979), and 27 percent higher than noncitizen foreign-born households ($33,980).

Regions

Real median money income of households did not change between 2001 and 2002 in 3 of the 4 regions; however, income in the Midwest declined 2.0 percent to $43,622. In 2002, the median income of households in the Northeast was $45,862, in the West it was $45,143, and in the South it was $39,522 (see Table 3).[15] Household money income continued to be the lowest in the South among the four regions.

Residence

Real median income remained unchanged between 2001 and 2002 for households outside metropolitan areas while income declined for the second consecutive year for households inside metropolitan areas. The real median money income of households in metropolitan areas was $45,257, down 1.5 percent (see Table 3). The median income of households inside central cities declined by 1.2 percent to $36,863 and 1.5 percent for households outside

[14] Native households are those in which the householder was born in the United States, Puerto Rico, or an outlying area of the United States or was born in a foreign country but had at least one parent who was a U.S. citizen. All other households are considered foreign-born regardless of the date of entry into the United States or citizenship status. The CPS does not interview households in Puerto Rico.

[15] The difference between the median household income in the Northeast and the median income in the West was not statistically significant.

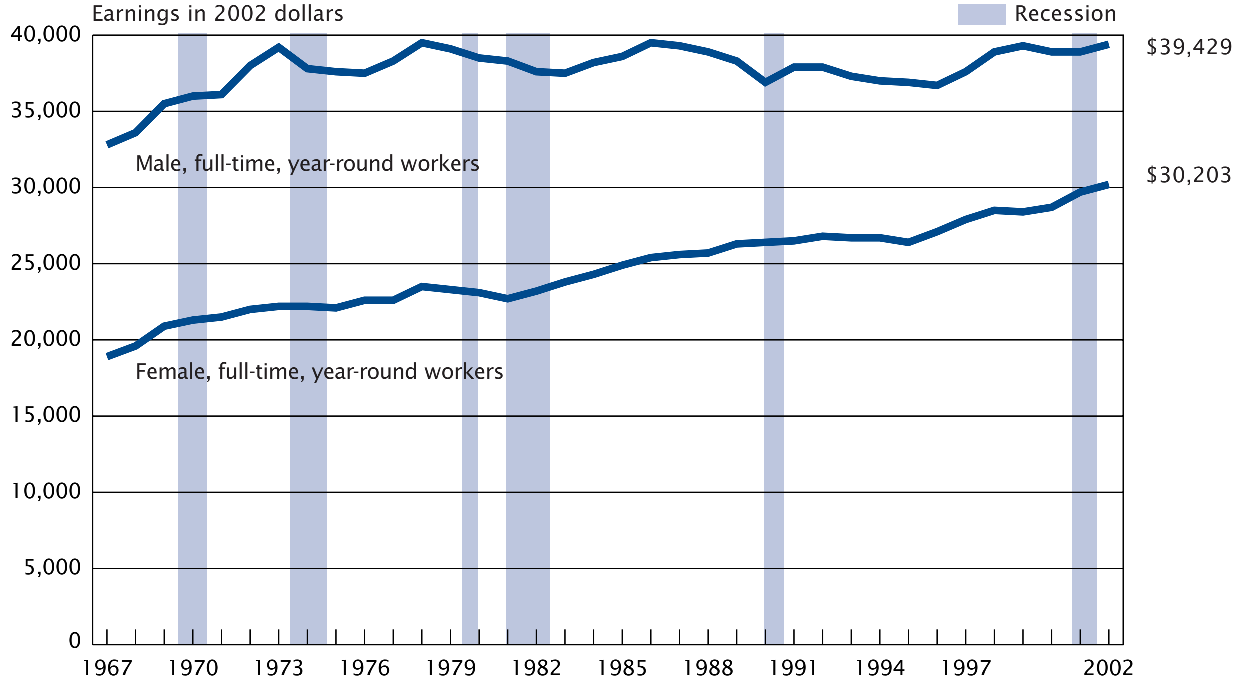
Table 3.
Comparison of Summary Measures of Money Income and Earnings by Selected Characteristics: 2001 and 2002

(Households and people as of March of the following year)

Characteristic	2001 Number (thousands)	2001 Median money income (in 2002 dollars) Value (dollars)	2001 Median money income (in 2002 dollars) 90-percent confidence interval[1] (± dollars)	2002 Number (thousands)	2002 Median money income Value (dollars)	2002 Median money income 90-percent confidence interval[1] (± dollars)	Percent change in real money income 2002 less 2001	90-percent confidence interval[1] (±) of percent change
HOUSEHOLDS								
All households	**109,297**	**42,900**	**216**	**111,278**	**42,409**	**229**	***–1.1**	**0.6**
Type of Household								
Family households	74,329	53,106	294	75,596	52,704	396	*–0.8	0.8
Married-couple families	56,747	61,433	348	57,320	61,254	327	–0.3	0.6
Female householder, no husband present	13,143	28,590	483	13,620	29,001	497	1.4	2.0
Male householder, no wife present	4,438	41,363	874	4,656	41,711	684	0.8	2.2
Nonfamily households	34,969	26,039	282	35,682	25,406	281	*–2.4	1.2
Female householder	19,390	20,586	353	19,662	20,913	316	1.6	1.9
Male householder	15,579	32,826	401	16,020	31,404	433	*–4.3	1.4
Age of Householder								
Under 65 years	86,821	50,010	333	88,619	49,510	352	*–1.0	0.8
15 to 24 years	6,391	28,644	812	6,611	27,828	748	–2.9	3.1
25 to 34 years	18,988	45,797	623	19,055	45,330	484	–1.0	1.4
35 to 44 years	24,031	54,168	700	24,069	53,521	679	–1.2	1.4
45 to 54 years	22,208	58,968	814	22,623	59,021	864	0.1	1.6
55 to 64 years	15,203	46,593	710	16,260	47,203	702	1.3	1.7
65 years and over	22,476	23,486	319	22,659	23,152	309	–1.4	1.5
Nativity of the Householder								
Native born	95,884	43,600	344	97,365	43,222	345	–0.9	0.9
Foreign born	13,413	38,552	958	13,912	37,979	883	–1.5	2.7
Naturalized citizen	6,069	44,667	1,537	6,423	45,430	1,323	1.7	3.7
Not a citizen	7,344	35,366	886	7,490	33,980	1,272	*–3.9	3.6
Region								
Northeast	21,128	46,443	625	21,229	45,862	566	–1.3	1.5
Midwest	25,755	44,531	583	25,630	43,622	627	*–2.0	1.5
South	39,151	39,523	515	40,107	39,522	490	–	1.5
West	23,263	45,804	752	24,313	45,143	674	–1.4	1.8
Residence								
Inside metropolitan areas	88,112	45,938	314	90,075	45,257	291	*–1.5	0.7
Inside central cities	32,540	37,315	353	33,543	36,863	357	*–1.2	1.1
Outside central cities	55,572	51,503	343	56,532	50,717	349	*–1.5	0.8
Outside metropolitan areas	21,185	34,135	613	21,203	34,654	609	1.5	2.1
EARNINGS OF FULL-TIME, YEAR-ROUND WORKERS								
Male	58,712	38,884	431	58,761	39,429	401	*1.4	1.3
Female	41,639	29,680	276	41,876	30,203	132	*1.8	0.9

– Represents zero or rounds to zero.
*Significantly different from zero at the 90-percent confidence level.
[1]For an explanation of confidence intervals, see "Standard errors and their use" at *www.census.gov/hhes/income/income02/sa.pdf.*
Source: U.S. Census Bureau, Current Population Survey, 2002 and 2003 Annual Social and Economic Supplements.

Figure 3.
Median Earnings of Full-Time, Year-Round Workers 15 Years Old and Over by Sex: 1967 to 2002



Source: U.S. Census Bureau, Current Population Survey, 1968 to 2003 Annual Social and Economic Supplements.

central cities, to $50,717. The income of households outside metropolitan areas ($34,654) has not shown a statistically significant change in the past 2 years.[16]

Work Experience and Earnings

Of the 80.5 million men aged 15 and over who worked in 2002, 73.0 percent worked full-time, year-round, unchanged from 2001. Of the 71.5 million women in the same age group who worked in 2002, 58.6 percent worked full-time, year-round — also unchanged from 2001 (see Table 3).

Between 2001 and 2002, the real median earnings of men who worked full-time, year-round increased by 1.4 percent, to $39,429 (see Table 3). The real earnings of women with similar work experience increased by 1.8 percent to $30,203.[17 18] In 2002, the female-to-male earnings ratio was 0.77, not statistically different from the all-time high of 0.76 reached in 2001.

What are . . .? Full-time, Year-round workers are people who worked 50 or more weeks and 35 or more hours per week during the calendar year. Paid vacations are counted as time worked.

What is . . .? Earnings consist of gross money wage or salary income, including commissions, tips and cash bonuses, before deductions; net income from nonfarm self-employment (gross receipts minus business expenses); and net income from farm self-employment (gross receipts minus farm expenses).

The increase in real earnings for men who worked full-time, year-round between 2001 and 2002 followed a year of stagnant earnings growth (2000-2001) and a year of declining earnings (1999-2000). In contrast, the comparable group of women have not experienced an annual decline in earnings since 1995 (see Figure 3).

[16] The differences between the percentage declines in income by residence are not statistically different.

[17] The demographic characteristics of full-time, year-round workers may be considerably different from one year to the next.

[18] The difference between the percentage increases in the median earnings of men and women was not statistically different.

Table 4.
Per Capita Money Income by Race and Hispanic Origin: 2001 and 2002

(See text for comparability issues regarding 2001 and 2002 race data using single and multiple race reporting methods. People as of March of the following year.)

Race and Hispanic origin	2001 Number (thousands)	2001 Per capita income (in 2002 dollars) Value (dollars)	2001 Per capita income (in 2002 dollars) 90-percent confidence interval[1] (± dollars)	Race and Hispanic origin	2002 Number (thousands)	2002 Per capita income Value (dollars)	2002 Per capita income 90-percent confidence interval[1] (± dollars)	Percent change in real income 2002 less 2001	90-percent confidence interval[1] (±) of percent change
All races	**282,082**	**23,214**	**175**	**All races**	**285,933**	**22,794**	**166**	***–1.8**	**0.9**
White	230,071	24,511	214	White alone or in combination	235,036	23,962	202	*–2.2	1.0
				White alone[2]	230,809	24,142	206	*–1.5	1.0
White, not Hispanic	194,822	26,550	254	White alone, not Hispanic	194,421	26,128	245	*–1.6	1.1
Black	36,023	15,191	304	Black alone or in combination	37,350	15,269	415	0.5	2.9
				Black alone[3]	35,806	15,441	421	1.6	2.9
Asian and Pacific Islander	12,500	24,663	1,171	Asian alone or in combination	12,504	23,252	1,181	*–5.7	5.5
				Asian alone[4]	11,558	24,131	1,257	–2.2	5.8
				Asian, Native Hawaiian and Other Pacific Islander, alone or in combination	13,523	22,810	1,110	*–7.5	5.3
				Asian and/or Native Hawaiian and Other Pacific Islander[5]	12,362	23,792	1,193	–3.5	5.6
Hispanic origin (of any race)	37,438	13,210	319	Hispanic origin (of any race)	39,384	13,487	342	2.1	2.7

*Significantly different from zero at the 90-percent confidence level.

[1]For an explanation of confidence intervals, see "Standard errors and their use" at *www.census.gov/hhes/income/income02/sa.pdf.*

[2]The 2003 Current Population Survey allowed respondents to choose more than one race. White alone refers to people who reported White and did not report any other race category. The use of this single-race population does not imply that it is the preferred method of presenting or analyzing data. The Census Bureau uses a variety of approaches. Information on people who reported more than one race, such as "White and American Indian and Alaska Native" or "Asian and Black or African American," in Census 2000 is forthcoming and will be available through American FactFinder in 2003. About 2.6 percent of people reported more than one race.

[3]Black alone refers to people who reported Black and did not report any other race category.

[4]Asian alone refers to people who reported Asian and did not report any other race category.

[5]Asian and/or Native Hawaiian and Other Pacific Islander refers to people who reported either or both of these categories, but did not report any other category.

Source: U.S. Census Bureau, Current Population Survey, 2002 and 2003 Annual Social and Economic Supplements.

Per Capita Income

Per capita money income declined by 1.8 percent, to $22,794, for the overall population between 2001 and 2002. This is the first annual decline in overall per capita income since 1991. By race, real per capita income declined by 2.2 percent, to $23,962, for people who reported White as their only race or White along with another race; by 1.5 percent, to $24,142, for those who reported White as their only race category; by 1.6 percent to $26,128, for non-Hispanics who reported White as their only race; by 5.7 percent, to $23,252, for those who reported only Asian or Asian with another race; and by 7.5 percent, to $22,810, for those who reported Asian or Native Hawaiian and Other Pacific Islander, either as his or her only race or with another race category (see Table 4).[19 20]

State Income

Median household income rose for one state and declined for 10 states and the District of Columbia, based on percent changes in 2-year-average medians comparing

[19] The differences between the per capita incomes were not statistically different for: the overall population compared with those who reported Asian as their only race or Asian with another race or those who reported Asian or Native Hawaiian and Other Pacific Islander either as their only race or with another race category; those who reported White as their only race or White along with another race, compared with those that reported White as their only race or who reported Asian as their only race or Asian with another race; those who reported White as their only race compared with those who reported Asian as their only race or Asian with another race; and those who reported their race as only Asian or Asian with another race compared with those who reported their race as Asian or Native Hawaiian and Other Pacific Islander either as their only race or with another race category.

[20] None of the differences between the percentage declines in this paragraph are statistically significant except: the difference between those who reported Asian or Native Hawaiian and Other Pacific Islander either as their only race or with another race category compared with the overall population and those who reported White as their only race, and those who reported being non-Hispanic and reported White as their only race.

Table 5.
Money Income of Households by State Using 2- and 3-Year-Average Medians

(Income in 2002 dollars)

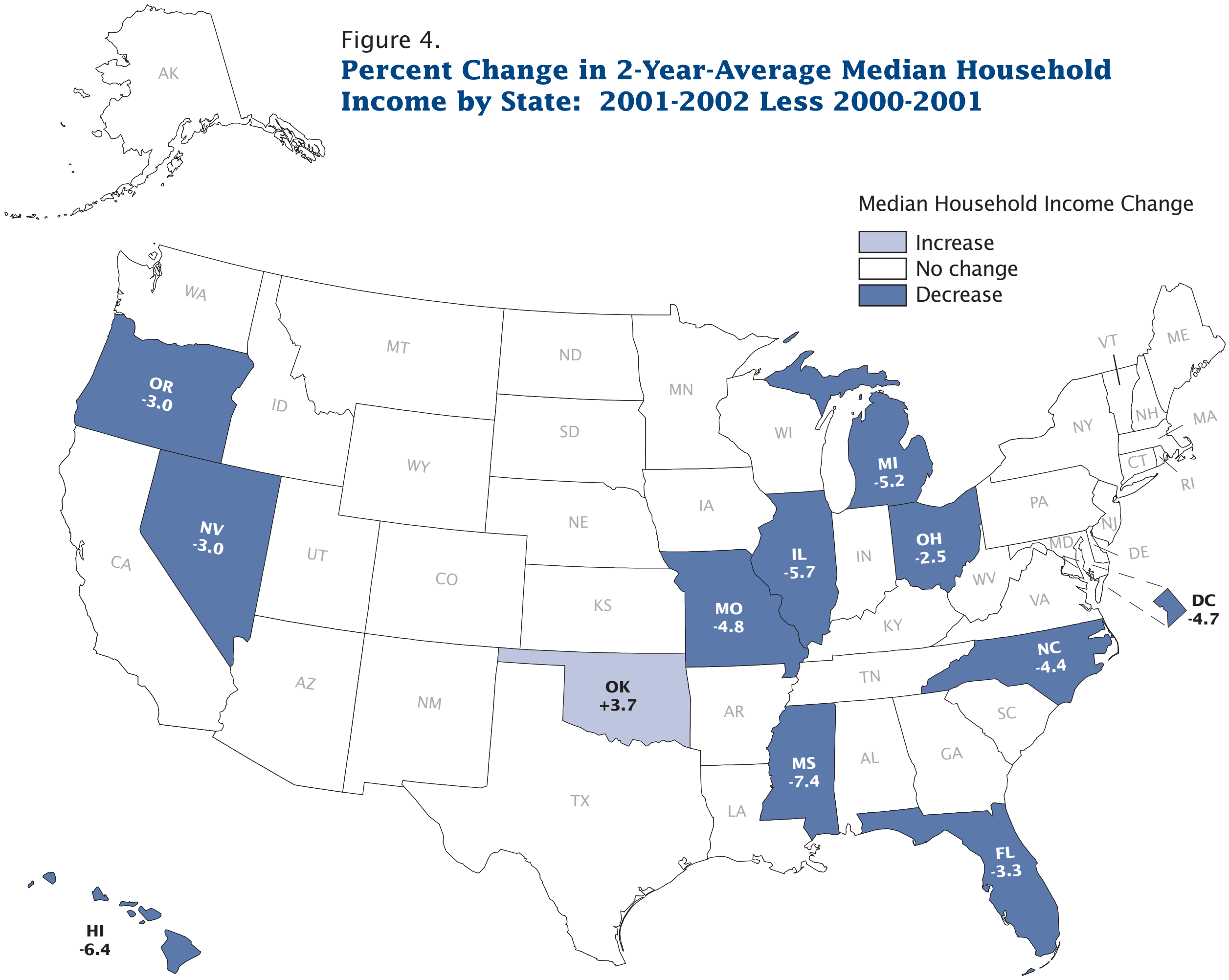
States	3-year-average median[1] 2000-2002		2-year-average medians[2] 2000-2001		2-year-average medians[2] 2001-2002		2001-2002 average less 2000-2001 average	
	Median money income (dollars)	90-percent confidence interval[3] (± dollars)	Median money income (dollars)	90-percent confidence interval[3] (± dollars)	Median money income (dollars)	90-percent confidence interval[3] (± dollars)	Difference	Percent change
United States	**43,052**	**156**	**43,374**	**182**	**42,654**	**183**	***–720**	***–1.7**
Alabama	36,771	1,224	36,355	1,448	36,661	1,408	306	0.8
Alaska	55,412	1,739	56,731	2,234	55,525	2,155	–1,206	–2.1
Arizona	41,554	1,458	42,463	1,845	41,559	1,681	–905	–2.1
Arkansas	32,423	1,082	32,440	1,341	33,128	1,323	688	2.1
California	48,113	852	48,451	983	47,725	1,017	–725	–1.5
Colorado	49,617	1,512	50,279	1,690	49,238	1,810	–1,041	–2.1
Connecticut	53,325	1,544	53,294	1,810	53,791	1,778	497	0.9
Delaware	50,878	1,814	51,492	2,072	50,020	2,148	–1,472	–2.9
District of Columbia	41,313	1,209	42,435	1,459	40,447	1,375	*–1,988	*–4.7
Florida	38,533	764	38,788	827	37,512	867	*–1,276	*–3.3
Georgia	43,316	1,185	43,504	1,327	43,096	1,485	–408	–0.9
Hawaii	49,775	1,491	51,010	1,704	47,748	1,789	*–3,262	*–6.4
Idaho	38,613	1,274	39,062	1,509	38,282	1,422	–780	–2.0
Illinois	45,906	1,057	47,504	1,286	44,808	1,182	*–2,696	*–5.7
Indiana	41,581	945	41,847	1,136	41,034	1,161	–813	–1.9
Iowa	41,827	1,224	42,216	1,358	41,338	1,556	–878	–2.1
Kansas	42,523	1,305	42,475	1,590	42,346	1,474	–129	–0.3
Kentucky	37,893	1,077	38,459	1,293	37,905	1,285	–554	–1.4
Louisiana	33,312	1,298	32,965	1,414	33,930	1,671	965	2.9
Maine	37,654	1,043	38,055	1,256	37,024	1,227	*–1,031	–2.7
Maryland	55,912	1,804	55,665	2,124	55,394	2,170	–271	–0.5
Massachusetts	50,587	1,598	50,953	2,001	51,470	1,830	516	1.0
Michigan	45,335	1,192	46,645	1,374	44,239	1,354	*–2,406	*–5.2
Minnesota	54,931	1,582	55,085	2,002	54,070	1,587	–1,015	–1.8
Mississippi	32,447	1,329	33,229	1,772	30,761	1,348	*–2,468	*–7.4
Missouri	43,955	1,362	44,545	1,664	42,386	1,554	*–2,158	*–4.8
Montana	33,900	1,138	33,432	1,220	33,736	1,343	304	0.9
Nebraska	43,566	1,246	43,951	1,485	43,550	1,468	–401	–0.9
Nevada	46,289	1,293	46,954	1,490	45,542	1,560	*–1,413	*–3.0
New Hampshire	53,549	1,251	52,664	1,396	53,734	1,390	1,071	2.0
New Jersey	53,266	1,376	52,615	1,340	53,581	1,752	966	1.8
New Mexico	35,251	1,397	35,148	1,731	34,554	1,570	–595	–1.7
New York	42,432	690	42,666	822	42,375	804	–291	–0.7
North Carolina	38,432	982	39,391	1,223	37,642	1,143	*–1,749	*–4.4
North Dakota	36,717	1,053	36,976	1,311	36,281	1,109	–695	–1.9
Ohio	43,332	843	43,656	971	42,567	980	*–1,090	*–2.5
Oklahoma	35,500	791	35,021	974	36,317	889	*1,295	*3.7
Oregon	42,704	989	43,155	1,181	41,866	1,095	*–1,289	*–3.0
Pennsylvania	43,577	867	44,117	993	43,344	1,034	–772	–1.8
Rhode Island	44,311	1,206	45,257	1,507	44,434	1,385	–824	–1.8
South Carolina	38,460	1,243	38,784	1,364	38,074	1,532	–710	–1.8
South Dakota	38,755	980	39,196	1,075	39,087	1,232	–108	–0.3
Tennessee	36,329	1,096	35,979	1,202	36,691	1,302	712	2.0
Texas	40,659	728	40,914	916	40,829	732	–84	–0.2
Utah	48,537	1,520	48,875	1,851	47,978	1,887	–897	–1.8
Vermont	41,929	1,060	41,395	1,298	42,221	1,210	826	2.0
Virginia	49,974	1,368	50,145	1,540	50,336	1,661	190	0.4
Washington	44,252	1,363	43,786	1,722	44,174	1,527	388	0.9
West Virginia	30,072	789	30,429	918	29,752	935	–677	–2.2
Wisconsin	46,351	1,193	46,575	1,444	45,985	1,413	–590	–1.3
Wyoming	40,499	1,262	40,867	1,546	40,057	1,463	–810	–2.0

*Significantly different from zero at the 90-percent confidence level.

[1]The 3-year-average median is the sum of 3 inflation-adjusted single-year medians divided by 3.
[2]The 2-year-average median is the sum of 2 inflation-adjusted single-year medians divided by 2.
[3]For an explanation of confidence intervals, see “Standard errors and their use” at *www.census.gov/hhes/income/income02/sa.pdf*.

Source: U.S. Census Bureau, Current Population Survey, 2001, 2002, and 2003 Annual Social and Economic Supplements.

Figure 4.
Percent Change in 2-Year-Average Median Household Income by State: 2001-2002 Less 2000-2001



Source: U.S. Census Bureau, Current Population Survey, 2001, 2002, and 2003 Annual Social and Economic Supplements.

data for 2000-2001 with data for 2001-2002 (see Table 5 and Figure 4).[21] Real median household income rose for Oklahoma. Four of the states that experienced declines were in the Midwest (Illinois, Michigan, Missouri, and Ohio), three in the South (Florida, Mississippi, and North Carolina), and three in the West (Hawaii, Nevada, and Oregon). States in the Northeast did not experience changes in income.

Comparing the relative ranking of states using 3-year-average medians for 2000-2002 shows that the median household income for Maryland, although not statistically different from the median incomes for Alaska and Minnesota, was higher than that for the remaining 47 states and the District of Columbia.

[21] To reduce the possibilities of misinterpreting changes in, or rankings of, income estimates for states, the Census Bureau uses 2-year-average medians for evaluating changes in state estimates over time and 3-year-average medians when comparing the relative ranking of states.

Model-Based State Estimates

The Census Bureau also produces improved (in the sense of having lower standard errors) annual estimates of median household income for states and counties, based on models using data from the ASEC, the decennial census, and administrative records, as well as personal income data published by the Bureau of Economic Analysis. Estimates for 1999 are available on the Internet at *www.census.gov/hhes/www/saipe.html.* Estimates for income year 2000 will be available later this fall.

Table 6.
Median Household Income by Income Definition: 2001 and 2002

(Income in 2002 dollars)

Definition of income	Median income 2001	Median income 2002	Percent change in real income 2002 less 2001	Percent of official definition of income
1. Money income excluding capital gains (losses) (MI)	42,900	42,409	*–1.1	100.0
1b. Definition 1 plus realized capital gains (losses) less taxes (MI-Tx)	37,376	37,066	*–0.8	87.4
2. Definition 1 less government cash transfers	39,630	39,102	*–1.3	92.2
3. Definition 2 plus realized capital gains (losses)	40,190	39,268	*–2.3	92.6
4. Definition 3 plus health insurance supplements to wage or salary income	42,004	41,294	*–1.7	97.4
5. Definition 4 less social security payroll taxes	39,390	38,602	*–2.0	91.0
6. Definition 5 less federal income taxes (excluding the EIC)	36,456	36,278	–0.5	85.5
7. Definition 6 plus the earned income credit (EIC)[1]	36,646	36,453	–0.5	86.0
8. Definition 7 less state income taxes	35,482	35,280	–0.6	83.2
9. Definition 8 plus nonmeans-tested government cash transfers	39,242	39,099	–0.4	92.2
10. Definition 9 plus the value of medicare	41,281	41,169	–0.3	97.1
11. Definition 10 plus the value of regular-price school lunches	41,300	41,183	–0.3	97.1
12. Definition 11 plus means-tested government cash transfers	41,468	41,363	–0.3	97.5
13. Definition 12 plus the value of medicaid	42,031	41,928	–0.2	98.9
14a. Definition 13 plus the value of other means-tested government noncash transfers less medicare and medicaid (MI-Tx+NC-MM)	39,553	39,426	–0.3	93.0
14. Definition 14a plus the value of medicare and medicaid (MI-Tx+NC)	42,194	42,061	–0.3	99.2
15. Definition 14 plus imputed return on home equity (MI-Tx+NC+HE)	43,925	43,760	–0.4	103.2

*Significantly different from zero at the 90-percent confidence level.

[1] Thirteen states (Colorado, Illinois, Iowa, Kansas, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island, Vermont, and Wisconsin) and the District of Columbia have an earned income credit (EIC) that uses federal eligibility rules to compute the state credit. The remaining states do not have such a program.

Note: Definition numbering reflects historical series identification.

Source: U.S. Census Bureau, Current Population Survey, 2002 and 2003 Annual Social and Economic Supplements.

Conversely, the median household income for West Virginia was lower than the incomes of the remaining 49 states and the District of Columbia. The relative standing of the remaining states and the District of Columbia was less clear because of sampling variability surrounding the estimates.

What is . . .? The **Gini Index** summarizes the dispersion of income across the entire income distribution. It ranges from 0, which indicates perfect equality (where everyone receives an equal amount), to 1, which denotes perfect inequality (where all the income is received by only one recipient or group of recipients).

INCOME INEQUALITY

There was no change in household money income inequality between 2001 and 2002. However, inequality declined between 2001 and 2002 under all four of the alternative income definitions.

The Gini index under the money income definition has not shown an annual change since 1993. However, the 2002 Gini index (0.462) was higher than in 1995 and earlier years (see appendix Table A-3 for historical Gini and other inequality measures).[22] Comparisons with years earlier than 1993 are not recommended because of substantial methodological changes in the 1994 CPS Annual Social and Economic Supplement.[23] Under the alternative income definitions, the Gini index in 2002 was 0.426 for MI-Tx; 0.421 for MI-Tx+NC-MM; 0.405 for MI-Tx+NC; and 0.400 for the most

[22] The Gini index in 2002 was not statistically different from the index in 1994. See *Current Population Reports*, Series P60-204, "The Changing Shape of the Nation's Income Distribution, 1947-98," for trends in other income inequality measures. A higher Gini index represents greater inequality.

[23] The Census Bureau introduced computer-assisted interviewing, increased income reporting limits, and introduced new Census 2000-based population controls in the 1994 CPS.

Table 7.
Percentage of Aggregate Household Income Received by Income Quintiles and Gini Index by Income Definition: 2001 and 2002

(For definition of Gini index, see text)

Definition of income	Quintiles										Gini index	
	Lowest		Second		Third		Fourth		Highest			
	2001	2002	2001	2002	2001	2002	2001	2002	2001	2002	2001	2002
1. Money income excluding realized capital gains (losses) (MI)	3.5	3.4	8.8	8.8	14.5	14.9	23.1	23.2	50.1	49.6	0.450	0.448
1b. Definition 1 plus realized capital gains (losses), less taxes (MI-Tx) .	4.1	4.1	9.6	*9.8	15.1	*15.5	22.6	*23.1	48.6	*47.5	0.434	*0.426
14a. Definition 1b plus value of employer-provided health benefits and all noncash transfers except medicaid and medicare (MI-Tx+NC-MM)	4.3	4.3	9.6	*9.8	15.2	*15.6	22.8	*23.3	48.1	*47.1	0.429	*0.421
14. Definition 14a plus medicaid and medicare.	4.5	4.5	10.3	10.4	15.6	*16.0	22.6	*23.1	47.0	*45.9	0.412	*0.405
15. Definition 14a plus imputed return on home equity (MI-Tx+NC+HE) .	4.7	4.7	10.4	10.6	15.6	*16.1	22.7	*23.1	46.5	*45.6	0.407	*0.400

*Difference between 2001 and 2002 statistically different from zero at the 90-percent confidence level.

Source: U.S. Census Bureau, Current Population Survey, 2002 and 2003 Annual Social and Economic Supplements.

comprehensive income definition, MI-Tx+NC+HE (the more comprehensive the measure, the lower the inequality). All the Gini indexes under the alternative income definitions were higher in 2002 than in 1996 for definitions MI-Tx+NC-MM and MI-Tx+NC+HE and were higher than in 1995 for definitions MI-Tx and MI-Tx+NC.

In addition to declines between 2001 and 2002 in the Gini indexes under the alternative income definitions, the share of income going to the middle 60-percent of households increased while the share going to the highest 20-percent of households decreased. The share of aggregate income received by each quintile was unchanged for the money income definition and for the lowest income quintile for all the alternative income definitions (see Table 7).[24]

What are . . .? Aggregate Shares are computed by ranking households from lowest to highest income and then dividing them into groups of equal numbers of households, typically quintiles. The aggregate income of each group divided by the overall aggregate income is each group's share.

THE EFFECTS OF INCLUDING NONCASH BENEFITS AND TAXES ON ESTIMATES OF INCOME

As shown in Table 6, real median household income declined between 2001 and 2002 for only 6 of the 17 definitions of income (only a few of which are discussed in this section).

Definition 1 (MI), the traditional definition of income, is based on money income before taxes and includes government cash transfers. As noted earlier, between 2001 and 2002, real median income for households declined, 1.1 percent, to $42,409.

Definition 4 reflects income generated by the private sector. It excludes cash transfers, adds net realized capital gains (losses), and adds employer contributions to health insurance. Between 2001 and 2002, real median household income under this definition declined by 1.7 percent. The 2002 median household income for Definition 4 was $41,294, which was 97.4 percent of money income.

Definition 8 reflects the net effect of deducting social security payroll taxes, federal and state income taxes, and adding the earned income tax credit. Real median household income showed no change between 2001 and 2002 under this definition. The 2002

[24] This report presents Gini indexes and shares of aggregate income received by each quintile using two methods. The first method, discussed in the text, sorts individual households by income yielding a Gini index for household money income of 0.462 and quintile shares of 3.5, 8.8, 14.8, 23.3, and 49.7. The second method, reported in Table 6, uses group data and employs several interpolation routines resulting in a Gini index of 0.448 and quintile shares of 3.4, 8.8, 14.9, 23.2, and 49.6.

median household income for Definition 8 was $35,280, which was 83.2 percent of money income.

Definition 11 includes nonmeans-tested cash transfers such as social security. Real median household income showed no change between 2001 and 2002 under Definition 11. The 2002 median household income under Definition 11 was $41,183, which was 97.1 percent of money income.[25]

Definition 14a (MI-Tx+NC-MM) includes the value of means-tested cash transfers and nonmeans-tested noncash transfers, except medicaid and medicare. Real median household income showed no change between 2001 and 2002 under this definition of income. The 2002 median household income for Definition 14a was $39,426, which was 93.0 percent of money income

Definition 14 (MI-Tx+NC) adds the value of medicare and medicaid. Real median household income showed no change between 2001 and 2002 under this definition of income. The 2002 median household income for Definition 14 was $42,061, which was 99.2 percent of money income.

The impact of including an estimated return on home equity is shown in Definition 15. Real median household income showed no change between 2001 and 2002 under this definition of income. The 2002 median household income for Definition 15 was $43,760, which was 103.2 percent of money income.

An important finding of the Census Bureau's tax and noncash benefit research is that government transfers have a greater impact on lowering income inequality than the tax system. In 2002, subtracting taxes and including the earned income credit (EIC) lowered the Gini index by 4.1 percent (from 0.508 to 0.487), while including transfers lowered the Gini index by 16.8 percent (from 0.487 to 0.405).

[25] The income ratio for Definition 11 was not different from Definition 4.

What are . . .? Government Cash Transfers include social security, railroad retirement, black lung, unemployment compensation, workers' compensation, veterans' benefits, government educational assistance, cash public assistance, and supplemental security income.

What are . . .? Nonmeans-Tested Cash Transfers include social security, railroad retirement, black lung, unemployment compensation, workers' compensation, nonmeans- tested veterans' benefits, and all government educational assistance including Pell Grants (which are means-tested).

What are . . .? Means-tested Cash Transfers include cash public assistance, supplemental security income, and means-tested veterans' benefits.

CPS DATA COLLECTION

The information in this report was collected in the 50 states and the District of Columbia and does not include residents of Puerto Rico and outlying areas. The estimates in this report are controlled to national population estimates by age, race, sex, and Hispanic origin and to state population estimates by age.

The CPS excludes armed forces personnel living on military bases and people living in institutions. For further documentation about the CPS Annual Social and Economic Supplement, see *www.bls.census.gov/cps/ads/adsmain.htm.*

USER COMMENTS

The Census Bureau welcomes the comments and advice of users of data and reports. If you have any suggestions or comments, please write to:

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APPENDIX TABLES

Table A-1.
Households by Total Money Income, Race, and Hispanic Origin of Householder: 1967 to 2002

(Income in 2002 CPI-U-RS adjusted dollars. Households as of March of the following year. See text for comparability issues regarding comparison of data for racial groups using single and multiple race reporting methods)

Race and Hispanic origin of householder and year	Number (thousands)	Percent distribution										Median income		Mean income	
		Total	Under $5,000	$5,000 to $9,999	$10,000 to $14,999	$15,000 to $24,999	$25,000 to $34,999	$35,000 to $49,999	$50,000 to $74,999	$75,000 to $99,999	$100,000 and over	Value (dollars)	Standard error (dollars)	Value (dollars)	Standard error (dollars)
ALL RACES															
2002	111,278	100.0	3.2	5.9	7.0	13.2	12.3	15.1	18.3	11.0	14.1	42,409	139	57,852	217
2001	109,297	100.0	3.1	5.7	6.8	13.2	12.4	15.3	18.3	11.0	14.3	42,900	131	59,134	236
2000[1]	108,209	100.0	2.8	5.7	6.8	12.6	12.6	15.2	18.7	11.0	14.5	43,848	138	59,664	235
1999[2]	106,434	100.0	2.7	5.7	6.7	13.3	12.3	15.3	18.5	11.0	14.4	43,915	205	59,067	306
1998	103,874	100.0	3.0	6.2	6.9	13.2	12.5	15.3	18.9	10.8	13.2	42,844	253	57,134	309
1997	102,528	100.0	3.0	6.5	7.3	13.8	12.5	15.5	18.8	10.3	12.3	41,346	191	55,522	311
1996	101,018	100.0	2.9	6.9	7.6	13.8	13.0	15.5	18.9	10.2	11.2	40,503	204	53,776	301
1995[3]	99,627	100.0	3.0	6.8	7.5	14.5	12.3	16.6	18.5	10.1	10.6	39,931	231	52,659	288
1994[4]	98,990	100.0	3.3	7.3	7.7	14.4	12.8	16.2	17.9	9.9	10.4	38,726	176	51,771	278
1993[5]	97,107	100.0	3.5	7.5	7.9	14.2	13.1	16.3	18.1	9.4	10.0	38,287	179	50,772	275
1992[6]	96,426	100.0	3.3	7.6	7.6	14.5	13.0	16.3	18.8	9.5	9.4	38,482	182	48,788	205
1991	95,669	100.0	3.0	7.6	7.4	14.1	13.4	16.5	18.9	9.5	9.4	38,791	187	48,829	201
1990	94,312	100.0	3.0	7.3	7.3	13.6	13.3	17.1	19.0	9.5	9.7	39,949	204	49,902	211
1989	93,347	100.0	2.8	7.0	7.3	13.7	12.4	17.2	19.4	10.0	10.1	40,484	223	51,148	223
1988	92,830	100.0	3.0	7.7	7.2	14.0	12.3	17.0	19.6	10.0	9.4	39,767	194	49,688	222
1987[7]	91,124	100.0	3.2	7.7	7.1	14.1	13.0	16.6	19.3	9.9	9.1	39,453	188	49,065	201
1986	89,479	100.0	3.4	7.8	7.1	14.1	13.1	16.8	19.3	9.7	8.6	38,975	202	48,152	196
1985[8]	88,458	100.0	3.3	8.0	7.6	14.5	13.4	17.5	18.9	9.3	7.6	37,648	204	46,332	183
1984	86,789	100.0	3.2	8.0	8.0	14.9	13.7	17.5	18.7	8.8	7.2	36,921	168	45,238	166
1983[9]	85,290	100.0	3.5	8.1	8.0	15.3	14.2	17.5	18.8	8.2	6.5	36,001	163	43,865	163
1982	83,918	100.0	3.4	8.4	8.2	15.2	13.7	18.4	18.3	8.1	6.1	35,986	162	43,369	161
1981	83,527	100.0	3.2	8.5	7.9	15.8	13.4	18.1	19.1	8.2	5.8	36,042	189	43,059	157
1980	82,368	100.0	2.9	8.3	8.2	15.0	13.6	18.5	19.6	8.1	5.9	36,608	188	43,539	159
1979[10]	80,776	100.0	2.9	8.1	7.5	14.4	13.9	17.9	20.6	8.3	6.4	37,784	179	44,883	170
1978	77,330	100.0	2.6	8.1	7.8	14.5	13.7	18.2	20.5	8.6	6.0	37,826	153	44,520	171
1977	76,030	100.0	2.8	8.7	8.5	15.3	14.2	18.7	19.5	7.4	4.9	35,545	134	42,166	128
1976[11]	74,142	100.0	2.8	8.8	8.3	15.3	14.4	19.2	19.6	7.1	4.5	35,345	131	41,575	128
1975[12]	72,867	100.0	3.0	9.0	8.5	15.5	14.4	19.6	19.1	6.7	4.2	34,763	141	40,593	127
1974[12, 13]	71,163	100.0	2.9	8.5	7.8	15.0	14.7	19.9	19.4	7.0	4.6	35,719	137	41,770	131
1973	69,859	100.0	3.4	7.9	8.0	14.6	13.6	20.3	19.8	7.4	5.0	36,855	140	42,623	130
1972[14]	68,251	100.0	3.8	8.2	7.9	14.4	14.4	20.1	19.5	6.9	4.8	36,126	138	42,046	130
1971[15]	66,676	100.0	4.3	8.7	7.5	15.2	15.2	20.9	18.2	6.1	3.9	34,669	134	39,873	127
1970	64,778	100.0	4.5	8.4	7.4	14.7	15.3	21.2	18.6	6.0	4.0	35,030	128	40,111	128
1969	63,401	100.0	4.4	8.5	7.1	14.1	16.1	21.1	19.2	5.9	3.8	35,266	130	40,122	126
1968	62,214	100.0	4.8	8.3	7.5	14.9	16.3	22.2	17.8	5.0	3.1	33,968	123	38,430	123
1967[16]	60,813	100.0	5.6	8.8	7.8	15.3	17.1	21.5	16.3	4.6	3.1	32,591	119	36,452	119
WHITE ALONE[17]															
2002	91,645	100.0	2.5	5.2	6.8	12.8	12.0	15.2	18.9	11.6	15.0	45,086	183	60,166	245
WHITE[18]															
2001	90,682	100.0	2.4	5.0	6.7	12.8	12.2	15.4	18.7	11.6	15.2	45,225	212	61,474	264
2000[1]	90,030	100.0	2.3	5.0	6.5	12.3	12.5	15.2	19.2	11.5	15.4	45,860	203	61,876	265
1999[2]	88,893	100.0	2.2	4.9	6.3	13.1	12.2	15.4	19.1	11.7	15.1	45,673	231	61,214	346
1998	87,212	100.0	2.4	5.2	6.6	12.8	12.4	15.5	19.6	11.4	14.2	45,077	226	59,726	351
1997	86,106	100.0	2.5	5.7	6.9	13.4	12.3	15.6	19.4	10.9	13.2	43,544	276	57,991	353
1996	85,059	100.0	2.3	6.0	7.2	13.5	13.0	15.6	19.7	10.7	12.0	42,407	219	55,911	331
1995[3]	84,511	100.0	2.4	5.9	7.1	14.2	12.3	16.9	19.2	10.5	11.5	41,911	219	54,758	318
1994[4]	83,737	100.0	2.7	6.2	7.4	14.1	12.8	16.6	18.6	10.4	11.1	40,843	229	54,053	314
1993[5]	82,387	100.0	2.7	6.4	7.4	13.9	13.1	16.8	19.0	9.9	10.8	40,394	235	53,048	306
1992[6]	81,795	100.0	2.5	6.5	7.2	14.1	13.1	16.7	19.7	10.1	10.1	40,458	196	50,991	227

See footnotes at end of table.

Table A-1.
Households by Total Money Income, Race, and Hispanic Origin of Householder: 1967 to 2002–Con.

(Income in 2002 CPI-U-RS adjusted dollars. Households as of March of the following year. See text for comparability issues regarding comparison of data for racial groups using single and multiple race reporting methods)

Race and Hispanic origin of householder and year	Number (thousands)	Percent distribution: Total	Under $5,000	$5,000 to $9,999	$10,000 to $14,999	$15,000 to $24,999	$25,000 to $34,999	$35,000 to $49,999	$50,000 to $74,999	$75,000 to $99,999	$100,000 and over	Median income: Value (dollars)	Median income: Standard error (dollars)	Mean income: Value (dollars)	Mean income: Standard error (dollars)
WHITE—Con.															
1991	81,675	100.0	2.3	6.5	7.0	13.9	13.4	16.9	19.8	10.1	10.1	40,649	197	50,890	221
1990	80,968	100.0	2.3	6.2	6.9	13.5	13.4	17.5	19.8	10.1	10.4	41,668	191	51,916	232
1989	80,163	100.0	2.2	6.0	6.9	13.4	12.4	17.5	20.4	10.4	10.9	42,585	207	53,278	246
1988	79,734	100.0	2.4	6.5	6.6	13.6	12.2	17.5	20.5	10.6	10.1	42,040	248	51,807	244
1987[7]	78,519	100.0	2.5	6.6	6.6	13.7	12.9	17.1	20.2	10.6	9.7	41,568	210	51,161	221
1986	77,284	100.0	2.7	6.9	6.7	13.7	13.0	17.2	20.2	10.4	9.2	40,976	199	50,157	214
1985[8]	76,576	100.0	2.7	6.9	7.2	14.1	13.4	17.9	19.7	9.8	8.3	39,704	212	48,234	202
1984	75,328	100.0	2.7	6.9	7.4	14.5	13.7	18.1	19.6	9.3	7.8	38,951	196	47,104	183
1983[9]	74,170	100.0	2.8	7.1	7.4	15.0	14.3	18.1	19.7	8.7	7.0	37,743	170	45,698	176
1982	73,182	100.0	2.9	7.4	7.6	14.7	13.9	18.9	19.2	8.8	6.7	37,674	171	45,156	177
1981	72,845	100.0	2.6	7.4	7.4	15.3	13.5	18.6	20.1	8.7	6.3	38,081	176	44,863	170
1980	71,872	100.0	2.4	7.3	7.6	14.5	13.6	19.0	20.6	8.6	6.4	38,621	198	45,296	174
1979[10]	70,766	100.0	2.4	7.2	7.0	14.0	13.8	18.3	21.5	8.8	6.9	39,616	188	46,653	186
1978	68,028	100.0	2.2	7.1	7.3	14.1	13.7	18.6	21.5	9.1	6.5	39,323	173	46,170	186
1977	66,934	100.0	2.5	7.7	7.9	14.7	14.2	19.3	20.6	7.8	5.4	37,378	157	43,813	141
1976[11]	65,353	100.0	2.5	7.8	7.7	14.9	14.4	19.6	20.5	7.6	4.9	37,025	153	43,174	139
1975[12]	64,392	100.0	2.7	8.0	8.0	15.1	14.3	20.2	20.1	7.1	4.6	36,354	133	42,093	138
1974[12 13]	62,984	100.0	2.6	7.7	7.3	14.5	14.6	20.5	20.4	7.5	5.0	37,355	140	43,317	140
1973	61,965	100.0	3.0	7.2	7.3	13.9	13.5	20.8	20.9	8.0	5.4	38,626	147	44,271	140
1972[14]	60,618	100.0	3.3	7.5	7.3	13.7	14.3	20.8	20.5	7.4	5.2	37,899	145	43,681	142
1971[15]	59,463	100.0	3.9	7.9	7.1	14.6	15.1	21.7	19.1	6.5	4.2	36,263	138	41,316	134
1970	57,575	100.0	4.0	7.7	6.9	14.1	15.2	21.9	19.5	6.3	4.3	36,486	140	41,515	136
1969	56,248	100.0	3.8	7.8	6.6	13.3	15.9	21.8	20.3	6.3	4.1	36,805	135	41,610	139
1968	55,394	100.0	4.2	7.7	6.9	14.2	16.4	23.0	18.9	5.3	3.3	35,367	132	39,811	132
1967[16]	54,188	100.0	5.0	8.1	7.1	14.6	17.3	22.4	17.3	4.8	3.3	33,988	123	37,784	128
WHITE ALONE, NOT HISPANIC[17]															
2002	81,166	100.0	2.3	5.0	6.6	12.2	11.5	15.0	19.2	12.2	16.0	46,900	184	62,115	264
WHITE, NOT HISPANIC[18]															
2001	80,818	100.0	2.3	4.9	6.5	12.2	11.8	15.1	19.0	12.0	16.2	47,041	195	63,437	288
2000[1]	80,527	100.0	2.2	4.8	6.4	11.7	12.2	15.0	19.4	12.0	16.4	47,642	191	63,759	286
1999[2]	79,819	100.0	2.0	4.7	6.0	12.6	11.8	15.2	19.5	12.1	16.1	47,650	314	63,221	391
1998	78,577	100.0	2.2	4.8	6.2	12.2	12.1	15.4	20.0	11.9	15.1	46,760	269	61,639	377
1997	77,936	100.0	2.2	5.2	6.6	13.0	12.1	15.6	19.9	11.5	14.0	45,338	237	59,849	(NA)
1996	77,240	100.0	2.1	5.6	6.9	12.9	12.8	15.6	20.2	11.2	12.7	44,263	304	57,602	(NA)
1995[3]	76,932	100.0	2.2	5.4	6.7	13.6	12.1	17.0	19.8	11.1	12.2	43,566	227	56,543	339
1994[4]	77,004	100.0	2.5	5.8	7.1	13.8	12.6	16.7	19.1	10.9	11.7	42,161	223	55,430	329
1993[5]	75,697	100.0	2.6	6.1	7.0	13.5	12.8	16.8	19.5	10.3	11.4	41,881	245	54,446	325
1992[6]	75,107	100.0	2.3	6.1	7.0	13.7	12.8	16.7	20.2	10.5	10.6	41,816	259	52,286	241
1991	75,625	100.0	2.1	6.2	6.8	13.6	13.3	16.9	20.2	10.4	10.5	41,619	205	51,981	232
1990	75,035	100.0	2.2	5.9	6.6	13.1	13.2	17.5	20.2	10.5	10.9	42,620	199	53,060	240
1989	74,495	100.0	2.0	5.7	6.7	13.2	12.2	17.5	20.7	10.8	11.4	43,501	213	54,341	266
1988	74,067	100.0	2.2	6.2	6.4	13.3	12.1	17.5	20.8	10.9	10.5	43,198	242	52,862	248
1987[7]	73,120	100.0	2.3	6.3	6.4	13.4	12.7	17.2	20.6	10.9	10.1	42,711	248	52,168	242
1986	72,067	100.0	2.5	6.6	6.5	13.3	12.9	17.3	20.6	10.7	9.6	41,907	216	51,159	235
1985[8]	71,540	100.0	2.6	6.6	7.0	13.8	13.3	17.9	20.1	10.0	8.7	40,597	207	49,176	223
1984	70,586	100.0	2.5	6.7	7.2	14.2	13.7	18.1	19.9	9.6	8.1	39,759	221	47,916	214
1983[9]	(NA)	100.0	2.7	6.8	7.1	14.7	14.2	18.1	20.1	9.0	7.3	(NA)	(NA)	(NA)	(NA)
1982	69,214	100.0	2.7	7.2	7.4	14.5	13.8	19.0	19.5	9.0	6.9	38,306	193	45,815	196

See footnotes at end of table.

Table A-1.
Households by Total Money Income, Race, and Hispanic Origin of Householder: 1967 to 2002–Con.

(Income in 2002 CPI-U-RS adjusted dollars. Households as of March of the following year. See text for comparability issues regarding comparison of data for racial groups using single and multiple race reporting methods)

Race and Hispanic origin of householder and year	Number (thousands)	Percent distribution: Total	Under $5,000	$5,000 to $9,999	$10,000 to $14,999	$15,000 to $24,999	$25,000 to $34,999	$35,000 to $49,999	$50,000 to $74,999	$75,000 to $99,999	$100,000 and over	Median income: Value (dollars)	Median income: Standard error (dollars)	Mean income: Value (dollars)	Mean income: Standard error (dollars)
WHITE, NOT HISPANIC—Con.															
1981	68,996	100.0	2.6	7.3	7.3	15.1	13.4	18.6	20.4	8.9	6.6	38,631	197	45,426	189
1980	68,106	100.0	2.3	7.1	7.5	14.2	13.5	19.1	20.9	8.8	6.6	39,306	108	45,889	207
1979[10]	67,203	100.0	2.3	7.1	6.8	13.8	13.7	18.3	21.8	9.0	7.1	40,173	223	47,192	207
1978	64,836	100.0	2.2	7.0	7.2	13.9	13.5	18.6	21.7	9.3	6.7	40,063	211	46,705	201
1977	63,721	100.0	2.5	7.6	7.8	14.4	14.0	19.3	21.0	8.0	5.6	38,120	215	44,366	210
1976[11]	62,365	100.0	2.5	7.6	7.5	14.6	14.3	19.7	20.9	7.8	5.1	37,780	220	43,743	195
1975[12]	61,533	100.0	2.6	7.9	7.8	14.8	14.2	20.2	20.5	7.3	4.7	36,628	194	42,599	206
1974[12 13]	60,164	100.0	2.5	7.6	7.1	14.2	14.5	20.5	20.7	7.7	5.1	37,674	185	43,799	191
1973	59,236	100.0	3.0	7.1	7.2	13.6	13.3	20.9	21.2	8.2	5.6	38,966	182	44,765	189
1972[14]	58,005	100.0	3.3	7.5	7.1	13.4	14.1	20.8	20.9	7.5	5.4	38,439	183	44,188	197
BLACK ALONE OR IN COMBINATION															
2002	13,778	100.0	6.9	10.7	9.5	16.3	14.5	14.8	13.9	6.7	6.6	29,177	384	40,334	470
BLACK ALONE[19]															
2002	13,465	100.0	7.0	10.8	9.6	16.4	14.5	14.8	13.9	6.7	6.4	29,026	391	40,011	462
BLACK[18]															
2001	13,315	100.0	6.8	10.7	8.8	16.3	14.3	14.9	15.4	7.0	5.9	29,939	353	39,872	421
2000[1]	13,174	100.0	5.9	10.5	8.8	16.1	14.1	15.7	15.3	7.0	6.7	30,980	410	40,912	415
1999[2]	12,838	100.0	5.8	11.3	9.3	15.9	13.9	14.6	14.9	6.6	7.6	30,118	561	41,505	596
1998	12,579	100.0	6.7	13.2	9.4	16.9	13.4	14.5	14.0	6.4	5.6	27,932	437	37,615	502
1997	12,474	100.0	6.4	12.6	10.0	16.9	14.1	14.5	14.7	6.1	4.6	27,989	482	36,830	528
1996	12,109	100.0	6.9	13.0	10.7	16.8	13.6	15.0	14.0	5.4	4.5	26,797	527	37,043	724
1995[3]	11,577	100.0	7.0	13.4	10.5	17.5	13.2	15.1	13.1	6.5	3.7	26,240	448	35,623	609
1994[4]	11,655	100.0	7.3	15.1	10.4	17.0	13.5	13.2	13.3	5.6	4.6	25,238	469	35,119	504
1993[5]	11,281	100.0	8.5	15.3	11.8	16.2	13.7	13.5	12.0	4.9	4.0	23,939	473	33,370	554
1992[6]	11,269	100.0	8.7	15.9	10.6	16.9	13.4	13.7	12.7	4.6	3.5	23,558	481	31,968	433
1991	11,083	100.0	8.1	16.1	10.8	16.1	13.3	14.3	12.9	5.0	3.3	24,216	509	32,246	421
1990	10,671	100.0	7.8	15.7	11.1	15.5	13.6	14.5	13.3	4.7	3.8	24,917	568	33,106	447
1989	10,486	100.0	7.6	15.3	10.4	16.5	13.0	15.0	12.6	6.0	3.6	25,326	515	33,606	457
1988	10,561	100.0	7.1	16.7	11.5	16.5	12.8	13.6	12.9	5.6	3.4	23,965	500	32,832	479
1987[7]	10,192	100.0	7.7	17.0	10.3	17.2	14.4	13.0	12.2	4.8	3.4	23,725	457	32,035	441
1986	9,922	100.0	8.9	15.4	10.7	17.1	13.5	13.7	13.1	4.4	3.1	23,607	463	31,672	430
1985[8]	9,797	100.0	7.2	16.7	10.8	18.3	13.5	14.4	12.2	4.7	2.3	23,622	459	30,821	400
1984	9,480	100.0	7.4	16.8	12.4	18.4	13.9	13.4	11.1	4.4	2.1	22,189	427	29,593	364
1983[9]	9,243	100.0	8.3	16.9	12.7	18.4	13.6	13.2	11.3	3.9	1.8	21,365	399	28,458	349
1982	8,916	100.0	8.1	17.1	12.2	19.1	12.6	15.1	11.5	2.9	1.4	21,352	343	28,094	351
1981	8,961	100.0	7.5	17.7	12.3	19.5	12.7	13.8	11.5	3.8	1.2	21,370	359	28,072	340
1980	8,847	100.0	7.0	16.6	12.9	18.7	13.3	14.7	11.5	3.8	1.5	22,250	420	28,877	356
1979[10]	8,586	100.0	6.5	16.0	12.3	18.4	14.1	14.5	12.6	4.0	1.6	23,259	425	29,844	367
1978	8,066	100.0	5.3	16.8	12.2	17.9	14.0	15.5	12.3	4.3	1.7	23,631	500	30,200	394
1977	7,977	100.0	5.4	17.1	12.7	20.5	14.4	14.3	11.0	3.4	1.1	22,057	296	28,262	251
1976[11]	7,776	100.0	5.3	17.2	13.2	19.3	14.4	15.3	11.3	3.0	1.1	22,016	273	28,129	251
1975[12]	7,489	100.0	6.4	17.2	13.8	18.5	15.1	14.6	10.7	2.7	0.9	21,824	321	27,242	242
1974[12 13]	7,263	100.0	6.1	16.3	12.8	20.0	15.5	14.9	11.1	2.5	0.9	22,215	268	27,629	246
1973	7,040	100.0	6.8	14.3	13.7	19.7	14.9	16.0	10.4	3.0	1.3	22,737	354	28,234	280
1972[14]	6,809	100.0	7.8	14.6	13.0	19.9	15.4	14.2	11.5	2.3	1.3	22,122	332	27,945	298

See footnotes at end of table.

Table A-1.
Households by Total Money Income, Race, and Hispanic Origin of Householder: 1967 to 2002–Con.

(Income in 2002 CPI-U-RS adjusted dollars. Households as of March of the following year. See text for comparability issues regarding comparison of data for racial groups using single and multiple race reporting methods)

Race and Hispanic origin of householder and year	Number (thousands)	Percent distribution										Median income		Mean income	
		Total	Under $5,000	$5,000 to $9,999	$10,000 to $14,999	$15,000 to $24,999	$25,000 to $34,999	$35,000 to $49,999	$50,000 to $74,999	$75,000 to $99,999	$100,000 and over	Value (dollars)	Standard error (dollars)	Value (dollars)	Standard error (dollars)
BLACK—Con.															
1971[15]	6,578	100.0	8.5	15.8	11.8	20.7	16.3	14.4	9.3	2.3	0.8	21,421	319	26,543	273
1970	6,180	100.0	8.9	14.6	12.2	20.5	15.6	15.0	9.8	2.6	0.9	22,207	305	27,116	293
1969	6,053	100.0	8.7	14.6	12.1	20.6	17.0	14.9	9.2	2.2	0.7	22,247	328	26,484	282
1968	5,870	100.0	9.2	14.5	13.1	22.2	15.3	14.5	8.4	2.1	0.6	20,855	303	25,400	268
1967[16]	5,728	100.0	10.7	15.3	13.8	21.6	15.9	12.8	7.0	1.9	0.9	19,734	329	23,712	265
ASIAN ALONE OR IN COMBINATION															
2002	4,079	100.0	4.3	3.8	4.0	10.5	10.3	13.9	18.9	12.5	21.8	52,285	791	69,476	1,321
ASIAN ALONE[20]															
2002	3,917	100.0	4.3	3.6	4.0	10.5	10.5	13.6	18.8	12.6	22.1	52,626	921	70,047	1,366
ASIAN AND PACIFIC ISLANDER[18]															
2001	4,071	100.0	4.2	3.9	4.2	10.0	9.7	14.3	18.9	12.6	22.3	54,488	1,300	74,323	1,754
2000[1]	3,963	100.0	3.6	3.3	4.3	8.9	10.0	13.6	19.0	13.7	23.5	58,225	993	76,019	1,578
1999[2]	3,742	100.0	3.9	4.1	4.6	9.0	10.0	14.5	17.8	12.8	23.2	54,991	1,938	72,718	1,843
1998	3,308	100.0	4.4	4.1	4.8	10.0	10.8	14.8	18.3	13.6	19.1	51,385	1,430	66,338	1,916
1997	3,125	100.0	4.3	4.4	5.7	9.9	9.5	15.8	19.7	11.8	18.8	50,558	1,406	65,799	2,039
1996	2,998	100.0	3.9	5.9	5.4	10.0	10.1	15.7	18.2	13.4	17.5	49,386	1,770	64,530	2,314
1995[3]	2,777	100.0	4.8	4.3	6.6	10.7	9.4	17.3	19.4	12.2	15.3	47,592	1,194	64,717	2,611
1994[4]	2,040	100.0	4.4	4.9	5.6	10.8	10.3	15.4	19.5	13.3	15.8	48,590	1,841	63,089	2,248
1993[5]	2,233	100.0	4.6	6.3	6.5	11.8	10.3	13.4	18.3	13.0	15.9	46,996	2,311	61,577	2,479
1992[6]	2,262	100.0	4.2	4.7	5.6	12.4	9.9	16.0	19.4	12.8	15.0	47,482	1,370	58,849	1,618
1991	2,094	100.0	3.8	5.6	4.8	11.7	12.3	14.8	19.3	12.8	14.9	46,932	1,514	59,588	1,756
1990	1,958	100.0	3.8	4.0	5.5	10.8	9.8	14.7	21.4	13.4	16.6	51,299	1,520	61,922	1,753
1989	1,988	100.0	3.0	3.5	6.3	10.1	10.1	17.2	20.6	12.7	16.5	50,562	1,367	62,856	1,829
1988	1,913	100.0	3.1	4.7	6.1	12.6	10.2	15.4	20.6	11.5	15.8	47,132	1,937	58,925	1,760
HISPANIC (OF ANY RACE)[21]															
2002	11,339	100.0	4.3	6.7	8.1	17.2	15.7	16.4	16.9	7.5	7.2	33,103	482	44,887	600
2001	10,499	100.0	3.9	6.6	8.2	17.4	15.4	17.3	16.1	7.8	7.2	34,099	433	45,089	570
2000[1]	10,034	100.0	3.3	6.9	8.0	16.8	15.5	17.3	17.3	8.1	6.7	34,636	499	45,924	661
1999[2]	9,579	100.0	3.7	6.9	8.8	17.7	16.0	16.9	15.7	7.7	6.6	33,178	482	43,585	774
1998	9,060	100.0	4.5	9.2	9.4	17.2	15.6	15.9	15.4	6.5	6.2	31,214	602	42,177	897
1997	8,590	100.0	4.7	9.9	10.3	17.9	15.0	16.0	14.8	5.9	5.6	29,752	531	40,093	809
1996	8,225	100.0	4.4	10.3	10.6	19.0	15.3	15.4	14.1	5.9	4.8	28,422	551	38,806	898
1995[3]	7,939	100.0	5.1	11.5	10.7	20.0	14.3	15.5	13.5	5.2	4.3	26,788	584	36,562	820
1994[4]	7,735	100.0	4.9	11.6	10.7	18.1	14.9	15.7	13.5	5.7	4.8	28,112	522	37,907	946
1993[5]	7,362	100.0	4.4	10.7	11.4	18.8	15.4	16.3	13.3	5.6	4.1	28,048	564	37,123	781
1992[6]	7,153	100.0	4.8	10.5	10.3	18.9	15.6	16.3	13.9	5.7	4.0	28,384	587	36,204	569
1991	6,379	100.0	4.3	10.2	10.6	18.0	15.4	16.5	14.6	5.9	4.5	29,217	608	37,176	595
1990	6,220	100.0	4.3	10.0	10.8	17.8	15.2	17.2	14.8	5.6	4.3	29,792	611	37,320	615
1989	5,933	100.0	4.7	10.0	9.1	16.9	15.0	16.9	16.2	6.4	4.9	30,701	595	39,204	674
1988	5,910	100.0	5.2	10.0	9.6	18.6	13.8	16.8	15.5	5.8	4.5	29,738	733	37,967	805
1987[7]	5,642	100.0	5.1	10.9	9.6	18.3	15.4	15.8	14.9	5.6	4.5	29,272	642	37,523	695
1986	5,418	100.0	4.9	10.7	10.0	18.7	14.7	16.3	14.6	6.4	3.7	28,729	748	36,276	596
1985[8]	5,213	100.0	4.7	11.1	11.2	18.4	15.0	17.0	14.0	5.7	2.9	27,840	650	34,787	566
1984	4,883	100.0	5.3	11.4	10.5	18.7	13.7	18.0	14.4	4.8	3.1	27,989	702	34,803	679
1983[9]	4,666	100.0	5.1	11.5	11.8	18.4	15.7	17.0	13.4	4.5	2.7	27,053	690	33,137	637

See footnotes at end of table.

Table A-1.

Households by Total Money Income, Race, and Hispanic Origin of Householder: 1967 to 2002–Con.

(Income in 2002 CPI-U-RS adjusted dollars. Households as of March of the following year. See text for comparability issues regarding comparison of data for racial groups using single and multiple race reporting methods)

Race and Hispanic origin of householder and year	Number (thousands)	Percent distribution										Median income		Mean income	
		Total	Under $5,000	$5,000 to $9,999	$10,000 to $14,999	$15,000 to $24,999	$25,000 to $34,999	$35,000 to $49,999	$50,000 to $74,999	$75,000 to $99,999	$100,000 and over	Value (dollars)	Standard error (dollars)	Value (dollars)	Standard error (dollars)
HISPANIC (OF ANY RACE)[21]—Con.															
1982	4,085	100.0	5.2	11.0	12.4	18.5	15.4	16.9	13.5	4.9	2.3	27,078	715	33,419	678
1981	3,980	100.0	4.0	10.4	10.1	19.1	16.3	18.2	14.6	5.1	2.3	28,911	792	34,718	663
1980	3,906	100.0	4.6	10.2	9.9	20.1	15.6	17.1	15.2	4.5	2.6	28,218	765	34,467	686
1979[10]	3,684	100.0	3.4	9.8	9.4	18.9	16.1	18.8	15.5	5.1	3.1	29,936	863	36,221	728
1978	3,291	100.0	3.4	9.5	9.9	18.3	17.9	18.5	15.7	4.5	2.4	29,638	718	35,009	708
1977	3,304	100.0	3.3	10.0	11.2	20.0	18.3	18.2	13.3	3.8	1.9	27,884	490	32,908	508
1976[11]	3,081	100.0	3.7	12.0	11.2	20.1	17.3	17.6	13.8	2.7	1.7	26,661	568	31,506	513
1975[12]	2,948	100.0	4.2	11.6	10.8	21.5	16.8	19.2	11.7	2.7	1.4	26,116	577	31,004	551
1974[12 13]	2,897	100.0	3.3	9.3	10.8	21.1	17.1	19.8	13.3	3.6	1.6	28,410	622	32,911	536
1973	2,722	100.0	3.3	8.5	10.3	20.7	17.6	19.4	15.0	3.7	1.6	28,553	649	33,174	540
1972[14]	2,655	100.0	3.6	7.9	11.5	20.8	19.8	20.1	11.5	3.1	1.7	28,600	559	32,873	559

NA Not available.

[1]Implementation of a 28,000 household sample expansion.
[2]Implementation of Census 2000-based population controls.
[3]Full implementation of 1990 census-based sample design and metropolitan definitions, 7,000 household sample reduction, and revised race edits.
[4]Introduction of 1990 census sample design.
[5]Data collection method changed from paper and pencil to computer-assisted interviewing. In addition, the March 1994 income supplement was revised to allow for the coding of different income amounts on selected questionnaire items. Limits either increased or decreased in the following categories: earnings limits increased to $999,999; social security limits increased to $49,999; supplemental security income and public assistance limits increased to $24,999; veterans' benefits limits increased to $99,999; child support and alimony limits decreased to $49,999.
[6]Implementation of 1990 census population controls.
[7]Implementation of a new March CPS processing system.
[8]Recording of amounts for earnings from longest job increased to $299,999. Full implementation of 1980 census-based sample design.
[9]Implementation of Hispanic population weighting controls and introduction of 1980 census-based sample design.
[10]Implementation of 1980 census population controls. Questionnaire expanded to show 27 possible values from 51 possible sources of income.
[11]First year medians were derived using both Pareto and linear interpolation. Before this year, all medians were derived using linear interpolation.
[12]Some of these estimates were derived using Pareto interpolation and may differ from published data which were derived using linear interpolation.
[13]Implementation of a new March CPS processing system. Questionnaire expanded to ask 11 income questions.
[14]Full implementation of 1970 census-based sample design.
[15]Introduction of 1970 census sample design and population controls.
[16]Implementation of a new March CPS processing system.
[17]The 2003 CPS allowed respondents to choose more than one race. White alone refers to people who reported White and did not report any other race category. The use of this single-race population does not imply that it is the preferred method of presenting or analyzing data. The Census Bureau uses a variety of approaches. Information on people who reported more than one race, such as "White and American Indian and Alaska Native" or "Asian and Black or African American," in Census 2000 is forthcoming and will be available through American FactFinder in 2003. About 2.6 percent of people reported more than one race.
[18]For the year 2001 and earlier, the CPS allowed respondents to report only one race group.
[19]Black alone refers to people who reported Black and did not report any other race category.
[20]Asian alone refers to people who reported Asian and did not report any other race category.
[21]Because Hispanics may be of any race, data in this report for Hispanics overlap with data for other racial groups. Hispanic origin was reported by 11.4 percent of White householders (and no other race); 3.5 percent for Black householders (and no other race); 27.3 percent for American Indian or Alaska Native householders (and no other race); 1.4 percent for Asian householders (and no other race); and 19.0 percent for Native Hawaiian and Other Pacific Islander householders (and no other race). Data users should exercise caution when interpreting aggregate results for the Hispanic population because this population consists of many distinct groups that differ in socio-economic characteristics, culture, and recency of immigration. Data were first collected for Hispanics in 1972.

Source: U.S. Bureau of the Census, Current Population Survey, 1968 through 2003 Annual Social and Economic Supplements.

Table A-2.
Median Household Income for Selected Definitions of Income by Race and Hispanic Origin of Householder: 1979 to 2002

(Income in 2002 CPI-U-RS adjusted dollars. See text for comparability issues regarding comparison of data for racial groups using single and multiple race reporting methods)

Race and Hispanic origin of householder and year	Total money income (MI)	(MI - TX)[1]	(MI- TX + NC - MM)[2]	(MI - Tx + NC)[3]	(MI - TX + NC + HE)[4]
ALL RACES					
2002	42,409	37,066	39,426	42,061	43,760
2001	42,900	37,376	39,553	42,194	43,925
2000[5]	43,848	37,880	39,992	42,315	44,612
1999[6]	43,915	37,972	40,052	42,357	44,338
1998	42,844	37,014	39,141	41,508	43,310
1997	41,346	35,552	37,691	40,067	42,037
1996	40,503	34,602	36,910	39,392	41,493
1995[7]	39,931	34,239	36,654	39,028	41,317
1994[8]	38,726	33,407	35,690	37,872	40,192
1993[9]	38,287	33,051	35,248	37,251	39,329
1992[10]	38,482	32,996	34,940	36,896	39,129
1991	38,791	33,119	34,856	36,604	39,248
1990	39,949	(NA)	(NA)	37,110	39,619
1989	40,484	(NA)	(NA)	37,693	40,729
1988	39,767	(NA)	(NA)	36,949	40,272
1987[11]	39,453	(NA)	(NA)	36,852	40,145
1986	38,975	(NA)	(NA)	36,364	39,130
1985[12]	37,648	(NA)	(NA)	34,909	38,528
1984	36,921	(NA)	(NA)	34,264	38,382
1983[13]	36,001	(NA)	(NA)	33,590	37,348
1982	35,986	(NA)	(NA)	33,073	37,538
1981	36,042	(NA)	(NA)	32,755	38,321
1980	36,608	(NA)	(NA)	33,522	36,957
1979[14]	37,784	(NA)	(NA)	34,641	36,930
WHITE ALONE[15]					
2002	45,086	38,857	41,272	43,871	45,743
WHITE[16]					
2001	45,225	38,991	41,218	43,860	45,631
2000[5]	45,860	39,395	41,557	43,905	46,267
1999[6]	45,673	39,535	41,594	43,924	46,063
1998	45,077	38,861	41,019	43,282	45,201
1997	43,544	37,149	39,338	41,632	43,765
1996	42,407	36,156	38,597	40,988	43,241
1995[7]	41,911	35,770	38,271	40,544	43,076
1994[8]	40,843	34,951	37,206	39,291	41,768
1993[9]	40,394	34,763	36,992	39,026	41,181
1992[10]	40,458	34,642	36,719	38,632	40,991
1991	40,649	34,615	36,468	38,207	40,994
1990	41,668	(NA)	(NA)	38,567	41,249
1989	42,585	(NA)	(NA)	39,243	42,474
1988	42,040	(NA)	(NA)	38,648	42,120
1987[11]	41,568	(NA)	(NA)	38,560	42,102
1986	40,976	(NA)	(NA)	37,965	40,904
1985[12]	39,704	(NA)	(NA)	36,411	40,312
1984	38,951	(NA)	(NA)	35,768	40,158
1983[13]	37,743	(NA)	(NA)	35,015	38,906
1982	37,674	(NA)	(NA)	34,397	39,076
1981	38,081	(NA)	(NA)	34,100	39,995
1980	38,621	(NA)	(NA)	34,843	38,462
1979[14]	39,616	(NA)	(NA)	35,968	38,369

See footnotes at end of table.

Table A-2.
Median Household Income for Selected Definitions of Income by Race and Hispanic Origin of Householder: 1979 to 2002—Con.

(Income in 2002 CPI-U-RS adjusted dollars. See text for comparability issues regarding comparison of data for racial groups using single and multiple race reporting methods)

Race and Hispanic origin of householder and year	Total money income (MI)	(MI - TX)[1]	(MI- TX + NC - MM)[2]	(MI - Tx + NC)[3]	(MI - TX + NC + HE)[4]
WHITE ALONE, NOT HISPANIC[15]					
2002	46,900	40,212	42,623	45,203	47,199
WHITE, NOT HISPANIC[16]					
2001	47,041	40,254	42,521	45,171	47,033
2000[5]	47,642	40,612	42,822	45,135	47,609
1999[6]	47,650	40,872	42,918	45,259	47,583
BLACK ALONE OR IN COMBINATION					
2002	29,177	26,288	28,467	30,698	31,523
BLACK ALONE[17]					
2002	29,026	26,168	28,338	30,576	31,408
BLACK[15]					
2001	29,939	26,613	28,748	31,002	31,891
2000[5]	30,980	27,292	29,380	31,334	32,467
1999[6]	30,118	26,823	28,872	31,123	32,305
1998	27,932	25,192	27,187	29,434	30,366
1997	27,989	24,914	26,998	28,834	29,877
1996	26,797	24,140	26,316	28,489	29,520
1995[7]	26,240	23,678	25,922	28,031	29,056
1994[8]	25,238	22,618	24,890	26,821	28,166
1993[9]	23,939	21,528	23,718	25,515	26,510
1992[10]	23,558	21,230	23,263	25,007	26,128
1991	24,216	21,767	23,683	25,406	26,580
1990	24,917	(NA)	(NA)	25,856	27,228
1989	25,326	(NA)	(NA)	25,817	27,232
1988	23,965	(NA)	(NA)	24,569	25,874
1987[11]	23,725	(NA)	(NA)	24,538	25,901
1986	23,607	(NA)	(NA)	24,250	25,586
1985[12]	23,622	(NA)	(NA)	23,778	25,672
1984	22,189	(NA)	(NA)	22,525	24,696
1983[13]	21,365	(NA)	(NA)	22,254	24,590
1982	21,352	(NA)	(NA)	22,265	25,050
1981	21,370	(NA)	(NA)	22,250	25,294
1980	22,250	(NA)	(NA)	23,100	25,130
1979[14]	23,259	(NA)	(NA)	24,425	25,990
ASIAN ALONE OR IN COMBINATION					
2002	52,285	43,803	47,252	48,698	50,312
ASIAN ALONE[18]					
2002	52,626	44,080	47,501	48,954	50,604
ASIAN AND PACIFIC ISLANDER[15]					
2001	54,488	45,360	48,287	49,913	51,624
2000[5]	58,225	47,763	50,821	52,356	54,697
1999[6]	54,991	45,821	48,627	50,134	51,671
1998	51,385	42,573	45,486	46,652	48,634

See footnotes at end of table.

Table A-2.
Median Household Income for Selected Definitions of Income by Race and Hispanic Origin of Householder: 1979 to 2002—Con.

(Income in 2002 CPI-U-RS adjusted dollars. See text for comparability issues regarding comparison of data for racial groups using single and multiple race reporting methods)

Race and Hispanic origin of householder and year	Total money income (MI)	(MI - TX)[1]	(MI- TX + NC - MM)[2]	(MI - Tx + NC)[3]	(MI - TX + NC + HE)[4]
ASIAN AND PACIFIC ISLANDER[15]—Con.					
1997	50,558	42,059	44,917	46,510	48,796
1996	49,386	40,958	43,750	45,207	47,528
1995[7]	47,592	39,911	43,034	44,658	46,367
1994[8]	48,590	40,023	43,550	44,740	46,361
1993[9]	46,996	38,737	42,007	43,659	45,793
1992[10]	47,482	38,898	41,486	42,703	45,041
1991	46,932	38,196	40,197	41,695	44,011
1990	51,299	(NA)	(NA)	(NA)	(NA)
1989	50,562	(NA)	(NA)	(NA)	(NA)
1988	47,132	(NA)	(NA)	(NA)	(NA)
1987[11]	48,786	(NA)	(NA)	(NA)	(NA)
HISPANIC (OF ANY RACE)					
2002	33,103	30,291	32,651	34,633	35,447
2001	34,099	30,607	32,678	34,939	35,882
2000[5]	34,636	31,071	33,282	35,153	36,288
1999[6]	33,178	29,909	32,295	34,055	34,844
1998	31,214	28,346	30,374	31,967	32,818
1997	29,752	26,973	29,146	30,708	31,689
1996	28,422	26,017	28,317	30,128	31,049
1995[7]	26,788	24,817	27,245	28,862	29,732
1994[8]	28,112	25,356	27,435	29,260	30,465
1993[9]	28,048	25,249	27,468	29,303	30,233
1992[10]	28,384	25,435	27,434	29,073	30,213
1991	29,217	26,082	28,132	29,588	30,994
1990	29,792	(NA)	(NA)	29,545	31,012
1989	30,701	(NA)	(NA)	30,111	31,725
1988	29,738	(NA)	(NA)	29,060	31,034
1987[11]	29,272	(NA)	(NA)	28,488	30,168
1986	28,729	(NA)	(NA)	28,114	29,637
1985[12]	27,840	(NA)	(NA)	27,352	29,233
1984	27,989	(NA)	(NA)	27,681	29,781
1983[13]	27,053	(NA)	(NA)	26,957	28,878
1982	27,078	(NA)	(NA)	26,914	28,986
1981	28,911	(NA)	(NA)	27,951	31,103
1980	28,218	(NA)	(NA)	30,944	33,069
1979[14]	29,936	(NA)	(NA)	29,509	30,804

NA Not available.

[1]Money income, less taxes.
[2]Money income, less taxes, plus value of noncash transfers less Medicare and Medicaid.
[3]Money income, less taxes, plus value of noncash transfers.
[4]Money income, less taxes, plus value of noncash transfers, plus imputed value of home equity.
[5]Implementation of a 28,000 household sample expansion.
[6]Implementation of Census 2000-based population controls.
[7]Full implementation of 1990 census-based sample design and metropolitan definitions, 7,000 household sample reduction, revised race edits.
[8]Introduction of 1990 census sample design.
[9]Data collection method changed from paper and pencil to computer-assisted interviewing. In addition, the March 1994 income supplement was revised to allow for the coding of different income amounts on selected questionnaire items. Limits either increased or decreased in the following categories: earnings limits increased to $999,999; social security limits increased to $49,999; supplemental security income and public assistance limits increased to $24,999; veterans' benefits limits increased to $99,999; child support and alimony limits decreased to $49,999.
[10]Implementation of 1990 census population controls.
[11]Implementation of a new March CPS processing system.
[12]Recording of amounts for earnings from longest job increased to $299,999. Full implementation of 1980 census-based sample design.
[13]Implementation of Hispanic population weighting controls and introduction of 1980 census-based sample design.
[14]Implemenation of 1980 census population controls. Questionnaire expanded to show 27 possible values from 51 possible sources of income.
[15]The 2003 CPS allowed respondents to choose more than one race. White alone refers to people who reported White and did not report any other race category. The use of this single-race population does not imply that it is the preferred method of presenting or analyzing data. The Census Bureau uses a variety of approaches. Information on people who reported more than one race, such as "White and American Indian and Alaska Native" or "Asian and Black or African American," in Census 2000 is forthcoming and will be available through American FactFinder in 2003. About 2.6 percent of people reported more than one race.
[16]For 2001 and earlier years, the CPS allowed respondents to report only one race group. The reference race groups for 2001 and earlier income data are: White, non-Hispanic White, Black, and Asian and Pacific Islander.
[17]Black or African American alone refers to people who reported Black or African American and did not report any other race category.
[18]Asian alone refers to people who reported Asian and did not report any other race category.

Source: U.S. Census Bureau, Current Population Survey, 1980 to 2003 Annual Social and Economic Supplements.

Table A-3.
Share of Aggregate Income Received by Each Fifth and Top 5 Percent of Households: 1967 to 2002

(Households as of March of the following year. Income in 2002 CPI-U-RS adjusted dollars)

Year	Number (thousands)	Upper limit of each fifth (dollars)				Lower limit of top 5 percent (dollars)	Share of aggregate income						Mean income (dollars)	Gini index
		Lowest	Second	Third	Fourth		Lowest	Second	Third	Fourth	Highest	Top 5 percent		
2002	111,278	17,916	33,377	53,162	84,016	150,002	3.5	8.8	14.8	23.3	49.7	21.7	57,852	0.462
2001	109,297	18,256	33,844	53,843	84,828	152,893	3.5	8.7	14.6	23.0	50.1	22.4	59,134	0.466
2000[1]	108,209	18,713	34,461	54,483	85,385	151,647	3.6	8.9	14.8	23.0	49.8	22.1	59,664	0.462
1999[2]	106,434	18,492	34,445	54,370	85,500	153,234	3.6	8.9	14.9	23.2	49.4	21.5	59,067	0.458
1998	103,874	17,757	33,504	53,258	82,636	145,658	3.6	9.0	15.0	23.2	49.2	21.4	57,134	0.456
1997	102,528	17,207	32,626	51,397	79,888	141,397	3.6	8.9	15.0	23.2	49.4	21.7	55,522	0.459
1996	101,018	16,853	31,679	50,219	77,617	136,416	3.7	9.0	15.1	23.3	49.0	21.4	53,776	0.455
1995[3]	99,627	16,874	31,538	49,218	76,313	132,415	3.7	9.1	15.2	23.3	48.7	21.0	52,659	0.450
1994[4]	98,990	16,115	30,247	48,131	75,426	131,815	3.6	8.9	15.0	23.4	49.1	21.2	51,771	0.456
1993[5]	97,107	15,892	30,245	47,543	73,901	128,240	3.6	9.0	15.1	23.5	48.9	21.0	50,772	0.454
1992[6]	96,426	15,827	30,323	47,607	72,863	124,381	3.8	9.4	15.8	24.2	46.9	18.6	48,788	0.434
1991	95,669	16,208	30,903	47,732	73,085	124,126	3.8	9.6	15.9	24.2	46.5	18.1	48,829	0.428
1990	94,312	16,677	31,569	48,297	73,654	126,411	3.9	9.6	15.9	24.0	46.6	18.6	49,902	0.428
1989	93,347	16,941	32,212	49,509	75,223	128,499	3.8	9.5	15.8	24.0	46.8	18.9	51,148	0.431
1988	92,830	16,625	31,405	48,942	73,900	125,093	3.8	9.6	16.0	24.3	46.3	18.3	49,688	0.427
1987[7]	91,124	16,350	31,034	48,444	73,215	122,515	3.8	9.6	16.1	24.3	46.2	18.2	49,065	0.426
1986	89,479	16,215	30,969	47,832	72,199	122,459	3.9	9.7	16.2	24.5	45.7	17.5	48,152	0.425
1985[8]	88,458	15,940	30,051	46,262	69,833	116,784	4.0	9.7	16.3	24.6	45.3	17.0	46,332	0.419
1984	86,789	15,813	29,491	45,307	68,522	114,627	4.1	9.9	16.4	24.7	44.9	16.5	45,238	0.415
1983[9]	85,290	15,416	28,730	44,052	66,628	110,652	4.1	10.0	16.5	24.7	44.7	16.4	43,865	0.414
1982	83,918	15,200	28,563	43,817	65,421	109,019	4.1	10.1	16.6	24.7	44.5	16.2	43,369	0.412
1981	83,527	15,419	28,408	44,209	65,381	106,385	4.2	10.2	16.8	25.0	43.8	15.6	43,059	0.406
1980	82,368	15,619	29,146	44,670	65,527	106,455	4.3	10.3	16.9	24.9	43.7	15.8	43,539	0.403
1979[10]	80,776	16,088	29,920	45,964	66,788	108,949	4.2	10.3	16.9	24.7	44.0	16.4	44,883	0.404
1978	77,330	16,030	30,132	45,565	66,354	106,899	4.3	10.3	16.9	24.8	43.7	16.2	44,520	0.402
1977	76,030	15,224	28,547	43,295	63,118	102,039	4.4	10.3	17.0	24.8	43.6	16.1	42,166	0.402
1976[11]	74,142	15,265	28,232	42,971	61,831	98,580	4.4	10.4	17.1	24.8	43.3	16.0	41,575	0.398
1975[12]	72,867	14,804	27,840	41,969	60,381	96,278	4.4	10.5	17.1	24.8	43.2	15.9	40,593	0.397
1974[12 13]	71,163	15,704	29,010	42,746	62,055	99,162	4.4	10.6	17.1	24.7	43.1	15.9	41,770	0.395
1973	69,859	15,490	29,426	43,650	63,056	99,953	4.2	10.5	17.1	24.6	43.6	16.6	42,623	0.397
1972[14]	68,251	15,088	29,059	42,955	61,470	98,948	4.1	10.5	17.1	24.5	43.9	17.0	42,046	0.401
1971[15]	66,676	14,593	27,818	40,936	58,371	92,694	4.1	10.6	17.3	24.5	43.5	16.7	39,873	0.396
1970	64,778	14,788	28,332	41,214	58,801	92,960	4.1	10.8	17.4	24.5	43.3	16.6	40,111	0.394
1969	63,401	15,025	28,838	41,702	58,434	91,644	4.1	10.9	17.5	24.5	43.0	16.6	40,122	0.391
1968	62,214	14,578	27,638	39,614	55,661	87,081	4.2	11.1	17.5	24.4	42.8	16.6	38,430	0.388
1967[16]	60,813	13,688	26,692	37,898	54,027	86,692	4.0	10.8	17.3	24.2	43.8	17.5	36,452	0.399

[1]Implementation of a 28,000 household sample expansion.
[2]Implementation of Census 2000-based population controls.
[3]Full implementation of 1990 census-based sample design and metropolitan definitions, 7,000 household sample reduction, and revised race edits.
[4]Introduction of 1990 census-based sample design.
[5]Data collection method changed from paper and pencil to computer-assisted interviewing. In addition, the March 1994 income supplement was revised to allow for the coding of different income amounts on selected questionnaire items. Limits either increased or decreased in the following categories: earnings limits increased to $999,999; social security limits increased to $49,999; supplemental security income and public assistance limits increased to $24,999; veterans' benefits limits increased to $99,999; child support and alimony limits decreased to $49,999.
[6]Implementation of 1990 census population controls.
[7]Implementation of a new March CPS processing system.
[8]Recording of amounts for earnings from longest job increased to $299,999. Full implementation of 1980 census-based sample design.
[9]Implementation of Hispanic population weighting controls and introduction of 1980 census-based sample design.
[10]Implementation of 1980 census population controls. Questionnaire expanded to show 27 possible values from 51 possible sources of income.
[11]First year medians were derived using both Pareto and linear interpolation. Before this year, all medians were derived using linear interpolation.
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[15]Introduction of 1970 census-based sample design and population controls.
[16]Implementation of a new March CPS processing system.

Source: U.S. Census Bureau, Current Population Survey, 1968 to 2003 Annual Social and Economic Supplements.

Table A-4.
Selected Measures of Household Income Dispersion: 1967 to 2002

(In 2002 dollars. For further explanation of income inequality measures, see *Current Population Reports,* Series P60-204, “The Changing Shape of the Nation’s Income Distribution: 1947-1998”)

Measures of income dispersion	2002	2001	2000[1]	1999[2]	1998	1997	1996	1995[3]	1994[4]	1993[5]	1992[6]	1991	1990	1989	1988	1987[7]	1986	1985[8]
Household Income at Selected Percentiles																		
10th percentile upper limit	10,620	11,087	11,050	11,197	10,688	10,296	10,168	10,167	9,636	9,420	9,433	9,557	9,766	10,084	9,588	9,356	9,365	9,400
20th percentile upper limit	17,916	18,256	18,713	18,556	17,757	17,207	16,853	16,874	16,115	15,892	15,827	16,208	16,677	16,941	16,625	16,350	16,215	15,940
50th (median)	42,409	42,900	43,848	44,045	42,844	41,346	40,503	39,931	38,726	38,287	38,482	38,791	39,949	40,484	39,767	39,453	38,975	37,648
80th percentile upper limit	84,016	84,828	85,385	85,654	82,636	79,888	77,617	76,313	75,426	73,901	72,863	73,085	73,654	75,223	73,900	73,215	72,199	69,833
90th percentile upper limit	114,112	117,952	116,957	116,472	111,613	109,120	105,045	102,767	101,883	100,178	97,977	97,708	98,863	100,774	97,866	96,017	94,475	91,112
95th percentile lower limit	150,002	152,893	151,647	153,256	145,658	141,397	136,416	132,415	131,815	128,240	124,381	124,126	126,411	128,499	125,093	122,515	122,459	116,784
Household Income Ratios of Selected Percentiles																		
90th/10th	10.75	10.64	10.58	10.40	10.44	10.60	10.33	10.11	10.57	10.64	10.39	10.22	10.12	9.99	10.21	10.26	10.09	9.69
95th/20th	8.37	8.38	8.10	8.26	8.20	8.22	8.09	7.85	8.18	8.07	7.86	7.66	7.58	7.59	7.52	7.49	7.55	7.33
95th/50th	3.54	3.56	3.46	3.48	3.40	3.42	3.37	3.32	3.40	3.35	3.23	3.20	3.16	3.17	3.15	3.11	3.14	3.10
80th/50th	1.98	1.98	1.95	1.94	1.93	1.93	1.92	1.91	1.95	1.93	1.89	1.88	1.84	1.86	1.86	1.86	1.85	1.85
80th/20th	4.69	4.65	4.56	4.62	4.65	4.64	4.61	4.52	4.68	4.65	4.60	4.51	4.42	4.44	4.45	4.48	4.45	4.38
20th/50th	0.42	0.43	0.43	0.42	0.41	0.42	0.42	0.42	0.42	0.42	0.41	0.42	0.42	0.42	0.42	0.41	0.42	0.42
Mean Household Income of Quintiles																		
Lowest quintile	9,990	10,297	10,607	10,726	10,162	9,913	9,810	9,785	9,317	9,084	9,155	9,352	9,599	9,833	9,500	9,336	9,305	9,241
Second quintile	25,400	25,873	26,483	26,369	25,659	24,691	24,075	23,901	23,074	22,864	22,837	23,369	24,055	24,371	23,834	23,592	23,421	22,843
Third quintile	42,802	43,307	44,102	44,113	42,934	41,539	40,496	39,966	38,871	38,325	38,476	38,818	39,733	40,510	39,863	39,444	39,103	37,834
Fourth quintile	67,326	67,902	68,559	68,583	66,402	64,338	62,676	61,437	60,488	59,560	59,064	59,175	59,906	61,278	60,259	59,621	58,895	56,897
Highest quintile	143,743	148,291	148,566	146,113	140,513	137,167	131,822	128,209	127,163	124,091	114,445	113,477	116,257	119,786	115,042	113,385	110,114	104,953
Shares of Household Income of Quintiles																		
Lowest quintile	3.5	3.5	3.6	3.6	3.6	3.6	3.7	3.7	3.6	3.6	3.8	3.8	3.9	3.8	3.8	3.8	3.9	4.0
Second quintile	8.8	8.7	8.9	8.9	9.0	8.9	9.0	9.1	8.9	9.0	9.4	9.6	9.6	9.5	9.6	9.6	9.7	9.7
Third quintile	14.8	14.6	14.8	14.9	15.0	15.0	15.1	15.2	15.0	15.1	15.8	15.9	15.9	15.8	16.0	16.1	16.2	16.3
Fourth quintile	23.3	23.0	23.0	23.2	23.2	23.2	23.3	23.3	23.4	23.5	24.2	24.2	24.0	24.0	24.3	24.3	24.5	24.6
Highest quintile	49.7	50.2	49.8	49.4	49.2	49.4	49.0	48.7	49.1	48.9	46.9	46.5	46.6	46.8	46.3	46.2	45.7	45.3
Summary Measures																		
Gini index of income inequality	0.462	0.466	0.462	0.458	0.456	0.459	0.455	0.450	0.456	0.454	0.434	0.428	0.428	0.431	0.427	0.426	0.425	0.419
Mean logarithmic deviation of income	0.514	0.515	0.490	0.476	0.488	0.484	0.464	0.452	0.471	0.467	0.416	0.411	0.402	0.406	0.401	0.414	0.416	0.403
Theil	0.398	0.414	0.404	0.386	0.389	0.396	0.389	0.378	0.387	0.385	0.323	0.313	0.317	0.324	0.314	0.311	0.310	0.300
Atkinson:																		
e=0.25	0.095	0.098	0.096	0.092	0.093	0.094	0.093	0.090	0.092	0.092	0.080	0.078	0.078	0.080	0.078	0.077	0.077	0.075
e=0.50	0.186	0.189	0.185	0.180	0.181	0.183	0.179	0.175	0.180	0.178	0.160	0.156	0.156	0.158	0.155	0.155	0.155	0.151
e=0.75	0.279	0.282	0.275	0.268	0.271	0.272	0.266	0.261	0.268	0.266	0.242	0.237	0.236	0.239	0.236	0.238	0.237	0.231

See footnotes at end of table.

Table A-4.
Selected Measures of Household Income Dispersion: 1967 to 2002—Con.

(In 2002 dollars. For further explanation of income inequality measures, see *Current Population Reports,* Series P60-204, "The Changing Shape of the Nation's Income Distribution: 1947-1998")

Measures of income dispersion	1984	1983[9]	1982	1981	1980	1979[10]	1978	1977	1976[11]	1975[12]	1974[12 13]	1973	1972[14]	1971[15]	1970	1969	1968	1967[16]
Household Income at Selected Percentiles																		
10th percentile upper limit	9,384	9,005	9,029	9,184	9,302	9,422	9,590	9,172	9,066	9,015	9,273	9,214	8,788	8,249	8,126	8,307	8,090	7,442
20th percentile upper limit	15,813	15,416	15,200	15,419	15,619	16,088	16,030	15,224	15,265	14,804	15,704	15,490	15,088	14,593	14,788	15,025	14,578	13,688
50th (median)	36,921	35,774	35,986	36,042	36,608	37,784	37,826	35,545	35,345	34,763	35,719	36,855	36,126	34,669	35,030	35,266	33,968	32,591
80th percentile upper limit	68,522	66,628	65,421	65,381	65,527	66,788	66,354	63,118	61,831	60,381	62,055	63,056	61,470	58,371	58,801	58,434	55,661	54,027
90th percentile upper limit	89,655	86,526	85,640	84,664	84,544	86,165	85,375	80,168	78,849	76,891	79,524	80,639	78,984	74,883	74,904	74,139	70,191	68,628
95th percentile lower limit	114,627	110,652	109,019	106,385	106,455	108,949	106,899	102,039	98,580	96,278	99,162	99,953	98,948	92,694	92,960	91,644	87,081	86,692
Household Income Ratios of Selected Percentiles																		
90th/10th	9.55	9.61	9.48	9.22	9.09	9.14	8.90	8.74	8.70	8.53	8.58	8.75	8.99	9.08	9.22	8.93	8.68	9.22
95th/20th	7.25	7.18	7.17	6.90	6.82	6.77	6.67	6.70	6.46	6.50	6.31	6.45	6.56	6.35	6.29	6.10	5.97	6.33
95th/50th	3.10	3.09	3.03	2.95	2.91	2.88	2.83	2.87	2.79	2.77	2.78	2.71	2.74	2.67	2.65	2.60	2.56	2.66
80th/50th	1.86	1.86	1.82	1.81	1.79	1.77	1.75	1.78	1.75	1.74	1.74	1.71	1.70	1.68	1.68	1.66	1.64	1.66
80th/20th	4.33	4.32	4.30	4.24	4.20	4.15	4.14	4.15	4.05	4.08	3.95	4.07	4.07	4.00	3.98	3.89	3.82	3.95
20th/50th	0.43	0.43	0.42	0.43	0.43	0.43	0.42	0.43	0.43	0.43	0.44	0.42	0.42	0.42	0.42	0.43	0.43	0.42
Mean Household Income of Quintiles																		
Lowest quintile	9,234	8,974	8,926	9,138	9,267	9,443	9,559	9,201	9,133	8,938	9,286	9,003	8,628	8,164	8,138	8,227	8,037	7,419
Second quintile	22,458	21,918	21,833	21,899	22,364	23,002	22,880	21,714	21,676	21,223	22,244	22,319	21,973	21,232	21,638	21,927	21,242	20,227
Third quintile	37,139	36,150	36,029	36,169	36,809	37,862	37,690	35,804	35,557	34,725	35,747	36,470	35,858	34,427	34,845	35,039	33,687	32,295
Fourth quintile	55,912	54,242	53,568	53,877	54,197	55,532	55,192	52,427	51,603	50,427	51,618	52,429	51,475	48,943	49,119	49,076	46,997	45,185
Highest quintile	101,545	98,153	96,632	94,371	95,196	98,677	97,405	91,903	90,049	87,818	90,147	92,983	92,414	86,723	86,968	86,263	82,308	81,883
Shares of Household Income of Quintiles																		
Lowest quintile	4.1	4.1	4.1	4.2	4.3	4.2	4.3	4.4	4.4	4.4	4.4	4.2	4.1	4.1	4.1	4.1	4.2	4.0
Second quintile	9.9	10.0	10.1	10.2	10.3	10.3	10.3	10.3	10.4	10.5	10.6	10.5	10.5	10.6	10.8	10.9	11.1	10.8
Third quintile	16.4	16.5	16.6	16.8	16.9	16.9	16.9	17.0	17.1	17.1	17.1	17.1	17.1	17.3	17.4	17.5	17.5	17.3
Fourth quintile	24.7	24.7	24.7	25.0	24.9	24.7	24.8	24.8	24.8	24.8	24.7	24.6	24.5	24.5	24.5	24.5	24.4	24.2
Highest quintile	44.9	44.7	44.5	43.8	43.7	44.0	43.7	43.6	43.3	43.2	43.1	43.6	43.9	43.5	43.3	43.0	42.8	43.8
Summary Measures																		
Gini index of income inequality	0.415	0.414	0.412	0.406	0.403	0.404	0.402	0.402	0.398	0.397	0.395	0.397	0.401	0.396	0.394	0.391	0.388	0.399
Mean logarithmic deviation of income	0.391	0.397	0.401	0.387	0.375	0.369	0.363	0.364	0.361	0.361	0.352	0.355	0.370	0.370	0.370	0.357	0.356	0.380
Theil	0.290	0.288	0.287	0.277	0.274	0.279	0.275	0.276	0.271	0.270	0.267	0.270	0.279	0.273	0.271	0.268	0.273	0.287
Atkinson:																		
e=0.25	0.073	0.072	0.072	0.070	0.069	0.070	0.069	0.069	0.068	0.067	0.067	0.068	0.070	0.068	0.068	0.067	0.067	0.071
e=0.50	0.147	0.147	0.146	0.141	0.140	0.141	0.139	0.139	0.137	0.136	0.134	0.136	0.140	0.138	0.138	0.135	0.135	0.143
e=0.75	0.225	0.226	0.226	0.220	0.216	0.216	0.213	0.213	0.211	0.210	0.207	0.210	0.216	0.214	0.214	0.209	0.208	0.220

See footnotes at end of table.

Table A-4.
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[1]Implementation of a 28,000 household sample expansion.
[2]Implementation of Census 2000-based population controls.
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Source: U.S. Census Bureau, Current Population Survey, 1968 to 2003 Annual Social and Economic Supplements.

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ATTACHMENT 13

Report of Commissioner Kevin M. McCarty
Florida Office of Insurance Regulation
The Use of Occupation and Education as Underwriting/Rating Factors for Private Passenger Automobile Insurance
March, 2007

REPORT OF COMMISSIONER, KEVIN M. MCCARTY

FLORIDA OFFICE OF INSURANCE REGULATION

THE USE OF OCCUPATION AND EDUCATION AS UNDERWRITING/RATING FACTORS FOR PRIVATE PASSENGER AUTOMOBILE INSURANCE

MARCH 2007

EXECUTIVE SUMMARY

The Office of Insurance Regulation ("Office") held a public hearing on February 9, 2007 in Tallahassee to review the use of occupation and education as underwriting or rating factors for private passenger auto insurance and its potential impact on Floridians.

In Florida, as well as nationally the insurance industry has had a checkered past in its use of race and other proxy factors that intentionally or unintentionally negatively impact minorities and low-income individuals. While the use of race as a rating factor was outlawed in Florida, the two factors mentioned above, occupation and education, have emerged in the rating and underwriting of auto insurance and appear to be highly correlated to race and income-level.

Under some rating plans, consumers with more professional occupations (doctors, lawyers, architects), and advanced college degrees are being offered preferred driver rates. Conversely, individuals with blue-collar jobs, and a high school education or less are paying higher premiums for similar risk factors, as exhibited by several online quotes for auto insurance requested by the Office from one of the major auto insurance writers in Florida. With all other factors remaining equal, except for changes to the online applicant's education and occupation, the results were startling. One online quote comparison demonstrated a significant difference in the quoted auto insurance rate when the two factors are adjusted, accounting in that instance in a 300% higher rate for the less educated and less skilled applicant.

Testimony at the public hearing on February 9, 2007, and documents received and reviewed prior, during and after the hearing reveal:

- ***There is a demonstrable correlation between occupation, education and income-level and ethnicity, which was not disputed by the insurance industry.***

- ***Insurance industry representatives all claim ignorance of the relationship between occupation, education and income-level and race despite the existence of publicly available U.S. Census Bureau Data***

- ***Insurers do not collect data from consumers on race or income-level, and refuse to study the impact of underwriting practices on minority and low-income consumers.***

- ***The insurance industry does not believe that corporate responsibility extends to ensuring its practices do not disparately impact minority or low-income Floridians; but instead maintains that it is the Florida Legislature's responsibility to define public policy on this matter in the insurance marketplace***

- ***It appears that wealthier individuals are more likely to pay small claims out-of-pocket, and avoid making insurance claims, giving some occupations better loss ratios despite higher accident rates.***

- ***As measured by one company's use of occupation and education the magnitude of the premium difference can be very significant.***

- ***Companies that do not use occupation and education as rating factors may potentially be at a competitive disadvantage because they may lose the wide range of business offered by higher income policyholders. Foregoing whatever predictive value these factors may have might also put these companies at a disadvantage. Thus, from an economic point of view, this practice is likely to proliferate regardless of its negative effects on policyholders struggling to overcome disadvantages.***

- ***While the prohibition of the use of these factors, much like in the prohibition of the use of race, could lead to some economic inefficiencies in insurance markets, it may be beneficial to the overall economy and citizenry to prohibit use of these factors as a matter of public policy***

- ***At least one major auto insurer that currently uses education and occupation as part of its underwriting, asserts it would absolutely not use these factors if it were determined the factors had a disparate impact on protected classes.***

- ***A national insurance organization whose members write 56 percent of the private passenger auto insurance market in Florida stated that a public policy concern can override the use of these factors even if there is an actuarial basis for it.***

The transcript of the public hearing held on February 9, 2007, consisting of two volumes, is attached to this Report as **Exhibits 1 and 2**.

BACKGROUND ON THE USE OF EDUCATION & OCCUPATION AS RATING FACTORS

One of Florida's greatest strengths is its rich culture and ethnically diverse population. Regrettably, Florida has another history: one of slavery, Jim Crow laws, as well as discrimination that led to the modern civil rights era. This willful discrimination was pervasive and permeated the institutions of education, government, and commerce --- even the insurance industry. While Florida leaders have since prohibited the use of factors such as race in determining employment and housing decisions, some vestiges of discrimination remain.

In 2000, the National Association of Insurance Commissioners ("NAIC") initiated a Race-Based Premium Working Group to examine the use of race-based premiums for life insurance. The Office was an active participant in this endeavor, which included a questionnaire to all life insurance companies nationwide about past practices. This ultimately resulted in several multi-state market conduct examinations, and multi-million dollar settlements to correct past wrongdoing.

The review period varied based on the company, but usually encompassed 1900-1970, although many policies were still "on the books." The findings were disturbing. Historically several life insurance companies bifurcated rate tables for "Caucasian" and "not-Caucasian," charging higher rates for non-whites. Company documents offered a very interesting defense for this policy: they claimed this was not discriminatory, but merely reflected the statistical differences between life expectancies for Whites versus non-Whites. Although there may have been some validity to this statement, the insurance industry does not exist in a moral, ethical, or historical vacuum. Despite this "actuarial justification," legislatures around the country banned the use of race regardless of the statistical reasoning.

In reaction to these changes, some companies adjusted their underwriting standards in an unexpected manner: they began to use other factors that served as proxies for race and income status. The two most notable factors included education and occupation.

According to one multi-state examination report concluded by Maryland[1], after the race question was deleted from the application in the 1960s, several companies "appeared to use occupation as a substitute for race." ***Occupations subject to substandard rating included maids, bootblacks, busboys, car wash workers, garbage or ash collectors and janitors.*** The multi-state reported noted, "Non-Caucasian workers were disproportionately represented in the [these] disadvantaged occupations."

The report further compared rating books before and after race was removed from the application and noted:

1) The rating books removed race from the rating methodology, and
2) Occupational Rating Classification replaced the use of race, and
3) No other changes were made.

Both the company and regulators agreed the company engaged in "socio-economic underwriting." All four states involved in the examination, Maryland, Florida, Pennsylvania and Virginia believed there was enough evidence to conclude that the use of occupation in this instance violated all four states' statutes regarding non-discriminatory practices.

In a similar examination conducted by the State of Ohio a rating book for Cooperative Life Insurance Company[2] (CLIC), not only was there ***a substandard rating for occupations like butlers, barbers, valets, cooks, elevator operators and waiters — but the rating book warned against, "low-grade industrial or illiterate types."***

[1] The State of Florida, Pennsylvania, and Virginia also joined this examination. Monumental Multi-State Exam Report # 789-00 (Maryland).

[2] Actuarial Report – Race Based Pricing Activities with Respect to the Life Insurance Business of Nationwide Life Insurance Company, July 6, 2004 – State of Ohio.

THE USE OF OCCUPATION AND EDUCATION AS RATING FACTORS CONTINUES

The presumption that the use of occupation and education as rating factors ended with the conclusion of the aforementioned life insurance industry multi-state examinations is erroneous. The venue, however, has changed --- to the underwriting and rating of private passenger auto policies.

On March 20, 2006 the Consumer Federation of America ("CFA") issued a press release warning that the nation's fourth largest auto insurer, GEICO, was using occupation and educational attainment to rate auto insurance policies, and that Liberty Mutual Insurance and Allstate Insurance were beginning to use these rating factors as well. J. Robert Hunter, Director of Insurance for CFA, and the former Insurance Commissioner for the State of Texas, challenged state insurance regulators to ban the use of education and occupation for rating policies as these factors are highly correlated with race and income level.

In response, The Property Casualty Insurers Association of America (PCI), a trade association that represents 1,000 member companies that write roughly 40% of the nation's property & casualty business issued its own press release on March 21, 2006. The PCI defended GEICO's use of education and occupation as "valid factors for insurers to use in the marketplace."

While Florida law specifically outlaws the use of race for rating insurance policies, there is no specific statutory prohibition against using potential proxy factors that are highly correlated to race, such as educational attainment and occupation that would create a disparate impact on racial minorities and low income Floridians.

Section 627.917, Florida Statutes, states that the Financial Services Commission can establish a uniform statewide risk classification reporting system for auto policies provided it does not discriminate based upon race, creed, color or national origin. Pursuant to this private passenger auto risk classification reporting system statute: "The classification system may include any difference among risks that can be demonstrated to have a probable effect upon losses or expenses ..."

The insurers that have begun to use occupation and/or education as rating factors claim these factors are predictive of losses, and thus are not prohibited by Florida Statute, regardless of the potential impact. The auto rating statute states that rates are not unfairly discriminatory with respect to a group even though they are lower (and, by implication, higher) than rates for nonmembers of the group. Rates are only unfairly discriminatory if they clearly fail to reflect equitably the difference in expected losses and expenses or if they are not actuarially measurable and credible and sufficiently related to actual or expected loss and expense experience of the group to assure that nonmembers of the group are not unfairly discriminated against. It is this definition that governs the Office's determination of whether a rate is unfairly discriminatory.

THE PUBLIC HEARING ON THE USE OF OCCUPATION AND EDUCATION AS RATING FACTORS FOR PRIVATE PASSENGER AUTO INSURANCE

The Florida Insurance Commissioner, through a Notice of Hearing to the industry, as well as subpoenas directed to auto insurers currently using occupation and education as rating factors, compelled testimony from the industry, consumer advocacy groups, and from the public to explore this issue, and the rationalization underlying the use of these factors. Members from four insurance groups testified including GEICO, Liberty Mutual, the AIG Insurance Group, and New Jersey CURE Auto Insurance. In addition, members from insurance trade organizations including the Property and Casualty Insurance Association of America (PCI), the Consumer Federation of America, the National Association of Mutual Insurance Companies (NAMIC), the Insurance

Information Institute (III), the Florida Insurance Council, the Florida Justice Association, and Florida's Consumer Advocate also testified.

The issue is simple: allowing the use of occupation and education as rating factors appear to disproportionately favor non-minorities and higher-income individuals while negatively impacting minorities and low-income individuals by charging these groups, albeit somewhat indirectly, higher auto-insurance rates relative to others with similar risk characteristics.

The Office has been monitoring this trend, and has been very specific in not "approving" the rate filings that use the two factors at issue, but instead, warning companies that although the Office is concerned about the impact of these practices, it does not have statutory authority to deny these practices. While the Office has not "approved" these plans, it had no other recourse under current statutes and rules but to allow them to come into effect due to the deemer provisions of the law.

This issue also has gained national attention following the Consumer Federation of America's letter to all insurance commissioners explaining its research regarding GEICO's practices. In 2006, Commissioner McCarty commissioned an internal study of the correlation between education/occupation and ethnicity and income, which found strong correlations, ultimately concluding that logically any plan that utilized these factors would negatively impact minorities and low-income individuals.

Prior to the public hearing, the Office identified eight main investigatory questions to understand these issues:

1. Is there a correlation between occupation/education and race and/or income status?
2. Is the insurance industry aware of such correlation between occupation/education and race or income?
3. Does the insurance industry believe its corporate responsibility extends to ensuring its policies do not negatively impact people due to race or income-level?
4. Has the insurance industry researched the impact of its practices on Floridians as it relates to minority or low-income individuals?

5. Is there a correlation between occupation/education and loss ratios and or accident statistics?
6. If it is demonstrated the use of occupation and education negatively impact protected classes, what is the magnitude of this impact?
7. If the Florida Legislature does not change the laws, and this practice is allowed to proliferate, what will be the potential impact on the auto insurance industry?
8. If these factors were not allowed for underwriting factors, would the auto insurance industry still be competitive?

THE CURRENT USE OF OCCUPATION AND EDUCATION AS RATING FACTORS

Even before the eight investigatory questions are explained, it is important to understand how the industry is currently using occupation and education. Although a few industry representatives stated broadly, "they have been using these factors for years," the current incarnation of the usage of these factors is a relatively new phenomenon, and is utilized in different forms by three auto insurers in Florida that collectively write approximately 17.1% of the auto insurance market in Florida, insuring over 1.9 million vehicles.

The testimony elicited the forms of current use, and revealed several critical facts. It is important to understand that these factors can be used in two different phases: (1) Underwriting --- which is to determine whether to insure the individual; and (2) Rating – which is to determine the actual premium paid by the customer. During this investigation, the Office learned about another practice, which is a blending of underwriting and rating, the practice of "tiering"

GEICO utilized "tiering" most directly, and this report will use this company's experience as an example. Currently GEICO has four companies that operate in the State of Florida: Government Employees Insurance Company (which is the origin of the name "GEICO" but does not technically incorporate that acronym), GEICO General, GEICO Indemnity, and GEICO Casualty. During the underwriting phase, a customer will apply for coverage on-line or via a telephone operator, and believes they are applying for coverage from "GEICO." Based on the underwriting criteria (including occupation and education), customers are placed into different companies. The preferred-risk customers are placed into Government Employees Insurance Company or GEICO General (with the lowest rates), the intermediate-risk customers are placed into GEICO Indemnity, while the sub-standard risk customers are placed into GEICO Casualty. Based on GEICO's placement statistics, it appears that customers gaining the preferred status (and lowest premiums) are far more common:

GEICO Coverage in Florida, 2006

Company	# of Insured Vehicles	Avg. Annual Premium
GEICO /GEICO General	990,262	$938.70
GEICO Indemnity	174,823	$1,183.70
GEICO Casualty	110,613	$1,474,90

It also appears that GEICO is not equally receptive to all segments of the population (favoring those with higher education and better occupational status). During the testimony, the Office learned that customers are usually not informed they were rejected for the preferred company (Government Employees Insurance Company or GEICO General), and placed into another company.[3]

Liberty Mutual has two companies writing auto insurance in Florida, Liberty Mutual Insurance Co. (the preferred company with lower rates), and Liberty Insurance Co. (sub-standard risks and higher rates). In the initial determination, occupation, employment status, and education are determinants for being offered coverage from Liberty Mutual Ins. Co. In response to direct questioning during the public hearing, Christopher Cunniff, VP of Personal Marketing, stated, "Yes, it is possible that some small segment of customers, the use of that variable [education and occupation] does push their slotting decision from one company to another."[4] However, once in the insurance companies,

[3] GEICO is currently defending itself against a lawsuit filed in 2006 in federal court by several African-Americans who were either former or current GEICO policyholders, alleging that the use of education and occupation factors are discriminatory or have a discriminatory impact, Patricia Amos, et al. v. GEICO, U.S. District Court for the District of Minnesota, Case # 06-cv-1281. Transcript of public hearing, Volume 1, page 81, lines 2 – 14; Vol. 1, page 88, lines 8 – 13. GEICO states the allegations are "absolutely baseless".

[4] Transcript of public hearing, Volume 1, page 97, lines 14 – 17.

education and occupation are not used as rating factors by the Liberty Mutual Companies. This contrasts with GEICO, where further tiering decisions are made within each company.

One potential problem of this "slotting" technique is that individuals may be "parked" in the substandard risk company. Even if a person achieves a higher level of education, or changes to a more preferred occupation, they can only switch companies after three years, "if they are clean," remarked VP Cunniff.[5]

The American International Group, Inc. ("AIG") Companies use occupation, but do not use education in their underwriting and premium practices. While AIG does have three auto insurers writing in Florida, AIG does not use the same type of "tiering" techniques used by GEICO and Liberty Mutual, but places customers based on their distribution channels. However, within their underwriting tiers (which ultimately affects rating and premiums), occupation is used as a determining factor.

The Office is vested with the responsibility to ensure rates are not "excessive, inadequate, or unfairly discriminatory,"[6] and it appears that these underwriting and rating factors will *prima facie* result in higher premiums for those who can least afford it: lower-income, and less educated individuals.

[5] Vol. 1, page 97, lines 23 – 25.
[6] Section 627.0651, Florida Statutes.

I. IS THERE A CORRELATION BETWEEN THESE FACTORS AND RACE AND/OR INCOME STATUS?

Although racial differences between education and occupation have narrowed since the "Jim Crow" period examined during the race-based life insurance premiums initiative --- a wide gap still exists.

The U.S. Census Bureau conducted a comprehensive study of race/ethnicity and occupation in for its *Selected Occupational Groups by Race and Hispanic Origin for the United States, 2000.* The table below, based on U.S. Census Bureau Data, shows disparities among the types of jobs by different races & ethnicities:

Category	Management, Professional, & Related Occupations
White & Asian*	**37%**
Black/African American	**25%**
Hispanic or Latino**	**18%**
American Indians, Native Alaskans, Hawaiians, & Pacific Islanders	**24%**

** Non-Hispanic*
*** Any Race*

Although this is national data, we can still observe dramatic differences: Whites and Asians are twice as likely as Hispanics to have management or professional jobs.

The chart below, based on data from he U.S. Census Bureau, shows educational attainment also has large disparities across ethnic and racial groups in Florida:

Bachelor's Degree or Higher
Florida, 2005

Category	Percent with Degrees
White & Asian*	29%
Black/African American*	13%
Hispanic or Latino**	21%

** Non-Hispanic*
*** Any Race*

Source: U.S. Census Bureau: Educational Attainment of the Population 18 Years and Over, by Age, Sex, Race Alone, and Hispanic Origin, for the 25 Largest States: 2005

Unlike the occupational data, this is Florida specific data, and also shows large disparities: White and Asian non-Hispanics are more than twice as likely to have a college degree as Blacks/African Americans.

For both occupation and education, as a group, Whites and Asians are more likely to have professional and managerial jobs, as well as college degrees. Not only would utilizing these factors negatively impact minorities (as a group), but also using a combination of these factors may magnify the "inequality effect."

II. Is the Insurance Industry Aware of Such Correlation Between Occupation/Education and Race or Income?

Although one may think it is "common knowledge," that there are inequalities in America that contribute to minorities being less likely to obtain college degrees, or have higher incomes, shockingly the representatives of the insurance industry claim to be oblivious of such a relationship. In fact, at times the public hearing was reminiscent of hearings involving the tobacco industry where tobacco lobbyists claimed there were no studies proving tobacco use caused cancer.

Asked pointedly by Commissioner McCarty whether the use of occupation and education would disparately impact protected classes of minorities, Hank Nayden, VP and General Counsel for the GEICO group answered, "…to our knowledge, there is no credible data and no credible study reflecting that."[7] Later in the testimony, Commissioner McCarty asked the same witness if he has looked at the U.S. Census Bureau data on this relationship between occupation and race, Mr. Nayden conceded, "I have not."[8]

The Commissioner again emphasized this question with representatives testifying on behalf of Liberty Mutual. Asking whether the company had looked at U.S. Census Bureau data regarding the relationship between occupation, education, and race and/or income, Christopher Cunniff, VP of Liberty Mutual's Personal Marketing admitted, "I have not, and I'm not aware of anyone at Liberty who has."[9]

Similarly, during the questioning of AIG company representatives, when asked by Deputy Commissioner Belinda Miller about studies showing relationships between occupation and income or race, Mr. Fedak VP of AIG Direct's Southeast Region, answered, "I'm not aware of any studies, other than analyzing our own book of

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7 Vol. 1, page 38, lines 7 - 10.
8 Vol. 1, page 50, line 24.
9 Vol. 1, page 101, lines 23 – 24.

business."[10] Further questioning revealed that since AIG does not collect data regarding ethnicity or income, no such relationship studies could be performed based on their book of business.

The industry's denial of knowing about the statistical correlations between education, occupation and race and/or income strained credulity, Steve Parton, General Counsel for the Office asked rhetorically whether this was "willful blindness" by the industry. However, it should be noted that CFO Eric Poe of New Jersey CURE Auto Insurance Company committed to not using this factors stated:

> ***"...for an entire industry that is predicated on how smart we are, we would be probably the dumbest industry in the world not to know that those statistical correlations exist."[11]***

III. DOES THE INSURANCE INDUSTRY BELIEVE ITS CORPORATE RESPONSIBILITY EXTENDS TO ENSURING ITS POLICIES DO NOT NEGATIVELY IMPACT PEOPLE DUE TO RACE OR INCOME-LEVEL?

Based on the testimony presented February 9, 2007, the simple answer appears to be "no."

During his testimony at the public hearing, Alex Hageli of the Property & Casualty Insurance Association of America (PCI) stressed that as long as the outcomes are actuarially based, the insurance company should be allowed to use it. Moreover, when asked about disparities in outcomes and whether that should be allowed he stated, "I believe that's a question the Legislature needs to address."[12]

[10] Vol. 2, pages 160 – 11, lines 25 and 1.
[11] Vol. 1, page 33, lines 14 – 17.
[12] Vol. 2, page 128, lines 15 –18.

When asked to contemplate hypothetical variables like eye color, cell phone usage, the number of plasma TVs in the household or birth order, Mr. Hageli answered plaintively, "If there's an actuarial basis for it, it should be used unless there is some overriding public policy concern"[13] Later when asked pointedly about the use of race in rating life insurance (as it was conceded African-American's have lower life expectancies than Caucasians), Mr. Hageli implied it could be used, "Except for the fact that it's prohibited by law."[14]

Other industry representatives did not go this far. Commissioner McCarty asked GEICO representatives, "If, in fact, it were determined, hypothetically, that it [using occupation and education as rating factors] had a disparate impact on protected classes, would GEICO continue to use it?"[15] Mr. Nayden of GEICO responded, "absolutely not."[16] However, after presented with U.S. Census data showing disparities, Mr. Nayden seemed unconvinced of the relationship: "And to our knowledge, there is no credible data and no credible study reflecting that [disparate impact]."[17]

When Commissioner McCarty asked the same question of Liberty Mutual's representatives: "If education and occupation criteria used in underwriting or rating were shown to have a disparate impact on protected classes of people ...would your company continue to use it?"[18] Mr. Cunniff of Liberty Mutual waffled: "Well that's a hypothetical question which I can't answer, and certainly we wouldn't comment in advance on business plans with our company."[19]

While they too did not specifically state it is the companies' responsibility to understand these relationships, the AIG companies were less vociferous in defense of this practice. Mr. John Fedak, VP of AIG Direct's Southeast Region summarized their companies' position: "...if the OIR requires insurance carriers to remove occupation from the rating

[13] Vol. 2, page 135, lines 17 – 21.
[14] Vol. 2, page 141, lines 13 – 14.
[15] Vol. 1, page 37, lines 20 – 23.
[16] Vol. 1, page 37, line 24.
[17] Vol. 1, page 38, lines 7 – 8.
[18] Vol. 1, page 101, lines 3 – 8.
[19] Vol. 1, page 101, lines 9 – 12.

process, our tiering model will be revised and will become less accurate in predicting losses."[20]

In summary, the industry does not seem to believe that it is within their corporate responsibility to ensure that rating and underwriting practices do not negatively impact society, as long as the practices have actuarial justification. Instead, it is the perception of the industry that this is a public policy question, and it is the responsibility of the Florida Legislature and regulators --- not the insurance industry to ensure these practices do not negatively impact society.

IV. Has the insurance industry researched the impact of its practices on Floridians as it relates to minority or low-income individuals?

The insurance industry professes ignorance as to the relationship between occupation, education and income-status or race, and believes it is the Florida Legislature's responsibility, not that of the industry, to determine what factors are inappropriate. Given these facts, it should not be surprising the industry has not researched this question. It has not.

Yet what is surprising is the industry has established a mechanism that makes it impossible for any auditor to research this specific information by intentionally never collecting any relevant data. While the industry portrays this as the moral high road because policyholders may be offended by being asked information about income or race, it uses the resulting ignorance to claim that anything it may do cannot possibly be discriminatory because it does not even have race or income information. The argument confuses intent with results but sounds appealing at first.

The State of Florida application for employment asks the ethnicity and age of the applicant on a voluntary basis for information purposes (to ensure non-discrimination),

[20] Vol. 2, page 155, lines 1 – 4.

while mortgage companies and credit card companies routinely request income information. Insurers make hyperbolic statements such as, "No study has shown our policies have a disparate impact". Such statements are true by tautology --- no study can be conducted without the information of the race and income level of the applicant.

This opinion was most passionately advocated by Mr. Nayden of GEICO who stated, "There is no study that finds that the use of education or occupation as a risk selection characteristic has an adverse impact on minorities or low income individuals."[21] Yet, when asked whether GEICO could collect and/or analyze this data to determine potentially negative impacts, Mr. Nayden responded emphatically, "We have no interest in collecting or analyzing any data on race."[22] This comment was echoed by Mr. Cunniff of Liberty Mutual: "Liberty does not ask or measure or track either income or race, so we have no internal studies …"[23] We may observe that no external studies are possible either, given that the entities in control of the information desire to remain blissfully ignorant.

To demonstrate the nexus between occupation groups and income level, Eric Poe of the CURE New Jersey Auto Insurance showed that GEICO's rating manual offered the worst (highest premium) category for military personnel in Pay Grade E-4 or lower, which equates to someone earning less than $24,000 a year.[24] Based on GEICO's 2004 rating manual filed with the Office of Insurance Regulation – this is correct.

In response Mr. Nayden remarked the Office has "an old underwriting guideline," but the newer guidelines do not use military pay grades.[25] However, upon further questioning by Susan Dawson, Assistant General Counsel with the Office, Mr. Nayden admitted GEICO currently uses military rank, which is highly correlated to income level within the military.[26]

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[21] Vol. 1, page 46, lines 5- 8.
[22] Vol. 1, page 38, lines 20 – 22.
[23] Vol. 1, page 113, lines 17 – 21.
[24] Vol. 1, page 22, lines 9 – 23.
[25] Vol. 1, pages 41 - 42.
[26] Vol. 1, page, 42, lines 22 – 25, and page 43.

The industry's position is that using education and/or occupation is "blind" based on race or income. Yet, without collecting any data on this issue, the impact itself must remain invisible. Some of the occupations in GEICO's preferred auto group include doctors, lawyers, and engineers while those in the lowest rating categories include blue and gray-collar workers, service and long-haulers, it is difficult to fathom how their policies could not produce a negative impact on disadvantaged groups.

While the Office agreed that collecting information about race and income could be perceived as offensive, minorities and low-income individuals may be equally offended to learn much larger proportions of them are paying higher rates than the majority racial group and higher income white-collar professionals, and are being rejected by the preferred companies within an insurance group without their knowledge.

V. Is there a correlation between occupation/education and loss ratios and or accident statistics?

Underlying the industry's entire argument is a statistical correlation between occupation, education and auto loss ratios. Representatives from AIG were even more specific, in that by using multivariate regression analysis, there is an *independent* relationship between occupation and auto loss ratios, which can be demonstrated when other factors are held constant. Regrettably, these data cannot be reviewed in this report as some of this involves proprietary information.

During the public hearing, Attorney Susan Dawson elicited testimony from representatives from GEICO regarding a 2003 study completed by Quality Planning Corporation, a division of Insurance Services Office, Inc. (ISO). This study showed that several white-collar careers had higher risk for an accident:

2004 Quality Planning Corporation Study
Accidents Per 1,000 Per Year

Rank	Occupation	Accidents per 1,000
# 1	Student	152
# 2	Medical Doctor	109
# 3	Attorney	106
# 4	Architect	105
# 5	Real Estate Broker	102
# 6	Enlisted Military	99
# 7	Social Worker	98
# 8	Manual Laborer	96
# 9	Analyst	95
# 10	Engineer	94

Many of these occupations including medical doctor, attorney, architect, and engineer appear in GEICO's most preferred rating class.

When asked to explain this apparent discrepancy, Mr. Hageli of PCI speculated that certain jobs may require travel at unusual hours, or be subject to greater distractions (including cell phone usage) causing a greater risk of accident.[27] When pressed for an example, he gave a real estate broker. Yet, Mr. Hageli's explanation seemed unconvincing, as high cell phone usage by attorneys, doctors, and real estate brokers should make their premiums higher --- not lower.

A better explanation was presented by Eric Poe of New Jersey CURE Auto Insurance who stated, "Studies have shown up to 50 percent of eligible claims are not even reported to insurance companies because of the fear that their rates will go up. Unfortunately, lower income individuals do not have the ability to make that choice."[28] For evidence, Mr. Poe cited a report by the 1998 Joint Economic Committee from the U.S. Congress.

Paul Lavrey, actuary for GEICO, agreed stating that "our experience would be based on what we know about, which is the losses that are reported." Moreover, "I'm sure some

[27] Vol. 2, page 126, lines 21 – 25.
[28] Vol. 1, page 14, lines 7 – 9.

claims aren't reported and we don't know about them so we wouldn't have that."[29] Regarding the number of claims that are not reported Mr. Nayden added, "We're not aware of a study, but we would certainly like to review it, if you have one."[30] Mr. Cunniff, of Liberty Mutual, did try to offer a better defense of this stating that many auto claims are third party claims that would be difficult to nonreport, moreover, there are some legal requirements that require multi-car accidents to be reported.[31]

Yet the end result is the same, assuming both the industry studies showing preferred white-collar jobs like doctors, lawyers and architects, have lower loss ratios, yet according to Quality Planning's study have greater amounts of car accidents, it does appear there is some "self-insurance." Basically, wealthier consumers are paying lower-amount claims out-of-pocket rather than filing claims.

VI. IF IT IS DEMONSTRATED THAT THE USE OF OCCUPATION AND EDUCATION NEGATIVELY IMPACT PROTECTED CLASSES, WHAT IS THE MAGNITUDE OF THIS IMPACT?

Another factor is the amount of the effect. Even assuming occupation and education are accurate predictors of auto loss ratios, and that industry data has roughly similar experience in this regard, it does seem odd that the variations among insurers are of such a significant magnitude, especially given its actuarial basis.

AIG Company representatives (which use only occupation, not education) assert the differences are not significant: "There's a potential in certain extreme circumstances for a person's tier that they're assigned to move by two tiers based on the occupation variables, and that would result in approximately a 30 percent rate difference."[32] When

[29] Vol. 1, page 77, lines, 16 – 22.
[30] Vol. 1, page 78, lines 8 – 12.
[31] Vol. 1, page 109, lines 11 – 20.
[32] Vol. 2, page 168, Mr. Bowman's testimony.

asked specifically whether it could be higher, Mr. Fedak stated, "That would be a maximum."[33]

While the Liberty Mutual testimony focused on other areas, the GEICO testimony elucidated several interesting numbers regarding differences in occupation, education, and its affect on premiums. One of the reasons GEICO is easy to analyze is that it has an interactive rate estimator on its website which can be used to see the effect of specific occupations and education levels while holding other demographic information constant. The Office of Insurance Regulation presented three comparisons:

	High School/ Blue-Collar	Advanced Degree/ Professional	% Difference
Comparison 1[34]	$4,225.36	$1,403.59	201%
Comparison 2[35]	$884.84	$714.04	24%
Comparison 3[36]	$1,027.29	$1,280.79	25%

Eric Poe of New Jersey CURE Auto Insurance stated the differences varied by as much as 50-70%, although in some cases the difference could be as much as 200% as in Commissioner McCarty's example.[37]

While GEICO representatives seem to imply these were isolated incidents, interestingly a reporter from the St. Petersburg Times conducted his own research on his vehicle comparing the rates for "Bob" --- a 50 year-old janitor with no high school education, and "Joe" a Ph.D. computer executive attempting to insure the same 2002 Toyota Camry in

[33] Vol. 2, page 168, line 6.

[34] Example included a single male, age 23, living in Hialeah, with a 2000 Chevrolet Malibu LS, 4 door sedan, Drives up to 15,000 miles a year, one speeding ticket, no accidents within 3 years. BI limits $15,000/$30,000; PD $10,000; PIP $10,000 with $250 deductible; UM: $15,000/$30,000; non-stacked, Comprehensive $500 deductible, Collision $500 deductible. Six-month policy.

[35] Example included a single male, age 25, living in Jacksonville, with a 2005 Honda Accord, 4-door sedan, Drives up to 15,000 miles a year, one speeding ticket, no accidents within 5 years. BI limits $25,000/$50,000; PD $25,000; PIP $10,000 with $0 deductible; UM: $25,000/$50,000; non-stacked, Comprehensive $500 deductible, Collision $500 deductible. Six-month policy.

[36] Example included a single male, age 24, living in West Palm Beach, with a 2002 Buick Park Avenue, 4-door sedan, Drives up to 15,000 miles a year, one speeding ticket, no accidents within 3 years. BI limits $15,000/$30,000; PD $10,000; PIP $10,000 with $250 deductible; UM: $15,000/$30,000; non-stacked, Comprehensive $500 deductible, Collision $500 deductible. Six-month policy.

[37] Vol. 1, page 12, lines 7 – 11.

the Tampa area.[38] His results: Bob the janitor would be pay premiums 66% higher for the exact same vehicle.

While GEICO claims their models incorporate up to 27 factors, it does appear that some factors are given greater weight than others --- and that education and occupation factors may be more important than miles driven, marital status or age in calculating an insurance premium.

VII. IF THE FLORIDA LEGISLATURE DOES NOT CHANGE THE LAWS, AND THIS PRACTICE IS ALLOWED TO PROLIFERATE, WHAT WILL BE THE POTENTIAL IMPACT ON THE AUTO INSURANCE INDUSTRY?

The problem is simple: if occupation and education are truly predictors of loss, the companies that do not adopt these practices are at a competitive disadvantage vis-à-vis insurance companies that do adopt this practice.

The most pervasive use of this practice is currently that of GEICO, which is the third largest private passenger auto writer in Florida, and the fourth largest writer in the United States.[39] In a statement to the Commissioner and the panel, Mr. Cunniff of Liberty Mutual observed, "I would say that as a general rule we are aware of what competitors are doing."[40]

In their defense, Mr. Nayden of GEICO used as evidence GEICO's double-digit growth and that "the company's growth across all occupations and educational levels give the lie to any notion that certain individuals are being harmed by our underwriting practices."[41] The fact that nearly 1 million policyholders are in GEICO's preferred company, while less than 300,000 have policies with the substandard companies casts serious doubt on

[38] "GEICO Gives Different Rates for Drivers Depending on their Jobs," St. Petersburg Times, Robert Trigaux, February 12, 2007.
[39] Vol. 1, page 35, lines 15 – 17.
[40] Vol. 1, page 119, lines 23 – 25.
[41] Vol. 1, page 48, lines 9 – 15.

this assumption --- while all companies may be growing, GEICO companies appealing to those with higher occupation and more professional occupations seem to have achieved greater market penetration.

In his testimony, Eric Poe stated about CURE New Jersey Auto, "...we [the insurance community & state government] have to make moves to ban the use of this or we are going to be compelled to adopt this rating practice."[42] The Consumer Federation of America voiced its agreement, "...GEICO's continued use of the education and occupation criteria will lead to negative competition in the insurance marketplace and that it will encourage GEICO's competitors to follow suit, because those competitors will see that GEICO is taking away their more affluent clients."[43]

Based on the testimony provided, it would appear that auto insurer's use of these factors is poised to increase. These factors, could lead proliferate within the auto insurance industry, in much the same way that the use of race as an underwriting factor became pervasive throughout the life insurance industry between 1900 to 1970.

VIII. IF THESE FACTORS WERE NOT ALLOWED FOR UNDERWRITING FACTORS, WOULD THE AUTO INSURANCE INDUSTRY STILL BE COMPETITIVE?

Other than having predictive value, the main argument for the inclusion of education and occupation as rating factors is the concept of competition. Perhaps best articulated by Dr. Robert Hartwig of the Insurance Information Institute, "...a system of rates that accurately reflects risk and costs is fair and it is equitable. States that restrict actuarially valid underwriting criteria implicitly subsidized drivers with relatively poor records at the expense of the state's better drivers."[44]

[42] Vol. 1, page 10, lines 7 – 18.
[43] Vol 2, page 149, lines 7 – 12.
[44] Vol. 2, page 193.

Even more dramatically, representatives from PCI stated this will lead to overall price increases: "When you have less competition, you have less market forces forcing prices down," Mr. Hageli continued, "If you begin, as regulators, to tell them what they can and cannot do, they're going to be more conservative. I mean, that to me seems to be pretty commonsensical."[45] NAMIC also agreed, "… limitations and restrictions on underwriting freedom stifle innovation and thereby hamper competition, ultimately harming consumers and society in general."[46]

These arguments do have some merit. However, this can be applied to all types of regulation --- as regulation, whether it be standardizing forms that people can understand, prohibiting use of specific language in advertising, or creating solvency requirements to ensure against bankruptcy --- all regulation implicitly limits freedom of insurance companies in exchange for a perceived societal benefit.

The one statement that remained unanswered was posed by the Insurance Commissioner Kevin McCarty during the testimony of PCI: "Certainly the life insurance business is as robust today as it's ever been and we don't allow race-based rates."[47] Moreover, in the same vein, disallowing the use of a factor by all companies (in this instance race) creates a level playing-field for all insurance companies to compete based on factors that are allowed.

Florida's Office of Consumer Advocate also agrees, "I believe that if a particular rating variable has an extraordinary disparate impact on a particular prohibited class or group of prohibited classes, that that variable in effect is a proxy for prohibited classes and should be prohibited."[48] Thus, even though some inefficiencies in the auto insurance market may be created by disallowing the use of factors such as race, income level, or factors that may be intentional or unintentional proxies for race and income levels such as credit scores, occupation and education --- the prohibition of such use may be in the public

[45] Vol. 2, page 131, lines 14 – 20.
[46] Vol. 2, page 185, lines 4 – 14.
[47] Vol. 2, page 131, lines 8 – 13.
[48] Vol. 2, page 217, lines 16 – 21.

interest, despite modest insurance sector inefficiencies. The relationship between race and income is illustrated by data from the U.S. Census' "Income, Earnings, and Poverty From the 2004 American Community Survey," issued August 2005:

Median Incomes by Race

Race and Hispanic Origin	Men	Women
Caucasian alone	$42,707	$32,034
Caucasian alone, not Hispanic	$45,573	$32,678
African-American alone	$32,686	$28,581
American Indian	$32,113	$25,752
Asian alone	$46,888	$36,137
Hawaiian and Pacific Islander	$32,403	$27,989
Other Race	$26,679	$23,565
Two or More Races	$37,025	$30,729
Hispanic Any Race	$26,749	$24,030

Median Incomes by Education

Education	Men	Women
Less than High School	$21,760	$13,280
High School Graduate	$31,183	$19,821
Some College or Associates Degree	$37,883	$25,235
Bachelor's Degree	$52,242	$35,195
Graduate or Professional Degree	$68,239	$46.004

Median Incomes by Occupation

Occupational Fields	Men	Women
Management	$65,393	$48,118
Business and Financial Operations	$57,922	$42,256
Computers and Math	$66,130	$56,585
Architecture	$64,496	$51,581
Health Care Practitioner	$69,124	$45,380
Health Care Support	$25,774	$22,658
Farming, Fishing	$22,124	$17,098
Construction	$33,064	$29,289
Transportation	$31,840	$22,434
Personal Care and Service	$27,258	$19,789
Educational	$47,963	$36,891
Office and Admin Support	$35,216	$29,006

One of Florida's greatest strengths is its rich culture and ethnically diverse population, and it would be unfortunate if the insurance industry, through its practices, either intentionally or unintentionally, engaged in discriminatory practices based on a person's ethnicity or income status. Similar to credit scoring, it is possible that clear legislation with rule making authority will be needed to restrict the use of education and occupation as underwriting and rating factors.

ATTACHMENT 14

Federal Trade Commission Report to Congress
Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance
July, 2007

CREDIT-BASED INSURANCE SCORES:
IMPACTS ON CONSUMERS OF AUTOMOBILE INSURANCE

A Report to Congress by the
Federal Trade Commission

July 2007

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I. EXECUTIVE SUMMARY

Section 215 of the FACT Act (FACTA)[1] requires the Federal Trade Commission (FTC or the Commission) and the Federal Reserve Board (FRB), in consultation with the Department of Housing and Urban Development, to study whether credit scores and credit-based insurance scores affect the availability and affordability of consumer credit, as well as automobile and homeowners insurance. FACTA also directs the agencies to assess and report on how these scores are calculated and used; their effects on consumers, specifically their impact on certain groups of consumers, such as low-income consumers, racial and ethnic minority consumers, etc.; and whether alternative scoring models could be developed that would predict risk in a manner comparable to current models but have smaller differences in scores between different groups of consumers. The Commission issues this report to address credit-based insurance scores[2] primarily in the context of automobile insurance.[3]

Credit-based insurance scores, like credit scores, are numerical summaries of consumers' credit histories. Credit-based insurance scores typically are calculated using information about past delinquencies or information on the public record (*e.g.*, bankruptcies); debt ratios (*i.e.*, how close a consumer is to his or her credit limit); evidence of seeking new credit (*e.g.*, inquiries and new accounts); the length and age of credit history; and the use of certain types of credit (*e.g.*, automobile loans). Insurance

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[1] 15 U.S.C. § 1681 note (2006). Appendix A contains the complete text of Section 215 of the FACT Act.
[2] The FRB will submit a report addressing issues related to the use of credit scores and consumer credit decisions.
[3] The Commission will conduct an empirical analysis of the effects of credit-based insurance scores on issues relating to homeowners insurance; the FTC anticipates that it will submit a report to Congress describing the results of this analysis in early 2008.

companies do not use credit-based insurance scores to predict payment behavior, such as whether premiums will be paid. Rather, they use scores as a factor when estimating the number or total cost of insurance claims that prospective customers (or customers renewing their policies) are likely to file.

Credit-based insurance scores evolved from traditional credit scores, and insurance companies began to use insurance scores in the mid-1990s. Since that time, their use has grown very rapidly. Today, all major automobile insurance companies use credit-based insurance scores in some capacity. Insurers use these scores to assign consumers to risk pools and to determine the premiums that they pay.

Insurance companies argue that credit-based insurance scores assist them in evaluating insurance risk more accurately, thereby helping them charge individual consumers premiums that conform more closely to the insurance risk they actually pose. Others criticize credit-based insurance scores on the grounds that there is no persuasive reason that a consumer's credit history should help predict insurance risk. Moreover, others contend that the use of these scores results in low-income consumers and members of minority groups paying higher premiums than other consumers.

Pursuant to FACTA, the FTC evaluated: (1) how credit-based insurance scores are developed and used; and, in the context of automobile insurance (2) the relationship between scores and risk; (3) possible causes of this relationship; (4) the effect of scores on the price and availability of insurance; (5) the impact of scores on racial and ethnic minority groups and on low-income groups; and (6) whether alternative scoring models are available that predict risk as well as current models and narrow the differences in scores among racial, ethnic, and other particular groups of consumers. In conducting this evaluation, the Commission considered prior research, nearly 200 comments submitted in response to requests for the public's views, information presented in meetings with a variety of interested parties, and its own original empirical research using a database of automobile insurance policies. Based on a careful and comprehensive consideration of this information, the FTC has reached the following findings and conclusions:

- Insurance companies increasingly are using credit-based insurance scores in deciding whether and at what price to offer coverage to consumers.

- Credit-based insurance scores are effective predictors of risk under automobile policies. They are predictive of the number of claims consumers file and the total cost of those claims. The use of scores is therefore likely to make the price of insurance better match the risk of loss posed by the consumer. Thus, on average, higher-risk consumers will pay higher premiums and lower-risk consumers will pay lower premiums.

- Several alternative explanations for the source of the correlation between credit-based insurance scores and risk have been suggested. At this time, there is not sufficient evidence to judge which of these explanations, if any, is correct.

- Use of credit-based insurance scores may result in benefits for consumers. For example, scores permit insurance companies to evaluate risk with greater accuracy, which may make them more willing to offer insurance to higher-risk consumers for whom they would otherwise not be able to determine an appropriate premium. Scores also may make the process of granting and pricing insurance quicker and cheaper, cost savings that may be passed on to consumers in the form of lower premiums. However, little hard data was submitted or available to quantify the magnitude of these benefits to consumers.

- Credit-based insurance scores are distributed differently among racial and ethnic groups, and this difference is likely to have an effect on the insurance premiums that these groups pay, on average.

    - Non-Hispanic whites and Asians are distributed relatively evenly over the range of scores, while African Americans and Hispanics are substantially overrepresented among consumers with the lowest scores (the scores associated with the highest predicted risk) and substantially underrepresented among those with the highest scores.

    - With the use of scores for consumers whose information was included in the FTC's database, the average predicted risk (as measured by the total cost of claims filed) for African Americans and Hispanics increased by 10% and 4.2%, respectively, while the average predicted risk for non-Hispanic whites and Asians decreased by 1.6% and 4.9%, respectively.

- Credit-based insurance scores appear to have little effect as a "proxy" for membership in racial and ethnic groups in decisions related to insurance.

    - The relationship between scores and claims risk remains strong when controls for race, ethnicity, and neighborhood income are included in statistical models of risk.

    - In models with credit-based insurance scores but without controls for race or ethnicity, African Americans and Hispanics are predicted to have average predicted risk 10% and 4.2% higher, respectively, than if scores were not used. In models with scores and with controls for race, ethnicity, and income, these groups have average predicted risk 8.9% and 3.5% higher, respectively than if scores were not used. The difference between these two predictions for African Americans and Hispanics (1.1% and 0.7%, respectively) is a measure of the effect of scores on these groups that is attributable to scores serving as a statistical proxy for race and ethnicity.

    - Several other variables in the FTC's database (*e.g.*, the time period that a consumer has been a customer of a particular firm) have a proportional proxy effect that is similar in magnitude to the small proxy effect associated with credit-based insurance scores.

    - Tests also showed that scores predict insurance risk within racial and ethnic minority groups (*e.g.*, Hispanics with lower scores have higher estimated risk than Hispanics with higher scores). This within-group effect of scores is inconsistent with the theory that scores are solely a proxy for race and ethnicity.

- After trying a variety of approaches, the FTC was not able to develop an alternative credit-based insurance scoring model that would continue to predict risk effectively, yet decrease the differences in scores on average among racial and ethnic groups. This does not mean that a model could not be constructed that meets both of these objectives. It does strongly suggest, however, that there is no readily available scoring model that would do so.

II. INTRODUCTION

Over the past decade, insurance companies increasingly have used information about credit history in the form of credit-based insurance scores to make decisions whether to offer insurance to consumers, and, if so, at what price. Because of the importance of insurance in the daily lives of consumers, the widespread use of these scores raises questions about their impact on consumers. In particular, some have expressed concerns about the effect of scores on the availability and affordability of insurance to members of certain demographic groups, especially racial and ethnic minorities.

In 2003, Congress enacted the Fair and Accurate Credit Transactions Act (FACTA) to make comprehensive changes to the nation's system of handling consumer credit information. In response to concerns that had been raised about credit-based insurance scores, in Section 215 of FACTA Congress directed certain federal agencies, including the FTC, to conduct a broad and rigorous inquiry into the effects of these scores and submit a report to Congress with findings and conclusions. The report is intended to provide policymakers with critical information to enable them to make informed decisions with regard to credit-based insurance scores.

Section 215 of FACTA sets forth specific requirements for studying the effects of credit-based insurance scores in the context of automobile and homeowners insurance. It directs the agencies to include a description of how these scores are created and used, as well as an assessment of the impact of scores on the availability and affordability of automobile and homeowners insurance products. Section 215 also requires a rigorous and empirically sound statistical analysis of the relationship between scores and membership in racial, ethnic, and other protected classes. The mandated study further must evaluate whether scores act as a proxy for membership in racial, ethnic, and other protected classes. Finally, Section 215 requires an analysis of whether scoring models could be constructed that both are effective predictors of risk and result in narrower differences in scores among racial, ethnic, and other protected classes.

Section 215 of FACTA also specifies the process to be used in conducting the study, and the contents of the report to be submitted. The Act directed the agencies to seek input from federal and state regulators and consumer and civil rights organizations, and members of the public concerning methodology and research design. The Act requires the report to include "findings and conclusions of the Commission, recommendations to address specific areas of concerns addressed in the study, and recommendations for legislative or administrative action that the Commission may determine to be necessary to ensure that . . . credit-based insurance scores are used appropriately and fairly to avoid negative effects."[4]

The Commission has conducted a study addressing credit-based insurance scores in the context of automobile insurance. Pursuant to statutory directive, the FTC published two Federal Register Notices[5] soliciting comments from the public concerning methodology and research design. The Commission supplemented this information with numerous discussions between its staff and representatives of other government agencies, private companies, and community, civil rights, consumer, and housing groups. The public comments and information obtained in meetings with the various interested parties

[4] 15 U.S.C. § 1681 note (2006).
[5] Public Comment on Data, Studies, or Other Evidence Related to the Effects of Credit Scores and Credit-Based Insurance Scores on the Availability and Affordability of Financial Products, 70 Fed. Reg. 9652 (Feb. 28, 2005); Public Comment on Methodology and Research Design for Conducting a Study of the Effects of Credit Scores and Credit-Based Insurance Scores on Availability and Affordability of Financial Products, 69 Fed. Reg. 34167 (June 18, 2004).

provided essential information that allowed the Commission to complete this report. In addition, feedback from state regulators, industry participants, and the consumer, civil rights, and housing groups had a substantial impact on the methodology and scope of the analysis.

This report discusses the information that the FTC considered, its analysis of that information, and its findings and conclusions. Parts I and II above present an Executive Summary and Introduction, respectively. Part III is an overview of the development and use of credit-based insurance scores, and Part IV discusses the relationship between credit history and risk. Part V addresses the effect of credit-based insurance scores on the price and availability of insurance. Part VI explores the impact of credit-based insurance scores on racial, ethnic, and other groups. Part VII describes the FTC's efforts to develop a model that reduces differences for protected classes of consumers while continuing to effectively predict risk. Part VIII is a brief conclusion.

III. DEVELOPMENT AND USE OF CREDIT-BASED INSURANCE SCORES

A. Background and Historical Experience

Consumers purchase insurance to protect themselves against the risk of suffering losses. They tend to be "risk averse," that is, consumers would prefer the certainty of paying the expected value of a loss to the possibility of bearing the full amount of the loss. For example, assume that a driver faces a 1% risk of being in an automobile accident that would cause him or her to suffer a $10,000 loss, which means that the expected value of his or her loss is $100 (1% of $10,000). If the driver is risk averse, he or she would be willing to pay $100 or more to avoid the possible loss of $10,000.

What makes insurance markets possible is that insurance companies do not simply take on the risk of their customers, they actually reduce risk. This does not mean that they reduce the total losses from car accidents or house fires, for example, but rather that they reduce the uncertainty that individuals face without themselves facing nearly the same amount of uncertainty. This is possible because the average loss on a large number of policies can be predicted much more accurately than the losses of a single driver or homeowner. For instance, while it is extremely difficult to predict who among a group of 100,000 drivers will have an accident, it may be possible to predict the total number of accidents for these 100,000 drivers with a low margin of error.[6] By selling many policies that cover the possible losses for many consumers, an insurance company faces much lower uncertainty as to total losses than would each consumer if they did not purchase insurance.

Insurance companies have a strong economic incentive to try to predict risk as accurately as possible. In a competitive market for insurance in which all firms have access to the same information about risk, competition for customers will force insurance companies to offer the lowest rates that cover the expected cost of each policy sold. If an insurance company is able to predict risk better than its competitors, it can identify consumers who currently are paying more than they should based on the risk they pose, and target these consumers by offering them a slightly lower price. Thus, developing and using better risk prediction methods is an important form of competition among insurance companies.

[6] This risk reduction is due to the "law of large numbers." Uncertainty is reduced as long as there is a sufficient degree of independence among the risk that individual consumers face. For example, selling flood insurance to those who live in a single flood plain reduces risks less than selling the policies to those who live in a broader geographic area.

For decades, insurance companies have divided consumers into groups based on common characteristics which correlate with risk of loss. Automobile insurance companies divide consumers into groups based on factors such as age, gender, marital status, place of residence, and driving history, among others. Once insurance companies have separated consumers into groups based on these characteristics, they use the average risk of each of these groups in helping to determine the price to charge members of the group.

Insurance companies report that during the last decade they have begun to use credit-based insurance scores to assist them in separating consumers into groups based on risk. Insurers have long used some credit history information when evaluating insurance applications, for example, considering bankruptcy in connection with offering homeowners insurance. In the early 1980s, insurance companies and others began assessing the utility of using additional information about credit history in assessing risk, leading to a more formal use of such information in a fairly simple manner by the early 1990s.[7]

In the early 1990s, Fair Isaac Corporation (Fair Isaac), drawing on its experience developing credit scores, led the initial research to develop credit-based insurance scores. The company developed the first "modern" credit-based insurance score and made it available to insurance companies in 1993.[8] This score was developed to predict the likelihood of claims being submitted for homeowners policies. Fair Isaac introduced a credit-based insurance score for automobile policies in 1995, and ChoicePoint introduced

[7] Meeting between FTC staff and State Farm (July 13, 2004); Meeting between FTC staff and MetLife Home and Auto (July 12, 2004); Meeting between FTC staff and Allstate (June 23, 2004).
[8] E-mail from Karlene Bowen, Fair Isaac, to Jesse Leary, Assistant Director, Division of Consumer Protection, Bureau of Economics (Jan. 30, 2006) (on file with FTC).

a competing score at about the same time.[9] These scores were developed to predict the loss ratios – claims paid out divided by premiums received – of automobile policies. Following the introduction of these third-party scores, some insurance companies began developing and using their own proprietary scores.

Since the mid-1990s, the use of credit-based insurance scores has grown dramatically. According to industry sources, some of this growth is attributable to changes in technology and industry practices that have made it easier for companies to develop[10] and use these scores.[11] For example, during the 1990s insurance company actuaries began using advanced statistical techniques that made it easier to control for many predictive variables at the same time.[12] This made it easier for them to develop proprietary scores and perhaps made them more receptive to using third-party scores. Insurers also explained that at this time they began combining more and more data from throughout their companies into integrated databases, and this "data warehousing" made it much easier for actuaries and others to engage in the research needed to develop scores.[13]

More fundamentally, however, insurance companies increasingly used credit-based insurance scores because their experience revealed that they were effective

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[9] *Id.*; E-mail from John Wilson, ChoicePoint, to Jesse Leary, Assistant Director, Division of Consumer Protection, Bureau of Economics (June 13, 2005) (on file with FTC).

[10] Developing scores is a fairly expensive process, requiring significant information technology resources and technical expertise. It also requires a large amount of data on loss experience. Many smaller firms, and even some larger firms, therefore do not develop their own scores. *See, e.g.*, Lamont Boyd, Fair Isaac Corporation, Remarks at the Fair Isaac Consumer Empowerment Forum (Sept. 2006) (noting only six firms use a proprietary scoring model).

[11] Industry participants estimate that of the firms that use credit-based risk scores, one-half (as measured by market share) use a proprietary score and one-half use a score that others developed. Among insurers who use a non-proprietary score, about two-thirds use a ChoicePoint score, and one-third use a Fair Isaac score.

[12] These techniques are known as Generalized Linear Models (GLMs). GLMs make it easier to control for many predictive variables at once, and can be used to develop credit-based scoring models. GLMs play a central role in the analysis presented in this report, and are discussed in more detail in Appendix D.

[13] Meeting between FTC staff and The Hartford (July 14, 2004).

predictors of risk. For example, according to a published case study, in the early 1990s, Progressive entered the lower-risk portion of the automobile insurance market. Progressive used sophisticated risk prediction techniques that it had developed in its other lines of business to identify consumers who other insurers were overcharging relative to the risk they posed. Progressive offered these consumers the same coverage at a lower price, thereby persuading some of them to switch to Progressive.[14] The success of Progressive's strategy provided a powerful incentive for incumbent firms to improve their own risk prediction techniques to compete more effectively.[15] Many of them responded to this incentive by increasing their development and use of credit-based insurance risk scores.[16]

Insurance companies now widely use credit-based insurance scores. Today, the fifteen largest automobile insurers (with a combined market share of 72% in 2005) all utilize these scores.[17] Many smaller automobile insurers also use credit-based insurance scores.[18]

The development and increased use of credit-based insurance scores has been accompanied by concerns and criticisms about the validity of the underlying relationship between scores and risk and the fundamental fairness of using credit history information to make decisions about insurance. According to critics, credit-based insurance scores: 1)

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[14] *See, e.g.*, F. Frei, *Innovation at Progressive (A): Pay as You Go Insurance*, Harv. Bus. Sch. Case Study 9-602-175 (Apr. 29, 2004).

[15] Incumbent firms had an incentive to use the new risk prediction technology in any case. The vigorous competition of Progressive, however, likely spurred incumbent firms to move more aggressively to use this technology than they otherwise would have.

[16] *See id*.

[17] National Association of Insurance Commissioners, "Auto Insurance Database Report 2003/2004" (2006) (on file with the FTC); FTC staff reviews of websites and discussions with industry representatives. No market share data more recent than 2005 was available.

[18] Fair Isaac Corporation states that it sells credit-based insurance scores to roughly 350 firms. Comment from Fair Isaac Corp. to FTC at 14 (Apr. 25, 2005), [hereinafter Fair Isaac Comment], *available at* http://www.ftc.gov/os/comments/FACTA-implementationscorestudy/514719-00090.pdf.

unfairly penalize consumers who have suffered from medical or economic crises, or who have made perfectly legitimate financial decisions that are penalized by scoring models; 2) affect consumers in arbitrary ways, because credit history information may contain errors; and, 3) have a negative impact on minority and low-income consumers.[19]

B. Development of Credit-Based Insurance Scores

According to score developers and insurance companies, credit-based insurance scores are developed in the same manner as credit scores generally. To construct a model, score developers obtain a sample of insurance policies for which losses are known. The period of time during which losses occurred or could have occurred is called the "exposure period." Score developers start with the credit information available about customers at the beginning of the exposure period and the known losses for them during the period. Score developers then use various statistical and other techniques to develop a model that predicts losses based on the credit information that was available at the start of the exposure period. If the relationship between the credit information and loss is sufficiently stable over time, the model can be applied to the credit histories of other consumers to predict the risk of loss they pose.

The details of the credit information used in particular models that produce credit-based insurance scores generally are not available. As emphasized above, insurance companies assert that risk prediction techniques are an important form of competition, so

[19] *Hearing Before the New York State Assembly Comm. on. Ins.* (Oct. 22, 2003) (statement of Birny Birnbaum, Executive Director, Center for Economic Justice).

firms generally do not want to reveal the credit-based insurance scoring models they use.[20]

Some states require by law that insurance companies make their models public. Insurance companies, however, explained that most insurance companies develop and use different scoring models in these states than they use in other states to minimize the competitive disadvantage elsewhere as a result of such mandated disclosures. An important exception is ChoicePoint, which has made its Attract Auto Scoring and other models available to the public.

Based on the information the agency reviewed, a general picture of what data are used in credit-based insurance scoring model emerges.[21] Table 1 presents examples of the types of information that often are used in models to predict credit-based insurance scores. Firms, however, vary significantly in the particular information they use in their models. For example, some insurance companies consider the type of credit granted, while others do not. Moreover, within a category of information, firms may consider different variables in calculating credit-based insurance scores. For instance, an insurance company may use the age of the oldest account in a credit report or may consider the average age of all accounts in the report.

Insurance companies explained that they use credit-based insurance scoring models to predict the amount they will pay out in claims, *i.e.*, claims risk. Some models simply predict the likelihood that a customer will file a claim. These models are most

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[20] *See* Comment from National Association of Mutual Insurance Cos. to FTC at 2 (Apr. 25, 2005) [hereinafter NAMIC Comment], *available at* http://www.ftc.gov/os/comments/FACTA-implementationscorestudy/514719- 00088.pdf.
[21] Although credit-based insurance scoring models are developed to predict insurance claims, instead of credit behavior, many of the same types of information are used. A discussion of the factors that Fair Isaac Corporation uses in calculating its credit scores of consumers ("FICO scores") is available at: http://www.myfico.com/CreditEducation/CreditInquiries.

useful in those situations in which credit information is predictive of claim frequency, but not particularly predictive of the size of claims.[22]

More commonly, however, models are used to predict the "loss ratio,"[23] which is the amount that an insurance company pays out on claims divided by the amount that the customers pay in premiums. This has the advantage of controlling for the effects of non-credit factors on risk, such as age or driving history, as premiums are determined by those other factors. For any particular customer, the loss ratio usually will be either zero (*i.e.*, no claims paid), or a number greater than one (*i.e.*, claims paid in an amount that exceeds premiums received). In contrast, for a group of customers, the loss ratio typically will be a positive number less than one (*i.e.*, some claims paid but in an amount that is less than total premiums received).[24] If there is a strong relationship between customers with a particular credit-related attribute and historic loss ratios, this information can be used to predict the risk of loss associated with a prospective customer who shares that attribute.[25]

Other models are used to predict "pure premiums." Pure premiums are the total amount that an insurance company pays on claims to consumers, not the amount that

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[22] From a technical perspective, modeling frequency is relatively straight-forward. There are a number of standard multivariate techniques that can be used to estimate either the likelihood of a claim occurring, such as logistic regression, or the number of claims that would be expected during a period of time, such as Poisson regression.

[23] Loss ratios can be modeled in a variety of ways. Because loss ratios of individuals have such an oddly-shaped distribution – many zeros and some positive numbers that extend over a wide range – the modeling is not trivial, but it can be handled by GLMs. Loss ratios can also be modeled by decomposing the ratio and modeling the two components – claims paid and premiums – separately. For example, some ChoicePoint models use this technique. *See* e-mail from John Wilson to Jesse Leary, *supra* note 9.

[24] Indeed, for an insurance company to be profitable, the amount that it pays out in claims must be less than the premiums it receives plus its return on investing those premiums.

[25] MetLife has developed a rules-based system under which credit history information is used to sort potential customers based on their predicted loss ratio. MetLife's "Personal Financial Management" uses combinations of various characteristics in an applicant's credit report to assign the applicant to one of several risk categories without ever calculating a numerical score. This type of system essentially is a sophisticated analog to the simple rules-based approach sometimes used prior to the development of credit-based scores, under which, for example, some companies would not write homeowners policies to applicants with recent bankruptcies.

customers pay in to the company. To build a credit-based insurance scoring model based on pure premiums, it is necessary to control for other risk variables and this can be done in one of two ways. One approach is to scale each consumer's losses by an index of how risky they appear, based on other non-credit risk factors (*e.g.*, age or driving history). This is analogous to the modeling of loss-ratios, with the non-credit-variable risk index playing the role of the premium, but avoids the complications that arise in loss ratio models if a credit score affected the premiums of the policies in the development database.

The other approach involves treating credit history variables just like any other variable in predicting risk. One benefit of this approach is that it allows for certain credit history variables to have different effects on predicted risk for different groups of drivers. For example, the age of a consumer's oldest account might be less predictive for young drivers than older drivers. Other credit characteristics might be very informative about drivers without prior claims or violations, but provide limited insight for drivers with poor driving records. Note that this approach may result in a model that does not produce a numerical score based solely on credit history information.

C. Use of Credit-Based Insurance Scores

All insurance companies who use credit-based insurance scores explained that they do so in making decisions concerning *potential* customers. Insurance companies, however, also indicated that their use of scores in policy renewals for *existing* customers is much more varied and complicated. Some states limit the ability of insurance companies to use scores when customers renew policies. Even where not precluded by state law, some insurance companies decide not to use scores when customers renew policies to avoid damaging their relationship with these customers. Other states mandate that firms must use, or must use if the customer requests,[26] updated credit-based insurance scores to modify premium rates. Even where not mandated by state law, some insurance companies use scores to modify premium rates for existing customers on request. In sum, insurance companies use credit-related insurance scores to assess premiums for potential customers and sometimes in determining premiums for existing customers who are renewing their policies.

Insurance companies report that they use credit-based insurance scores in a variety of ways as part of the process of determining whether to offer insurance to prospective customers, and, if so, at what price. Making these determinations usually consists of two steps, referred to as "underwriting" and "rating." In "underwriting," insurance companies use certain characteristics of a consumer to assign him or her to a pool based on the consumer's apparent risk of loss. The pool into which the consumer is placed sets the base premium rate for a policy, with the riskier pools having higher base premium rates. In "rating," the second step, the insurance company uses other risk characteristics to adjust the base premium rate up or down to determine the actual amount the consumer would be charged.[27]

Some insurance companies said that they use credit characteristics in the underwriting step. For example, a firm might assign a potential customer to a risk pool based on the number of claims an applicant has filed in the past several years and the

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[26] *See, e.g.*, R. I. Ins. Regulation 25 § 11 (although requiring firms to recalculate a consumer's score upon request every two years, firms generally can use a change in score only to lower premium rates), *available at* http://www.dbr.state.ri.us/documents/rules/insurance/InsuranceRegulation25.pdf.

[27] There has recently been some movement towards what can be called "continuous rating," in which the risk for each applicant is evaluated and priced without first being assigned to a risk pool, but the two-step process is still standard.

applicant's credit-based insurance score. Using credit-based insurance scores in underwriting thus may affect the premiums that a potential customer would have to pay to obtain coverage, as the risk pool in which the consumer is placed determines his or her base premium rate.

Other insurance companies report that they use scores in the rating step.[28] A simple way to include scores is to determine a consumer's base premium using non-credit factors, such as age or driving history, and then adjust that rate up or down in light of his or her score. A more complex method of using scores is to include credit as a rating factor when developing the entire rating scheme. Such an approach allows credit characteristics to be used interactively with other rating factors. Because how a credit-based insurance score predicts risk may vary with other rating variables, incorporating credit more fully into the rating step may assist in determining premiums that more accurately reflect risk.[29]

D. State Restrictions on Scores

As of June 2006, forty-eight states have taken some form of legislative or regulatory action addressing the use of consumer credit information in insurance underwriting and rating; Pennsylvania and Vermont are the only states that have not regulated insurance scoring.[30] Most of these laws and regulations are based on the

[28] While we are not aware that any insurance companies consider credit-based insurance scores at both the underwriting and rating stage, they could do so.

[29] An approach that is intermediate between having credit as an add-on or treating credit like any other rating factor is to make the size of a credit score discount or mark-up depend on other rating variables. For example, the good-credit discount for young single male drivers could be larger or smaller than the good-credit discount for middle-aged married drivers.

[30] The information in this section pertaining to state legislative and regulatory action addressing insurance scoring is from the National Association of Mutual Insurance Companies' (NAMIC) 2004 survey of state laws governing insurance scoring practices. The report is available at:

(continued)

National Conference of Insurance Legislators' (NCOIL) "Model Act Regarding Use of Credit Information in Personal Insurance," which was released in 2002.[31]

The NCOIL Model Act prohibits insurers from using credit information as the sole basis for increasing rates or denying, canceling, or not renewing an insurance policy. The model also prohibits consumer reporting agencies from providing or selling information to others that was submitted to the agency pursuant to an insurance company's inquiry about a consumer's credit information, credit report, or insurance score. Further, the NCOIL model requires insurers to comply with five conditions: insurance companies must (1) notify an applicant for insurance if credit information will be used in underwriting or rating; (2) notify the applicant in the event of an adverse action based on credit information and explain its reasoning for the adverse action; (3) re-write and re-rate a policyholder whose credit report was corrected; (4) indemnify insurance agents and brokers who obtained credit information or insurance scores according to an insurance company's procedures and according to applicable laws and regulations; and (5) file its scoring models with the applicable state department of insurance.[32] Twenty-seven states have adopted laws or regulations that adopt verbatim the language of the NCOIL model or incorporate restrictions that are very similar in scope and nature to those in the NCOIL model.

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http://www.namic.org/reports/credithistory/credithistory.asp. The information in NAMIC's survey has been updated to reflect newly enacted legislation and regulation through June 2006. Information on this new legislation and regulation is from NAMIC's annual surveys of new state insurance laws and NAMIC's 2007 state law bulletins. The 2005 survey is available at: http://www.namic.org/reports/2005NewLaws/default.asp, the 2006 survey is available at: http://www.namic.org/reports/2006NewLaws/default.asp, and the 2007 state law bulletins are available at: http://www.namic.org/stateLaws/2007stateLawBulletins.asp.

[31] A copy of the text of the NCOIL model is available at: http://www.assureusa.org/docs/NCOIL.doc.

[32] In 2003, the National Association of Insurance Commissions described the NCOIL model in testimony before the U.S. House of Representative, Committee on Financial Services, Subcommittee on Financial Institutions and Consumer Credit. This testimony is available at: http://www.ins.state.ny.us/speeches/pdf/ty030610.pdf.

In addition, twenty-one states have adopted some of the same types of restrictions included in the NCOIL model. Fifteen states prohibit certain uses of credit history information or ban the use of certain negative credit factors in the calculation of an insurance score. Eight states have adopted dispute resolution measures governing an insurance company's responsibility to re-write and re-rate a policyholder whose credit report was corrected. Seven states require insurance companies to notify consumers that their credit information will be used in underwriting or rating. Twelve states require insurers to notify and explain to consumers any adverse action based on credit information. Seven states further require insurers to file their insurance scoring methodologies.

There are several other types of restrictions that have been placed on the use of scores. Three states (Georgia, Illinois, and Utah) prohibit using credit history information as the sole basis in making underwriting or rating decisions. Oregon prohibits the use of credit history information to cancel or not renew existing customers or increase their rates, and Maryland bans the use of credit history when underwriting or rating existing customers.

Finally, four states either have or had effective bans on the use of credit history information in underwriting or rating automobile insurance. Hawaii by statute specifically bans the use of credit information. California and Massachusetts effectively ban the use of scores through their rate regulation processes. Formerly, New Jersey had an effective ban in place, but the use of credit-based insurance scores is now allowed.

IV. THE RELATIONSHIP BETWEEN CREDIT HISTORY AND RISK

Some prior researchers have studied the existence and nature of the relationship between credit history and insurance risk. To explore this relationship, the Commission conducted an analysis of a database of automobile insurance policies that the agency compiled for this study.[33] A consistent finding of prior research and the FTC's analysis is that credit information, specifically credit-based insurance scores, is predictive of the claims made under automobile policies. However, it is not clear what causes scores to be effective predictors of risk.

A. Correlation between Credit History and Risk

1. Prior Research

As discussed above, risk prediction is an important method of competition among insurance firms. Research that insurance companies have conducted about the relationship between credit history and insurance risk therefore typically is proprietary and non-public. Nevertheless, several studies have been made public during the past decade that show a relationship between credit history and insurance risk.

In 2000, James E. Monaghan, an actuary from MetLife Home and Auto, published a study analyzing the relationship between credit history variables and claims on automobile and homeowners insurance policies.[34] He separately assessed a number of credit history variables, including delinquencies, inquiries, and debt utilization rates. Monaghan found that customers with the worst values for these variables posed a greater

[33] See section IV.A.2 and Appendix C for a description of the database.
[34] James N. Monaghan, *The Impact of Personal Credit History on Loss Performance in Personal Lines, Casualty Actuarial Society Ratemaking Discussion Paper* (2000) (presented at the Winter 2000 CAS forum), *available at* http://www.casact.org/pubs/forum/00wforum/00wf079.pdf

risk (as measured by loss ratios) than customers with the best values - often roughly 50% more for automobile policies and over 90% more for homeowners policies.[35] He found the same pattern of increased risks when he conducted his analysis controlling for other non-credit risk factors one-by-one.

After this research, several insurance industry trade associations hired EPIC Actuaries (EPIC) to construct a database of automobile policies with information from a number of different insurers.[36] EPIC analyzed the link between credit history and risk, and described its results in a report issued in 2003.[37] EPIC reported the relationship between credit scores and different measures of risk. The study showed a strong relationship between credit-based insurance scores and the frequency with which claims were made, as well as between scores and the total dollar amount insurance companies paid on these claims.[38] It also showed: (1) no correlation between scores and the size of liability coverage claims; (2) a weak correlation between scores and the size of collision coverage claims; and (3) a strong correlation between scores and the size of comprehensive coverage claims.

In 2003, researchers at the Bureau of Business Research (BBR) at McCombs School of Business at the University of Texas used data from five automobile insurance companies in Texas to study the relationship between credit-based insurance scores and

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[35] As discussed in the section on the development of credit scores, the loss ratio can be used to control for the effects of the variables used to determine premiums. However, this relies on the assumption that the premiums accurately reflect the risks associated with those variables.

[36] The automobile policy data that form the core of the database that we used to conduct our analysis for this report are a subset of the data collected for use in the EPIC report. That database is discussed in more detail below, and in Appendix C.

[37] Michael J. Miller and Richard A. Smith, *The Relationship of Credit-Based Insurance Scores to Private Passenger Automobile Insurance Loss Propensity: An Actuarial Study by EPIC Actuaries, LLC* (June 2003) [hereinafter EPIC Study], *available at* http://www.progressive.com/shop/EPIC_CreditScores.pdf.

[38] EPIC also conducted a multivariate analysis that included controls for most non-credit risk variables used to underwrite and rate automobile polices. While the relationship between scores and the total amount paid out on claims was not as large once controls were included, it remained quite strong.

losses. The BBR researchers found that customers with lower scores were more likely to file claims under their automobile insurance policies than customers with higher insurance scores. In addition, the researchers reported that customers with lower scores filed claims for larger dollar amounts than customers with higher scores.[39] To control for the effects of non-credit risk factors, the BBR researchers used an analysis of loss ratios, and found that loss ratios were higher for customers with lower scores than for customers with higher scores.[40]

In 2004, the Texas legislature directed the Texas Department of Insurance (TDI) to conduct a study and issue a report addressing the relationship between credit-based insurance scores and risk for automobile and homeowner policies. In reports issued in late 2004 and early 2005,[41] TDI analyzed data from six large insurance firms operating in Texas, using each company's credit scoring model.[42] For automobile policies, it found that scores were negatively correlated with total dollars of claims, *i.e.*, as the scores of customers increased, the total amount that the insurance companies paid out in claims decreased. Insurance companies paid out less on automobile policies for customers with higher scores because they filed fewer claims than customers with lower scores.[43] For homeowners insurance, TDI found similar results. TDI found that scores were negatively

[39] Bureau of Business Research, McCombs School of Business, The University of Texas at Austin, "A Statistical Analysis of the Relationship Between Credit History and Insurance Loss" (Mar. 2003). The report does not make clear which particular types of automobile coverage were studied.
[40] *Id*.
[41] Texas Department of Insurance, "Use of Credit Information by Insurers in Texas: The Multivariate Analysis" (Jan. 31, 2005) (supplemental report) [hereinafter 2005 Texas Report]; Texas Department of Insurance, "Use of Credit Information by Insurers in Texas" (Dec. 30, 2004) [hereinafter 2004 Texas Report].
[42] All six insurance companies provided TDI with data on automobile policies, and three of them provided data on homeowners policies.
[43] TDI's findings with regard to automobile policies were consistent regardless of whether it controlled for other risk factors in its analysis.

correlated with both total dollars of claims and loss ratios, *i.e.*, as the scores of customers increased, the total amount that insurance companies paid out on their policies decreased.

2. Commission Research

a. FTC Database

The FTC undertook an analysis to determine the relationship between credit history and risk of loss. Five of the firms that provided automobile insurance policy data for the EPIC study described above provided the same information for the Commission's study.[44] This information included policy and driver characteristics, claims, and a ChoicePoint Attract Standard Auto credit-based insurance score for the customer who is named first on the policy. The information submitted to the Commission related to automobile insurance policies in place at any time between July 1, 2000, and June 30, 2001.

The FTC combined this information from insurance companies with data from a number of other sources to create its database. The agency included additional information in the database to broaden the range of credit history variables analyzed; to improve the set of other risk controls in the analysis; to provide an independent measure of claims; and to analyze issues relating to race, ethnicity, income, and national origin.[45] One important feature of the FTC database was that we created weights to make it

[44] The five firms together represented 27% of the automobile insurance market in 2000. The data were drawn in a way that ensured a nationwide representation of policies. More information about the companies and the database are provided in Appendix C. A discussion of the limitations of the database and of our analysis is presented in Appendix F.

[45] We obtained Fair Isaac credit-based insurance scores for a sub-sample of the people in the database. All of the results presented in the body of the report are for the ChoicePoint Attract score. All of the analysis was also conducted using the Fair Isaac score. The results were qualitatively similar regardless of whether the ChoicePoint or the Fair Isaac score was used. Descriptions of all "robustness checks" and other variations of the analysis are presented in Appendix F.

representative of car owners, by neighborhood income and race and ethnicity, throughout the United States.[46] A more detailed description of the construction and contents of the FTC database is provided in Appendix C.

In assessing the relationship between credit history and risk, the FTC focused its analysis on four major types of coverage included in automobile policies: property damage liability coverage, bodily injury liability coverage, collision coverage, and comprehensive coverage.[47][48] Property damage liability coverage insures the customer against liability for damage he or she causes to the cars and other property of others. Bodily injury liability coverage protects the customer from liability for bodily injuries he or she causes to others. Collision coverage insures the customer against damage to his or her own car from collision or rollover. Comprehensive coverage protects the customer against losses from theft of his or her own car and for damage to the car other than from collision or rollover (*e.g.*, vandalism, fire, hail, etc.).

The FTC first analyzed the simple relationship between credit-based insurance scores and claims for these four coverages. Table 2 shows, for each coverage and for each score decile, the average number of claims per year of coverage (per hundred cars, to show detailed differences across deciles), the average size of claims, and the average total amount paid out on claims per year of coverage (which is the product of the number of claims and the average size of claims).

[46] The weighting also makes the data representative by geographic area. See Appendix D for a discussion of the development of the weights.
[47] The FTC database also contains information on two first-party medical coverages, usually referred to as MedPay and personal injury protection, or "PIP." Claims on these policies are relatively infrequent, and the coverages vary from state to state. For these reasons, we do not focus our analysis on these coverages.
[48] These definitions come from the Insurance Information Institute, and are available in more detail at: http://www.iii.org/individuals/auto/a/basic/.

Figure 1 presents graphs of the relationship between scores and the average total amount paid out on claims. In Figure 1, the horizontal axis shows automobile drivers grouped into ten equal groups ("deciles") based on their credit-based insurance score,[49] with drivers in the decile with lowest scores located at the far left and drivers in the decile with the highest scores at the far right. The vertical axis measures the average dollars paid out on claims per year. This measure of risk is calculated relative to drivers with the highest credit-based insurance scores, which means that the value of the highest-score group (*i.e.*, those in the tenth decile) has been defined as one.

Figure 1 shows that there is a relationship between credit-based insurance scores and risk for all four types of coverage analyzed. Specifically, the downward slopes of the darker (higher) lines in Figure 1 show that as scores increase, the risk of loss consistently decreases. (These lines were produced simply by graphing the average total paid on claims – column (c) – from Table 2, relative to the highest score decile.) They show, for example, that insurance companies paid out nearly twice as much on the property damage liability policies of customers in the group with the lowest scores (*i.e.*, those in the first decile) as they did for the group with the highest scores (*i.e.*, those in the tenth decile). Credit-based insurance scores thus are predictive of the amount that insurance companies pay in claims to consumers.

The FTC then constructed statistical models of insurance claims. These models produce estimates of the relationship between scores and claims, and allow us to control for the effects of other risk variables.

[49] Score is measured by deciles because the units of scores are arbitrary, so there is no reason to believe that the relationship between changes in score and changes in risk is constant across the score distribution. For example, going from a score of 600 to 620 may have a different effect on predicted risk than going from 800 to 820.

The lighter (lower) lines in Figure 1 show the relationship between credit-based insurance scores and the amount paid out after controlling for other standard risk factors, such as age and driving history.[50] The slope of each line demonstrates that the relationship between scores and risk persists when controls for other risk variables are included, although the relationship is less strong. Once controls are included, for instance, the amount that insurance companies paid out on property damage liability claims to customers with the lowest credit-based insurance scores was 1.7 times the amount they paid to customers with the highest credit-based insurance scores, down from paying nearly twice as much if no controls are included. Because the relationship is less strong when other variables are included, customers who appear more risky based on non-credit variables are also more likely to have lower credit scores. Nevertheless, even when non-credit variables are included in the analysis, credit-based insurance scores continue to predict the amount that insurance companies are likely to pay out in claims to consumers.

Figure 1 therefore shows that there is a relationship between credit-based insurance scores and the total dollar amount of claims that insurance companies paid. To refine this analysis, the FTC assessed whether customers with the lowest scores were likely to cause insurance companies to pay out more because the customers file more claims, file claims for higher amounts, or both. As shown by the darker (higher) lines in Figure 2, customers with lower scores filed substantially more claims than those with

[50] These other factors are controlled for by estimating a Tweedie GLM model of total dollars of claims using score deciles and all of the other risk factors. Modeling details and the other variables included in the models are discussed in Appendix C. Race, ethnicity, and income are not included at this stage of the analysis.

higher scores.[51] For instance, customers with the lowest credit-based insurance scores were about 1.7 times more likely to file a property damage liability claim as customers with the highest credit-based insurance scores. On the other hand, as shown in the lighter (lower) lines in Figure 2, the average size of the claims paid was nearly constant regardless of credit-based insurance score. The one exception is comprehensive coverage, which does show a relationship between claim size and score. The different result for comprehensive coverage may be attributable to a correlation between having a lower score and a higher probability of being a victim of automobile theft, because theft claims are larger than claims resulting from most other events that this type of insurance covers.

The underlying claims data presented in Table 2 (which are simple averages without controls for other risk factors) show the same patterns as those in Figures 1 and 2, and provide additional information on the absolute size of claims risk for different coverages and different score deciles. One important point that comes out in Table 2 is the difficulty of predicting the claims of individual customers. While the average number of claims per year in the lowest score decile of collision coverage, for example, was more than twice that in the highest decile, there were still only 12 claims per hundred cars per year of coverage for the lowest score decile. So, the vast majority of customers in even the riskiest decile would not file a claim in a given year. As with other risk variables, credit-based insurance scores are able to separate consumers into groups with different average risk, but cannot predict the claims of individual consumers.

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[51] The results for the frequency and severity of claims come from models that include controls for other risk variables. Modeling details and the other variables included in the models are discussed in Appendix C.

b. Other Data Sources

In addition to this analysis of the information in the FTC database, the Commission evaluated alternative and independent information to assess the relationship between credit-based insurance scores and risk. ChoicePoint Inc. collects data on claims from most major automobile insurance firms in the United States. The data allow insurance companies to learn whether a potential new customer has filed a claim under a previous policy with another firm, and then use that information in underwriting and rating. ChoicePoint refers to this data set as the Comprehensive Loss Underwriting Exchange ("CLUE").

We obtained the CLUE reports for each person in the FTC database for the period July 1995 – June 2003. This encompasses three time periods: (1) the five years prior to the period of the firm-submitted data; (2) the period of the firm-submitted data (July 2000 – June 2001); and (3) the two-year period following the period of the firm-submitted data. The data on claims prior to the firm-submitted data (*i.e.*, prior to July 2000) were used to construct controls in the risk models that the FTC ran.[52] The CLUE data also give us an alternative and independent source of data on claims to use to measure the relationship between credit-based insurance scores and claims.

Figure 3 shows the average dollars paid out for each decile on policies for each of the four main coverages studied.[53] Each panel includes average claims for three data

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[52] We used three years of prior claims data to construct the risk variables used in the risk models. The use of information on prior claims is an improvement over previously published analyses of credit-based insurance scores, which have not included controls for prior claims filed on policies with consumers' prior insurers.

[53] The results in Figures 1 and 2 are for a stratified sub-sample of the database. The stratification was based on which policies had claims in the company-provided data. The sub-sample is discussed in Appendix C. The results in Figure 3 are for the entire sample of 1.4 million policies. We use the full sample because the stratified sub-sample does not have sufficient information to reliably measure claims in the CLUE data for the six-month period starting July 1, 2001. The results shown on these graphs are not controlled for other (continued)

sources and samples: (1) claims in the data set we received from the firms; (2) claims in CLUE for the year over-lapping with the company data set (July 2000 – June 2001); and, (3) claims in CLUE for the six-month period following the company data set (July 2001 – December 2001).[54]

These results show a consistent pattern of average total dollars paid out on claims being higher for individuals with lower credit-based insurance scores. The relationship is generally similar across the data sources for the year of overlap, with the exception that it is somewhat weaker for bodily injury liability coverage.[55] For the six months starting July 1, 2001, the results vary for different types of automobile insurance coverage. Comprehensive coverage results look very similar in the two time periods. The overall slope is similar for bodily injury but the relationship is less stable. The relationship becomes much flatter in the later time period for collision coverage, and somewhat flatter for property damage liability. This may be evidence that credit-based insurance scores become less predictive of claims for these coverages as more time passes from when the scores were calculated.

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non-credit risk variables, because we do not have reliable information about those variables outside of the time period covered by the company data and because CLUE does not contain information at the car level. For the same reasons, we use the sum of the earned car years for each coverage on each policy when analyzing the CLUE data.

[54] We used a six-month period because we were concerned that information on the number of insured vehicles and coverage choices would become less reliable the further in time the data were from the data that the companies provided. We also measured claims for the six-month period starting July 1, 2001, for a sample of drivers limited to those who did not have any claims during the period covered by the company-provided data. This gave results for that time period that were very similar to the results for the full sample for that same time period.

[55] Given the time it can take for the full cost of bodily injury liability claims to be determined, this may affect how claims for bodily injury coverage are reported to the CLUE database.

B. Potential Causal Link between Scores and Risk

Thus, two different data sets, and previously published research, show that credit-based insurance scores are correlated with the total amount that insurance companies pay out on claims under automobile insurance policies.[56] The question that naturally arises is why a customer's credit history makes it more or less likely that he or she will suffer a loss and file an insurance claim. The FTC considered various proposed explanations of such a link and the data available bearing on those explanations. The information available, however, does not allow the agency to draw any broad or definitive explanations why there is a relationship between credit-based insurance scores and risk.

We emphasize that assessing the relationship between credit history and insurance risk necessarily involves addressing the attributes and circumstances *on average* of consumers with particular levels of credit-based insurance scores. Of course, these attributes and circumstances do not necessarily apply to each consumer with a particular level of score. People may have negative information on their credit histories for reasons that would seem to be totally unrelated to insurance risk. The starkest example is when the information is simply incorrect. Consumers also may wind up in financial distress for all sorts of reasons that have no bearing on how risky they are as drivers.[57] In addition, consumers may have credit histories that lead to low scores because of a lack of an extensive credit history. This may reflect societal effects like a lack of mainstream credit offerings where a consumer lives, or a lack of sophistication

[56] Section VII of this report contains the results of the FTC's successful efforts to build scoring models that are predictive of risk. The FTC's scoring model predicts risk in the company-provided claims data, and in the CLUE data for an entirely different set of people and a different time period. These results provide additional evidence that credit history information can be used to predict automobile insurance claims.
[57] *Hearing Before the New York State Assembly of Comm. on Ins.* (Oct. 22, 2003) (statement of Birny Birnbaum, Executive Director, Center for Economic Justice).

about mainstream credit markets. Again, it is not apparent that these types of circumstances should lead to higher insurance risk.

A strong credit history, however, might indicate that a consumer has taken care in managing his or her financial affairs – avoiding loans that might be difficult to repay, avoiding high balances on credit cards, making sure that bills are not misplaced and are paid on time, etc. A consumer who is prudent in financial matters may also be cautious in other matters related to insurance, such as being more likely to put time, effort, and money into things like car and home maintenance, cautious driving habits, etc. An overall inclination to be prudent may lead a consumer both to have a strong credit history and file fewer insurance claims.

There is ongoing research reflected in the behavioral economics literature that tends to show that people who engage in risky behavior in an area of their lives are often willing to take on more risk in other areas, as well. Researchers have studied attitudes toward risk, as well as behavior, in financial settings and driving, as well as a range of other areas including smoking, occupational choice, and migration.[58] One recent article argues that existing research shows that physiological and psychological factors affect how much risk individuals are willing to take in their financial, driving, and other behavior. Many of the psychological studies surveyed in that article analyze the relationship between psychological factors and risk-taking in a single aspect of life. The authors connect these results between financial behavior and driving from studies on separate groups of people, and posit the theory that credit-based insurance scoring works

[58] *See, e.g.*, Thomas Dohmen, et al., *Individual Risk Attitudes: New Evidence from a Large, Representative, Experimentally-Validated Survey* (Sept. 2005), *available at* http://ftp.iza.org/dp1730.pdf.

because scores reflect the psychological makeup of the individual in ways that affect insurance risk.[59]

Others have suggested that credit history provides information about a consumer's circumstances and those circumstances affect the likelihood or size of claims. One example is that a driver with a low credit-based insurance score may be in a distressed financial situation. This may cause stress that makes the consumer a less attentive driver.[60] Being in a distressed financial situation also might give the driver a greater incentive to try to obtain payment under an insurance policy. For example, he or she may be more likely to file a claim for a small amount of damage to an automobile rather than paying for those expenses out of pocket.

Another circumstance that could explain a correlation between credit-based insurance scores and risk of loss under automobile insurance policies is differences in the number of miles driven. The number of miles that a car is driven is directly related to automobile insurance risk, but companies find it difficult to capture information on "miles driven" with a great deal of accuracy. Consumers with lower scores may put more miles on their cars than consumers with higher scores. For example, consumers with lower scores may put more miles on their cars because they have more drivers per car in their household, they share cars with others, etc. If there is a link between credit-based insurance scores and number of miles driven, this could lead to a correlation between credit-based insurance scores and risk.[61]

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[59] Patrick L. Brackett and Linda L. Golden, *Biological and Psychobehavioral Correlates of Risk Scores and Automobile Insurance Losses: Toward an Explication of Why Credit Scoring Works*, 74 J. OF RISK AND INS. 23 (2007).
[60] *Id.*
[61] *See, e.g.*, Patrick Butler, *Driver Negligence vs. Odometer Miles: Rival Theories to Explain 12 Predictors of Auto Insurance Claims* (Aug. 9, 2006) (presented at the American Risk & Insurance
(continued)

As discussed above, a circumstance that could explain the relationship between credit-based insurance scores and risk under automobile insurance policies is differences in the resources that consumers put into maintaining their cars. Consumers with lower scores may not be willing or able to spend as much money to maintain their cars. This may, in turn, make the cars more dangerous to operate and lead to more or larger claims. If this were an important part of the explanation for the relationship between scores and risk, one would expect the relationship to be weaker for newer cars, which presumably would not have had the chance to develop maintenance-related safety problems.

The FTC used its database to test this hypothesis. We divided cars in our database into three groups: model years 1992 and older, model years 1993 – 1996, and model years 1997 and later. Using policy information from 2000 to 2001, we estimated the relationship between credit-based insurance scores and property damage liability risk separately for these three groups.[62] Figure 4 shows that credit-based insurance scores are strongly correlated with risk for each group, that is, the slope of the lines reveal that within each of the three model-year categories, consumers with lower scores pose a greater risk of loss than consumers with higher scores.

The relationship between credit-based insurance scores and risk was slightly stronger for the oldest cars. For the oldest cars, consumers with the lowest scores are 1.81 times riskier than consumers with the highest scores. By contrast, for the newest cars, consumers with the lowest scores are 1.68 times riskier than consumers with the highest scores, and for middle-aged cars, consumers with the lowest scores are 1.64 times

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Association Annual Meeting), *available at* http://www.aria.org/meetings/2006papers/butler.pdf.

[62] We used property damage liability because (unlike collision or comprehensive coverage) the size of claims does not depend on the value of the car covered by the policy. Car values will vary with model year, so using coverages where the size of claims varies with the value of the car would complicate the analysis.

riskier than consumers with the highest scores. Our results are weakly consistent with the hypothesis that some of the relationship is attributable to consumers with lower scores spending less to maintain their vehicles, but also show that difference in maintenance is not the primary cause of the relationship.

In short, many explanations have been offered as to why the characteristics or circumstances of consumers might account for the relationship between scores and risk. Little empirical data testing these possible explanations are available. The FTC tested one possible explanation for the relationship between scores and risk under automobile policies, and the results were weakly consistent with the hypothesis that some of the relationship could be attributable to the lower amount that consumers with lower scores may spend on maintenance. Although this result provides some insight, the information available does not allow the agency to draw any broad or definitive conclusions as to the reason that there is a relationship between scores and risk.

V. EFFECT OF CREDIT-BASED INSURANCE SCORES ON PRICE AND AVAILABILITY

Credit-based insurance scores are predictive of risk for automobile policies. Insurance companies therefore are able to use these scores to underwrite and rate policies in ways that correspond more closely to individual risk, on average. Enhanced accuracy results in decreased premiums for lower-risk consumers and in increased premiums for higher-risk consumers, and reduces the extent to which lower-risk consumers subsidize higher-risk consumers. Enhanced accuracy also may have broader effects in the marketplace. It may make insurance companies willing to offer policies to consumers posing a wider range of risk and it may reduce adverse selection among consumers.

A. Credit-Based Insurance Scores and Cross-Subsidization

Every insurance policy written for a consumer can be thought of as posing a true level of claims risk, that is, the expected cost to the insurance company of claims that the customer will submit. If the firm knew this true level of risk, it could base premiums on this risk. Because of practical limitations on the ability of firms to obtain and process information, they cannot determine the true level of risk that any particular consumer poses.[63] Instead, they must use the information available to them to estimate the expected claims cost for each consumer. Traditionally, insurance companies have divided customers into groups based on their characteristics and calculated expected average losses for the group, after which group members are charged premiums based on these expected losses.

Because the true expected claims costs will vary within any group of customers, some in the group will be paying premiums that are higher and others will be paying premiums that are lower than their own individual true expected claims cost. Those in the group with lower expected claims costs (*i.e.*, the lower-risk customers) subsidize those with the higher expected claims cost (*i.e.*, the higher-risk customers).[64] In the absence of perfect information about individual customer risks, there will always be some consumers in an insured group who subsidize other consumers in the group.[65]

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[63] Because insurers never have complete information about consumers, their estimates of expected claims costs are, at best, only correct on average; some estimates are over-estimates and others under-estimates. Such a situation is referred to as "imperfect information" about consumer risk.

[64] This is *ex ante* cross-subsidization (or, cross-subsidization "in expectation"). It is a distinct concept from *ex post* cross-subsidization. Inherent in the concept of insurance is *ex post* cross-subsidization, that is, customers who do not experience loss subsidize customers who do.

[65] Note that if information is symmetric between insurers and consumers (*i.e.*, they both have the same imperfect beliefs about expected claims costs), consumers will not know whether they are beneficiaries or contributors to the subsidization. Given that consumers do not know whether they are paying more or less

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Better risk prediction techniques allow insurance companies to more effectively separate higher-risk consumers from lower-risk consumers. This information assists insurance companies in charging consumers prices that correspond more closely to the true risk they pose, on average. This, in turn, decreases the premiums of lower-risk consumers and increases the premiums of higher-risk consumers, on average. Improved risk prediction techniques therefore reduce the extent to which lower-risk consumers subsidize higher-risk consumers.[66]

Even though improved risk prediction techniques will make firms' estimates of the riskiness of consumers on average more accurate, the predicted risk of some individual consumers may become less accurate. For example, there are some consumers who are very safe drivers but have low credit-based insurance scores. If scores are used, the predicted risk for these specific individuals will become less accurate. This result is unavoidable in any scheme used to make predictions about the risk consumers pose. Therefore, even if risk predictions become more accurate overall as additional predictive information is considered, there will always be some people who are much safer – or much riskier – than they appear.

The FTC analyzed the information in its automobile insurance database to estimate the extent to which the use of credit-based insurance scores (a risk prediction technique) could reduce cross-subsidization. Many of the premiums for policies included in the database were calculated without using scores, [67] and the data do not indicate

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than their true risk, their decisions will be unaffected by the existence of cross-subsidization.

[66] This is true even for customers of firms that do not adopt the more accurate prediction method, because those firms will wind up with a riskier and more homogenous pool of customers. Because the pool of customers is more homogenous, there will be less cross-subsidization within that group of consumers.

[67] E-mail from Rick Smith, Towers Perrin, to Jesse Leary, Assistant Director, Division of Consumer Protection, Bureau of Economics (Apr. 13, 2005) (on file with FTC).

which policies these were. The FTC database contains information from 2000-2001, shortly after the introduction of scores. As discussed above, scores typically are used in determining the premiums to be charged to *prospective* customers. Customers who renewed their policies during 2000-2001 thus were not likely to have had scores used to determine their premiums. In addition, although by 2000 insurance companies were using scores to determine premiums in many states, their use was not universal. Accordingly, many, and probably most, of the premiums charged to consumers during this period of time were determined without the use of credit-based insurance scores.

Because most of the premiums in the database likely do not reflect the use of credit-based insurance scores, the FTC used risk, measured in expected total dollars of claims, as a substitute for premiums in an analysis of the effects of scores. We believe that this calculation of risk is a reasonable substitute for premiums in this context, because the premiums that an insurance company charges consumers in a competitive marketplace should be roughly proportional to the risk they appear to pose.[68]

The FTC used a three step analysis to evaluate how expected risk changes if insurance companies consider credit-based insurance scores. The first step was to use a model to calculate a predicted dollar risk for each consumer using all risk factors in the database, except score.[69] The second step was to calculate a predicted dollar risk for each consumer using all risk factors plus a score. Both of these steps to calculate predicted

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[68] Some industry participants have stated that homeowners and automobile insurance markets are fiercely competitive. *See, e.g.*, Comment from State Farm Ins. Co. to FTC at 3-4 (Apr. 25, 2003) [hereinafter State Farm Comment], *available at* http://www.ftc.gov/os/comments/FACTA-implementationscorestudy/514719-00100.pdf; Comment from the American Ins. Ass'n to FTC at 14 (Apr. 25, 2005) [hereinafter AIA Comment], *available at* http://www.ftc.gov/os/comments/FACTA-implementationscorestudy/514719-00084.

[69] This was done using a Tweedie GLM model. Modeling details are provided in Appendix C. Race, ethnicity, and income were not considered at this stage of the analysis.

dollar risk were conducted separately for property damage liability, bodily injury liability, collision, and comprehensive coverage.[70] The third and final step was to sum the predicted dollar risks for all four types of insurance coverage with and without the use of credit-based insurance scores.[71] This produced two estimates of total risk for each insurance policy in the database: an estimate without using a score, and an estimate using a score.

The FTC's analysis predicts that the use of credit-based insurance scores redistributes premium costs from consumers with higher scores to those with lower scores.[72] This is a zero-sum calculation: the total increases in premiums predicted if scores are used must be exactly the same as the total decreases in premiums predicted.

Figure 5 shows the results of the FTC's analysis of the effect of credit-based insurance scores on changes in premiums. It shows what share of consumers would be predicted to have changes of different sizes. Figure 5 also reveals that if credit-based insurance scores are used, more consumers (59%) would be predicted to have a decrease in their premiums than an increase (41%).

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[70] We also conducted this analysis using a single-equation model of all coverages, instead of separate models by coverage. As discussed in Appendix F, this yielded similar results.

[71] This approach uses the actual coverage choices of individuals. That is, we predict claims cost for individuals only for the coverages they had, and measure the change in their total predicted claims for those coverages. This has the advantage of taking into account the real choices people made when purchasing insurance, but the disadvantage of not allowing for the possibility that individuals would change their coverage choices in response to changing premiums. To generate the overall distribution of changes, we weighted consumers by the earned car years on their property damage liability coverage.

[72] We emphasize that this is not a measure of how firms are actually using scores to price consumers. Scores are not used to underwrite or rate all customers, especially existing customers. In addition, firms may not adjust premiums in response to scores as much as our analysis would predict. For these two reasons, this exercise may overstate the redistributive effects of using scores. The fundamental assumption of the analysis, that premiums will be proportional to predicted risk, is likely to be violated in the short-term, especially if existing customers are not fully re-underwritten and re-rated every year. In sum, this approach probably overstates the redistributive effects to date of using scores, but should be a reasonable substitute for the long-term effects of using scores.

The increased premiums for consumers whose premiums would rise are larger than the decreased premiums for those whose premiums would fall. This can be seen in the longer "tail" on the right-hand side of the graph, which shows larger changes in the direction of an increase. The median increase for those with an increase in predicted risk is 16% (*i.e.*, one-half the increases in predicted risk are greater than 16% and one-half are less than 16%), while the median decrease is 13%.

1. Possible Impact on Car Ownership

If using credit-based insurance scores results in consumers paying premiums that are closer to the true risk that they pose, this could result in car owners incurring costs closer to the real costs of owning and operating their cars. Internalizing these costs could affect consumer decisions whether to own cars, thus resulting in more efficient car ownership.

If consumers decide how many cars to own based on the benefits and costs of car ownership, their decisions can be said to be "efficient" in that they will choose to own cars only when the benefits are at least as great as the costs. If consumers pay premiums that are lower than the risk they actually pose, they will own more cars than is efficient, because other people are helping to pay for the cost of their driving.[73] And, if consumers pay premiums that are higher than the risk they pose, they will own fewer cars than would be efficient, because they face costs higher than the true total costs of their driving. The use of credit-based insurance scores to charge premiums that more accurately reflect

[73] This is a classic "negative externality." Negative externalities arise any time consumers or businesses pay costs for a product that are less than the costs to society. Because societal costs are not considered in the decision of consumers or businesses, their decisions will be inefficient for society.

the true cost of driving, on average, thus could lead to a more efficient level of car ownership.

The FTC was not able to determine whether and to what extent credit-based insurance scores have an effect on automobile ownership. We are not aware of information addressing specifically how much of an increase or decrease in the cost of driving will cause consumers to decide whether to own a vehicle.[74] Moreover, even if we were able to determine the effect of insurance scores on car ownership, this study does not assess whether such an outcome would be equitable.

2. Possible Impact on Uninsured Driving

Using credit-based risk scores to determine premiums also could have an effect on the number of drivers who drive without insurance. Although most states have requirements that drivers carry specified minimum amounts of liability insurance, there are still significant numbers of drivers who drive without insurance. Raising premiums of drivers with lower scores could lead to more of them driving without insurance. Lowering premiums of drivers with higher scores could lead to fewer of them driving without insurance. Whether the use of scores on balance leads to more or fewer people driving without insurance depends on which of these two effects is greater.[75]

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[74] Even though there is published work on the effects of prices on new car sales, *see, e.g.,* Patrick S. McCarthy, *Market Price and Income Elasticity of New Vehicle Demands*, 78 REV. OF ECON. AND STATS. 543 (1996), we are not aware of studies that measure the effect of the cost of insurance on the number of cars that households choose to own.

[75] Although it is not obvious which change would be larger, there is strong intuition that suggests people with higher scores are relatively less likely to be driving without insurance even when scores are not used to determine premiums. This would be true if scores were correlated with wealth or if scores were a measure of caution or responsibility. The value of liability insurance to an individual depends in part on that individual's wealth, because people with very little wealth may be nearly "judgment proof," and therefore face very little effective risk from liability claims. A company that issues a policy, however, is liable up to the policy limits. So, liability insurance may be worth less to a low-wealth driver than it costs,
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The FTC sought to estimate the impact of credit-based insurance scores on the prevalence of consumers driving without insurance. It is difficult to obtain reliable data concerning the number or share of drivers who drive without insurance, because this conduct is illegal in most states. In an effort to derive such an estimate, the FTC compared the number of uninsured motorist claims relative to other claims filed during 1996 to 2003 (*i.e.*, when credit-based insurance scores were becoming more widely used) for states in which these scores were used and in states in which they were not.

We assessed how often consumers filed uninsured motorist claims relative to how often they filed bodily injury claims and property damage liability claims. Figure 6 shows that the number of uninsured motorist claims filed compared to the number of bodily injury claims filed increased in states where credit-based insurance scores were allowed, but decreased slightly in states where they were not.[76] Figure 6 also shows the number of uninsured motorist claims filed compared to the number of property damage claims filed was basically unchanged in states where scores were allowed and decreased somewhat in states where they were not.

These results are consistent with the hypothesis that scores, because they raise the premiums of some consumers, cause a larger share of consumers to drive without insurance[77] and/or more risky consumers to drive without insurance.[78] These results,

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because – if uninsured – the driver would have to pay out less to cover others' losses from an accident than would the insurance company if the drivers bought insurance.

[76] The states identified as not allowing the use of scores during the relevant period of time are California, New Jersey, Massachusetts, and Hawaii. Because of limitations in the data, Texas and South Carolina are not included in either group.

[77] If reduced cross-subsidization leads to more consumers driving without insurance, this could actually lead to lower overall losses from accidents. Research shows that the effect on accidents of requiring drivers to buy liability insurance in order to operate a car legally is unclear. Some drivers may choose not to purchase insurance and then either not drive or drive less often or more carefully, to avoid detection, leading to fewer accidents. Other drivers may purchase insurance they otherwise would have foregone, and then drive more often or more riskily, because they no longer bear the liability risk of causing an accident,

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however, should be treated with caution. First, the relative change between the groups of states took place during the period 1997 – 2000. While scores were becoming widely used during this period, credit-based insurance scoring had probably not yet affected most consumers' premiums, given that insurance companies generally do not use scores when renewing customers. Perhaps more importantly, the FTC's analysis could be affected by any state-specific changes in insurance markets. Because the number of states not allowing the use of credit-based insurance scores for automobile insurance was small (California, Hawaii, Massachusetts, and New Jersey), any such changes could render them unreliable as a comparison group. In addition, because the analysis relies on uninsured motorist claims to indirectly measure the level of driving without insurance, differences over time in which consumers carried uninsured motorist coverage in states which allow the use of scores and those that do not could affect the results.

3. Adverse Selection

Credit-based insurance scores also may make insurance markets more efficient if they decrease the extent to which consumers make insurance purchasing decisions using better risk information than that available to insurance companies. In a competitive market, insurers will offer prices to groups of consumers reflecting the average expected risk of loss for each group. But if a consumer has better information than the insurance

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leading to more accidents. One study has reported that the latter effect predominates over the former effect. Alma Cohen and Rajeev Dehejia, *The Effect of Automobile Insurance and Accident Liability Laws on Traffic Fatalities*, 47 J. OF LAW AND ECON. 357 (Oct. 2004).

[78] If these results do reflect effects of credit-based insurance scores, they could have the indirect effect of mitigating some of the savings that higher-score drivers get from the use of scores. If more higher-risk drivers are uninsured, this could increase the expected cost of uninsured motorist claims that insured drivers submit under their policies. In turn, this could increase the premiums that insurance companies must charge lower-risk consumers to cover these increased uninsured driver claims. Accordingly, even these increases in the cost of uninsured motorist coverage may offset somewhat the decrease in premiums that higher-score consumers receive from the use of scores.

company about his or her own true expected risk of loss, he or she will know whether the group price is higher or lower than his or her true expected claims cost. The consumer may use this superior knowledge to determine whether and how much insurance to purchase, a phenomenon known as "adverse selection."[79]

Adverse selection may be occurring if higher-risk consumers are more likely to have insurance or more complete coverage than lower-risk consumers. A higher-risk consumer who realizes that he or she is being charged a price that is lower than his or her actual risk of loss cost will have an incentive to purchase more insurance coverage.[80] A lower-risk consumer who realizes that he or she is being charged a price higher than his or her actual risk of loss will have an incentive to purchase less insurance coverage.[81] If higher-risk consumers purchase more insurance coverage and lower-risk consumers purchase less insurance coverage, the average risk of the group of consumers who do buy insurance will be higher. Premiums then would have to increase for insurance companies to cover the total claims costs, providing a further disincentive for lower-risk consumers to purchase insurance. If consumers know more about the risk of loss they pose than

[79] The discussion here is of market-wide adverse selection, where consumers know more about their risk than any firm does. A firm competing in an insurance market can face another form of adverse selection if one of its competitors is able to do a better job of predicting risk and entices away low-risk customers while leaving behind high-risk customers. *See* State Farm Comment, *supra* note 66, at 8.

[80] It is conventional wisdom in the insurance industry, however, that the riskiest drivers are those who choose to buy the least amount of coverage possible, and would buy no insurance if it were not legally required. This conventional wisdom probably reflects, at least in part, that the "riskiest drivers" in question are riskiest based on characteristics that are used to underwrite and rate policies, like driving history, and they are charged the highest rates. If these drivers really are very risky, simple theory would predict that they would still be willing to pay very high rates. Explanations for why these drivers would be unwilling to buy insurance at rates that reflect their true risks could include: that the drivers have very limited assets and are therefore "judgment proof," and therefore face less actual risk than the firm would face; that these drivers are less risk-averse than other drivers, or even risk-loving, and therefore unwilling to buy insurance at market rates; that the drivers believe themselves to be less risky than firms judge them to be; or that the drivers are cash-constrained, and do not buy insurance even though they would rather have the insurance than face the risk of a large loss.

[81] A consumer may do this by purchasing a policy with large deductibles or low liability limits, by not purchasing certain types of coverage, or by not purchasing insurance at all.

insurance companies, it therefore can affect insurance purchasing decisions in ways that cause economic inefficiency.[82]

If scores allow insurance companies to predict risk more accurately, it could decrease the difference between what consumers and insurance companies know about the risk that individual consumers pose. Insurance companies therefore would be able to charge consumers premiums that more accurately reflect the true risk. This would reduce the incentive of higher-risk consumers to purchase more insurance and lower-risk consumers to purchase less. Accordingly, scores may reduce the extent of adverse selection and make insurance markets more efficient.[83]

The FTC considered whether adverse selection exists in automobile insurance markets in the United States.[84] It seems unlikely that consumers have better information about the risk they pose than do insurance companies. Although consumers might have some sense of how much risk they pose based on their own experience, it seems unlikely that this sense is more accurate than the assessment insurance companies can make.

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[82] Insurers who realize that adverse coverage selection is occurring may attempt to separate the higher- from the lower-risk consumers by offering different price-coverage combinations. One theoretical analysis suggests that under some conditions, this approach can reduce the inefficiency caused by adverse selection. Michael Rothschild and Joseph Stiglitz, *Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information*, 90 THE Q. J. OF ECON. 629 (Nov. 1976). In fact, firms do offer different deductible choices, which could be a mechanism for separating high-risk and low-risk customers. It may also be a pricing response by firms to differing levels of risk-aversion among customers.

[83] The American Insurance Association has stated that an insurance company found that, after introducing the use of credit-based insurance scores, "there is some evidence that higher limits of liability coverage *and* lower physical damage deductibles are being purchased…" AIA Comment, *supra* note 66, at 14 (emphasis in original). This would be consistent with a reduction in adverse selection resulting from the use of scores.

[84] Empirical studies have found only limited evidence for adverse selection in automobile markets in other countries, and even then only in very special circumstances. *See* Alma Cohen, *Asymmetrical Information and Learning: Evidence from the Automobile Insurance Market*, 87 REV. OF ECON. AND STATS. 197 (May 2005) (finding evidence that lower risk drivers in Israel purchased less insurance coverage than higher risk drivers, but only for experienced drivers for a limited period of time after switching policies and in a country in which insurance companies do not share data on prior claims); Pierre-Andre Chiappori, et al., *Asymmetrical Information in Insurance: General Testable Implications*, (Feb. 24, 2004) (finding no evidence that lower risk drivers in France bought less insurance than higher risk drivers), *available at* http://www.iue.it/FinConsEU/papers2004/salanie.pdf.

Specifically, companies make their assessment also using information about the consumer's past experience, such as extensive prior claim information included in a database that insurance companies share and public record information, such as convictions for driving while intoxicated or speeding.

Moreover, even assuming that consumers have better knowledge than insurance companies of the risk they pose, there are significant limitations on the extent to which consumers can use this advantage to alter their insurance purchasing decisions. Most states mandate minimum liability coverage for cars, and lenders typically require even greater coverage on cars they finance. Even though consumers retain some ability to make choices concerning insurance coverage, such as deductibles and limits, these choices are limited considerably.[85]

The FTC analyzed its automobile insurance database to test whether there was any indication that adverse selection may be occurring. We found that lower-risk drivers tend to have policies with higher deductibles than do higher-risk drivers, that is, lower-risk drivers have less insurance coverage than higher-risk drivers. This is consistent with (but does not prove) adverse selection is occurring in automobile insurance markets.[86]

If credit-based insurance score information is considered in the analysis, *i.e.*, the risk information available to insurance companies relative to consumers is enhanced, then adverse selection would be expected to decrease. However, when the FTC considered scores in its analysis, lower-risk drivers were still found to have insurance

[85] It is clear that adverse selection experienced by a single firm can be a powerful force. When different firms have significantly different risk prediction technology, consumers will see the different prices charged and will tend to choose the firms with lower premiums. This can lead to a negative-feedback loop that can even cause a firm to collapse.
[86] One alternative explanation is moral hazard. If people with more complete coverage take less care, because they bear less of the cost of any accident or other damage or loss, this would result in the same relationship.

policies with higher deductibles than higher-risk drivers. This suggests that adverse selection may not be occurring, or, if it is occurring, then scores may not reduce it.

B. Other Possible Effects of Credit-Based Insurance Scores

Innovations in risk prediction techniques like credit-based insurance scores may affect the availability of insurance and some of the costs associated with selling insurance. First, some consumers may have a broader range of options to choose from when purchasing insurance. Because credit-based insurance scores predict risk more accurately for consumers, insurance companies now may be willing to offer coverage to some higher-risk consumers. In addition, credit-based insurance scores may make the process of underwriting and rating quicker and cheaper, and competition between insurance companies may cause cost savings from these process improvements to be passed on to consumers in the form of lower premiums.

Insurance companies and industry representatives stated that the use of credit-based insurance scores gives firms greater confidence in their ability to predict the risk that consumers pose. That is, if firms have more confidence in their risk estimates, they may be able to offer insurance to customers for whom they would otherwise not be able to determine an appropriate premium. The American Insurance Association, for example, has stated "(m)ore precise pricing enables insurers to accept greater risk by ensuring that both good risks and more marginal risks are properly priced to reflect the exposure they represent."[87] Several firms, including The Hartford and MetLife Home and Auto, have stated that the use of credit-based risk scores enabled them to offer

[87] AIA Comment, *supra* note 66, at 4.

policies to higher-risk consumers than they had previously.[88] This could lead to higher-risk consumers having more choices as they shop for insurance. No data, however, were submitted or obtained to assess the extent to which credit-based insurance scores actually have expanded insurance choices for higher-risk consumers.

In addition, several insurance companies and score developers emphasized that the use of scores can save costs. Specifically, they asserted that the use of scores facilitates automation, speeds up policy underwriting and rating, and otherwise reduces the costs of underwriting and rating.[89] No data was submitted or obtained to allow the FTC to develop reliable estimates of cost-savings associated with credit-based insurance scores. Assuming that there are such savings, the FTC would anticipate that competition in the market for automobile insurance would result in these savings being passed on to consumers in the form of lower prices.

Further, banning the use of factors that are known to be correlated with risk could have negative effects on insurance markets. If firms cannot adjust prices based on the risk associated with a characteristic, they will have an incentive to refuse to offer policies to people with the characteristic.[90] If the law prohibits firms from refusing to sell policies to people with that characteristic, they will still have an incentive to try to avoid insuring them. This could cause firms to expend resources on finding ways to avoid higher-risk consumers, reducing the availability of insurance to higher-risk consumers and making otherwise profitable distribution channels untenable.

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[88] Meeting between FTC staff and The Hartford (July 14, 2004); Meeting between FTC staff and MetLife Home and Auto (July 12, 2004); Meeting between FTC staff and USAA, (July 14, 2004). *See also* AIA Comment, *supra* note 66, at 7-8; NAMIC Comment, *supra* note 20, at 6-7.
[89] AIA Comment, *supra* note 66, at 12; Fair Isaac Comment, *supra* note 18, at 15; State Farm Comment, *supra* note 66, at 4.
[90] *Id*. at 10.

A simple example illustrates the possible impact of banning the use of a characteristic in making the decision whether to offer insurance to consumers. Assume that geographic location is correlated with risk on insurance policies[91] and that firms are allowed to refuse to sell insurance based on geography but are not allowed to charge different prices based on geography. This would give insurance companies an incentive to refuse to sell policies to people living in riskier areas.[92] If firms could not outright refuse to sell policies based on geography, and could not charge different prices based on geography, they would have an incentive to use other means to avoid insuring those who live in more risky geographic areas, for example, not establishing offices, working with independent agents, or advertising in these locations.

It is not clear, however, whether banning the use of credit-based insurance scores would lead to distortions of the insurance market like those associated with banning the use of geography. An insurance company does not see a consumer's score until he or she applies for insurance coverage. It therefore would be difficult for insurance companies to directly avoid selling insurance to consumers with low scores. There may be, however, different marketing approaches, such as alternative types of advertising, which bring in consumers with different average scores. If firms cannot use scores to underwrite or rate, they would have an incentive to market only through channels that bring in consumers with higher scores. This could reduce the availability of information about insurance options, particularly to consumers with lower insurance scores. No data was submitted or obtained, however, to permit the FTC to determine whether restrictions on the use of scores actually would have this type of effect.

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[91] *Id*.

[92] Firms might specialize geographically, with firms with higher premiums offering policies everywhere but mainly getting customers from high risk areas, while lower-cost firms refuse to write in high-risk areas.

Banning credit-based insurance scores may also give firms greater incentives to invest in developing other risk-prediction tools. If the use of scores is banned, firms may have an incentive to spend more on developing new risk variables to capture some of the same risk prediction benefits of scores.[93] This could be seen as an unnecessary societal cost, given that scoring technology has already been developed and scores are a fairly low-cost risk prediction technique.

C. Effects on Residual Markets for Automobile Insurance

The introduction and growth in the use of credit-based insurance scores has taken place during a time when one particular measure of the functioning of the market, the share of consumers buying insurance through state-run "residual markets," indicated the market was working well. All states run some type of program to allow consumers to purchase automobile insurance when they are unable to find a private firm willing to sell them policies voluntarily.[94] To avoid attracting consumers who could otherwise obtain private insurance coverage, these state-run programs typically charge higher prices than private insurance companies.

Figure 7 shows the share of automobile policies that were purchased through state-run programs during the years 1996 – 2003, broken down by states that allow the use of credit-based insurance scores, and those that do not.[95] It shows that a larger share of consumers participated in these programs in the states that did not allow the use of

[93] *See* Cheng-Sheng Peter Wu, Deloitte and Touche, *What to do When You Cannot Use Credit* (Sept. 2000) (presentation at the CAS Special Interest Seminar), *available at* http://www.casact.org/education/specsem/f2005/handouts/credit.ppt.
[94] *See* https://www.aipso.com/about.asp.
[95] The states identified as not allowing the use of scores during the relevant period of time are California, New Jersey, Massachusetts, and Hawaii. Because of limitations in the data, Texas and South Carolina are not included in either group.

scores. However, this was true both before and after the introduction of scores, and therefore this difference in levels of participation presumably reflects other differences between states. Figure 7 shows that the state-run program share fell during the second half of the 1990s, as score were being introduced, and then leveled off after 2000. The pattern is nearly identical in states that allowed the use of scores and states that did not. Therefore, Figure 7 is probably best interpreted as meaning that scores at least did not interfere with the smooth functioning of automobile insurance markets.

VI. EFFECTS OF SCORES ON PROTECTED CLASSES OF CONSUMERS

FACTA requires that the FTC analyze the extent to which the use of credit-based insurance scores affects the availability and affordability of insurance for members of certain categories of consumers. The statute mandates that the Commission consider the impact of these scores on categories of consumers based on race, ethnicity, national origin, geography, income, religion, age, sex, and marital status. In particular, the agency was instructed to assess whether scores act as a proxy for membership in these groups.

In fulfilling the statutory mandate, the FTC focused its analysis on the effect of credit-based insurance scores on consumers in different racial, ethnic, national origin, and income groups. The Commission did not focus its assessment on consumers in different religious groups because we are not aware of any reliable data relating scores to religious affiliation. In addition, the FTC also did not focus its analysis on consumers in different geographic, age, sex, and marital status groups. In most locations in the United States, insurance companies can and do use geography, age, sex, and marital status directly in determining automobile insurance premiums.[96] While credit-based insurance scores may vary based on these factors, the direct effect of using these factors to price insurance far outweighs any indirect effects these factors may have through their impact on scores. The FTC therefore did not try to measure any such indirect effects.

A. Credit-Based Insurance Scores and Racial, Ethnic, and Income Groups

1. Difference in Scores across Groups

The FTC analyzed whether there was a relationship between credit-based insurance scores and race, ethnicity, national origin, and income. In undertaking this analysis, the Commission first reviewed and considered prior research. In 1999, the Virginia State Corporation Commission's Bureau of Insurance issued a report assessing the relationship at the ZIP code level between scores and race as well as between scores and income.[97] The report stated that "nothing in (our) analysis leads the Bureau to the conclusion that income or race alone is a reliable predictor of credit scores." Nevertheless, the absence of more detailed information about the results of this study leaves unclear the relationship between scores and race and income.

The State of Missouri Department of Insurance released a study in 2004 that relied on similar data.[98] The Missouri study used ZIP-code level data on scores and race, income, and other demographic variables. The scores analyzed were credit-based insurance scores that twelve large insurance companies used for automobile or

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[96] While the use of income to underwrite policies or set rates may not be expressly prohibited in some locations, it appears to be generally regarded as an illegitimate variable for those purposes.

[97] Report of the State Corp. Comm'n's Bureau of Ins. to the Sen. Commerce and Labor Comm. of the Gen. Assemb. of Va., *Use of Credit Reports in Underwriting* (1999) [hereinafter Virginia Study].

[98] Brent Kabler, Ph.D., *Insurance-Based Credit Scores: Impact on Minority and Low Income Populations in Missouri* (Jan. 2004) [hereinafter Missouri Study], *available at* http://www.insurance.mo.gov/reports/credscore.pdf.

homeowners policies. The Missouri study found that scores were correlated with the racial, ethnic, and income characteristics of ZIP codes. Specifically, as the proportion of racial and ethnic minorities or lower-income consumers in a ZIP code increased, scores decreased.[99] These correlations remained after controlling for education, marital status, and housing values.

Unlike prior researchers, the Texas Department of Insurance (TDI) in its 2004 study moved beyond aggregate data and obtained data about individuals to analyze the relationship between scores and race, ethnicity, and income. The TDI used automobile and homeowners policy data from six large insurance companies. The TDI obtained race data for each consumer from the Texas Department of Public Safety and ethnicity data for each consumer from a Hispanic surname match. The TDI used median income for the ZIP code in which consumers lived, because individual income information was not available.

The TDI's analysis of this data showed that African Americans and Hispanics tended to have lower scores than Asians and whites.[100] It revealed mixed results for income. For some insurance companies, consumers in higher-income areas had higher scores, while this was not the case for other insurance companies. It is not clear whether these different results for income reflect differences in the credit scoring models that the insurance companies used, or in the mix of customers at each firm.

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[99] An attempt was also made in the Missouri study to use the ZIP code level data to draw inferences about individual-level differences in credit scores by race and income. The results of this analysis were more speculative, but did demonstrate that it would be very unlikely that the differences found at the ZIP code level could have been found if there were no differences at the individual level.

[100] The TDI characterized the scores in this way: "In general, Blacks have an average credit score that is roughly 10% to 35% worse than the credit scores for Whites. Hispanics have an average credit score that is roughly 5% to 25% worse than those for Whites. Asians have average credit scores that are about the same or slightly worse than those for Whites." 2004 Texas Report, *supra* note 41, at 13.

After reviewing the prior research, the FTC analyzed the information in its own automobile insurance database to assess the relationship between scores and race, ethnicity, national origin, and income. Figure 8 shows how non-Hispanic whites, African Americans, Hispanics, and Asians are distributed across the range of scores. The horizontal axis shows score deciles, and the vertical axis shows the share of each group that falls in each decile. The deciles are defined using the overall distribution of scores. If a group had the same distribution of scores as the overall sample, then 10% of that group's population therefore would fall in each of the ten deciles.

Figure 8 shows that non-Hispanic whites and Asians are fairly evenly distributed across the score range, resulting in a roughly flat line near 10%. In contrast, African Americans and Hispanics are strongly over-represented in the lowest deciles and under-represented in the highest deciles. For example, 26% of African Americans are in the group with the lowest 10% of credit-based insurance scores, while only 3% are in the highest 10% of scores. Similarly, 19% of Hispanics are in the group with the lowest 10% of scores, and 5% are in the highest 10% of scores.

Another way of measuring these differences is to look at where the median person[101] for each racial or ethnic group falls in the overall distribution of scores. If scores were distributed identically across racial and ethnic groups, the median score for each group would equal the overall median – the 50th percentile. The FTC's data show that the median scores for non-Hispanic whites and Asians are quite similar to that of the overall sample, with the median score for non-Hispanic whites and Asians falling in the 54th and 52nd percentile, respectively. In contrast, the median scores for the African

[101] One-half of the group will have a score lower than the median person and one-half will have a score higher than the median person.

Americans and Hispanics are much lower, with the median scores of African Americans and Hispanics falling in the 23rd and 32nd percentile, respectively. So, more than one-half of all African Americans have credit scores in the lowest quarter of the overall score distribution, and one-half of all Hispanics have credit scores in the lowest third of the overall score distribution.

Figure 9 presents an alternative way of viewing these differences. It shows the racial and ethnic makeup of each decile in the score distribution, which varies considerably across the range of scores. Because non-Hispanic whites make up such a large share of the populations, they are a majority in every score decile. But, as Figure 8 shows, African Americans and Hispanics are heavily over-represented in the lower score deciles.

In addition to race and ethnicity, the FTC examined the relationship between scores and national origin. To assess this relationship, the Commission compared scores for foreign-born consumers with those of consumers born in the United States. The scores for consumers born outside the United States were slightly lower than those of consumers born in the United States, with the median score of the foreign-born consumers falling in the 44th percentile of all scores.

The FTC also compared the scores for recent immigrants and other consumers.[102] Recent immigrants have scores that are slightly lower than other immigrants and lower than consumers overall, with the median score for recent immigrants falling in the 39th percentile of all scores. We found that recent immigrants whose information is included

[102] The FTC database does not contain information on the actual date of anyone's arrival in the United States. For this reason, recent immigrants were defined as people who first applied for a Social Security card during the previous ten years, and who were 30 years old or older at the time of the sample. These restrictions were an attempt to limit "recent immigrants" to people who arrived in the United States as adults.

in the FTC database were much more likely to be Hispanic or Asian than consumers born in the United States. This makes it complicated to evaluate and describe the relationship between scores and race or ethnicity apart from the effect of national origin. Because race and ethnicity are associated with much larger differences in scores than national origin, the Commission focused its further analysis on race and ethnicity.

Finally, the FTC study evaluated the relationship between scores and income. The Commission did not have access to information about the income of the particular consumers in its database. The FTC instead used the median income of the United States Census tract in which consumers live to divide them into low-to-moderate income, middle income, and high-income neighborhood groups. [103] Figure 10 shows the share of people in each income category in each decile of the distribution of scores. Low-to-moderate income consumers are somewhat over-represented in the lower score deciles, with 15% of these individuals in the lowest 10% of scores, and only 8% in the highest 10% of scores. Middle-income consumers are essentially evenly distributed across the distribution of scores. High-income consumers are under-represented in the lowest 10% of the score distribution, but otherwise fairly evenly distributed. Figure 11 shows the income breakdown of each score decile. Again, it shows that there is some relationship between neighborhood income and score.

The results for the FTC's database show that as income increases, scores tend to increase. These results, however, are much weaker than the results for race and ethnicity.

[103] This approach follows methods used to analyze income in FRB studies of mortgage markets. The groups were: (1) Low-to-moderate income: Tract median < 80% of MSA median income; (2) Middle income: Tract median >= 80% of MSA median income and <%120 of MSA median income; and (3) High income: Tract median >= %120 of MSA median income. As discussed in Appendix F, we have also done much of the analysis using absolute median income, instead of income relative to the MSA, and the results are not qualitatively different.

This may be because the relationship between score and income actually is weaker, or it may simply be the result of only having data on income at the neighborhood level.

2. Possible Reasons for Differences in Scores across Groups

As discussed above, the FTC's analysis shows a relationship between credit-based insurance scores and race, ethnicity, and, to a lesser extent, income. The Commission examined other information in its sample to determine what factors could account for differences in scores among racial and ethnic groups. The FTC's database contains some information on factors that could explain some of the differences in scores among racial and ethnic groups. Specifically, it includes information on the median income of the neighborhood in which each consumer lives, and consumers who live in lower-income neighborhoods tend to have lower scores. It also contains information from which the age of the consumers whose score is in the database can be inferred,[104] and older consumers tend to have higher scores. Finally, the FTC's database contains information about the gender of the consumers whose score is included (the "first named insured" on the policy), and men in the FTC database tend to have higher scores than women, although the difference in average score between men and women in the FTC database cannot be generalized to the overall population.[105]

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[104] For single-driver households, we know the age of the person for whom we have a credit score. For multi-driver households, we need to make an assumption about whose age we have. We do this in several ways. From Social Security Administration ("SSA") data, we know the gender of the person whose credit score we have. If there is only one driver in a household with that same gender, we assume that person is the person for whom we have a credit score. If there are multiple people whose gender matches the SSA data, we take the oldest, on the assumption that that person is most likely to be the first named insured.

[105] We have a score for only one person covered by each policy. From examining our data, it is apparent that in households with male and female adults (*e.g.*, married couples), it is most often the male driver who is the first named insured, and therefore the person for whom we have a score. About 75% of multi-driver policies have a male first named insured, while the split for single-driver policies is 50/50. So, it appears that the men for whom we have scores are much more likely to be married than the women for whom we

(continued)

Table 3 presents median neighborhood income, age, and gender for racial and ethnic groups for consumers whose information is in the FTC database. It shows that African Americans and Hispanics live in neighborhoods with lower median incomes than non-Hispanic whites and Asians. It reveals that Hispanics and Asians are younger than non-Hispanic whites and African Americans. It further shows that the African-American customers in this sample are much more likely to be female than are customers in other racial and ethnic groups.[106] All of these differences are consistent with African Americans and Hispanics having lower credit scores.

Figure 12 shows the distribution of scores by race and ethnicity after controlling for neighborhood income, age, and gender of the person scored. It shows that large differences remain in the distributions of scores across racial and ethnic groups, and that these differences are only slightly smaller than they were prior to controlling for these factors.[107] In particular, prior to controlling for these factors, the median score for African Americans and Hispanics was in the 23rd and 32nd percentiles, respectively. After using these controls, the median score for African Americans and Hispanics rose to the 27th and 37th percentiles, respectively. In short, consideration of neighborhood income, age, and gender explains only a small part of the difference in credit-based insurance scores between racial and ethnic groups. It is not clear what explains the rest of the difference.

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have scores. The differences in score by gender in the FTC database, therefore, cannot be interpreted as the difference in scores that would be observed between all men and all women, because they also reflect differences in credit score by marital status and household size.

[106] Recall that age and gender, like score, are for the customer who was the "first named insured" on a policy.

[107] It is our understanding that the Federal Reserve Board is undertaking a similar analysis using a richer set of data about each individual.

3. Impact of Differences in Scores on Premiums Paid

a. Effect on Those for Whom Scores Were Available

The FTC assessed the implications of the differences in credit-based insurance scores for the premiums that members of different racial and ethnic groups would be predicted to pay. As discussed above, the FTC database can be used to predict differences in claims risk with and without the use of scores. These differences, in turn, can be used to estimate the effects of scores on expected insurance premiums for racial, ethnic, and income groups.

Figure 13 shows the results of the FTC's analysis. These are graphs that show the share of each group with different size changes in their predicted risk between models where scores were not used and models where scores were used. Comparing across groups clearly shows that a much larger share of African American and Hispanics had increases in their predicted risk than did non-Hispanic whites and Asians. When scores are used, the predicted risk decreased for 62% of non-Hispanic whites and 66% of Asians. On the other hand, the predicted risk increased for 64% of African Americans and 53% of Hispanics. These results flow from the fact that, as discussed above, the scores for African Americans and Hispanics are lower on average than the scores of non-Hispanic whites and Asians.

Table 4 shows the magnitude of changes in predicted risk for racial and ethnic groups as a result of the use of scores. The average predicted risk increased by 10% for

African Americans and 4.2% for Hispanics, and dropped by 1.6% for non-Hispanic whites and 4.9% for Asians.[108]

b. Effect on Those for Whom Scores Were Not Available

The FTC also sought to determine whether the likelihood that a credit-based insurance score could not be generated for a consumer varied across racial and ethnic groups, and what impact any such differences would be expected to have on the premiums paid by consumers. A score may not be available for a consumer for one of two reasons: either it cannot be located for a consumer (a "no-hit"), or a consumer may have a credit history file, but it may not contain information sufficient to calculate a credit-based insurance score (a "thin file").

The FTC database does not contain Social Security Administration race and ethnicity data for most customers who were "no hits" or "thin files."[109] The FTC therefore used United States Census data to determine whether there are differences in the proportions of racial and ethnic groups that do not have a credit score. Based on block-level data, the Commission estimates that credit reports could not be located for 9.7% of African Americans, 9.2% of Hispanics, 7.8% of non-Hispanic whites, and 6.4% of Asians. Similarly, 2.4% of Hispanics, 2.1% of African Americans, 1.8% of non-

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[108] The relatively large decrease in predicted risk for Asians relative to non-Hispanic whites was surprising, given how similar the score distributions are for these two groups. In addition, the increase in predicted risk for Hispanics was only half that of African Americans, even though Hispanics have average scores closer to African American than to the overall population. Further examination of the results of the models showed that the inclusion of scores affected the impact of other variables on predicted risk. This, in turn, affected the predicted risk of Asians and Hispanics. In particular, the impact that short tenure with a firm and low liability limits had on predicted risk shrank considerably when scores were included in the models. Asians and Hispanics have low average tenure and low average liability limits, so when the impact of those characteristics on predicted risk decreased, so did the average predicted risk of Asians and Hispanics.

[109] The process of obtaining SSA race and ethnicity data relied on obtaining Social Security Numbers or dates of birth from credit reports; thus we did not receive SSA information for people whose credit reports could not be located, or who had very little information in their reports. Similarly, we do not have SSA national origin information for these people, and therefore cannot analyze the impact on immigrants of a lack of a credit-based insurance score.

Hispanic whites, and 1.8% of Asians had credit reports, but with too little information available to calculate a score.[110] Note that because these results are based on geographic data, they may not exactly reflect actual differences between racial and ethnic groups.

The FTC's assessment indicates that consumers for whom scores were not available appeared slightly riskier when scores were considered than when they were not. The Commission compared the results from risk models without scores with results from risk models with scores that also included categories for "no hit" and "thin file" in making this determination. No-hit consumers were 1.06 times riskier in a model that included controls for scores compared to a model that did not. Thin-file consumers were 1.02 times riskier in a model that included controls for scores compared to a model that did not.

Given the relatively small differences across groups in the share of people who were "no hits" or "thin files," and the relatively small impact of not having a score on predicted risk (as opposed to the large impacts of using scores on the predicted risk of people in the lowest score deciles, for example), this is unlikely to be an important source of differences in premiums across racial and ethnic groups. Again, this analysis is limited by the lack of individual-level data on race and ethnicity for people for whom we do not have credit scores.

[110] The block data were used by assuming each person had a likelihood of being a member of each racial or ethnic group that was proportional to the share of the population of each group in that person's block. This is implemented similarly to how imputed race/ethnicity information for SSA data are used. See Appendix C for a discussion of that process.

B. Scores as a Proxy for Race and Ethnicity

Section 215 of FACTA mandates that the FTC create a statistical model of insurance claims that includes credit-based insurance scores, standard non-credit risk variables, and controls for protected classes under the Equal Credit Opportunity Act.[111] We understand this to require the agency to analyze whether credit-based insurance scores act as a "proxy" for membership in these classes. As discussed above, we focused our analysis on effects on different groups defined by race, ethnicity, and income.

Understanding how a proxy functions is critical to the FTC's analysis. Insurance companies build statistical models that relate a variety of characteristics of customers (*e.g.*, age or driving history) to risk. Firms then use these models to predict the average claims that customers with those characteristics will generate, and these predictions of risk play a central role in determining the premiums that firms charge.

The risk models that companies build do not include information about race, ethnicity, or income. If there are large differences in average risk based on race, ethnicity, or income, then models may attribute some of those differences in risk to other variables included in the model that differ across these groups. The included variable thus may act in whole or in part as a statistical "proxy" for the excluded variables of race, ethnicity, or income.[112]

The FTC sought to determine whether credit-based insurance scores act as a proxy for race, ethnicity, and income in insurance decisions. To determine whether there is such an effect, and, if so, its magnitude, the Commission conducted three related

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[111] FACTA § 215(a)(2) (2006); 15 U.S.C. §1681 note (2006).
[112] The econometric term for this effect is "omitted variable bias." The omission of a predictive variable (such as race, ethnicity, or income) causes the estimated effect of a variable that is correlated with the omitted variables, such as score, to be "biased" away from the true effect. In this scenario, the direction of the bias would be to overstate the relationship between score and claims.

analyses. First, the Commission analyzed whether scores predict risk within racial, ethnic, and income groups. If scores do not predict risk within any group defined by race, ethnicity, and income, then the sole reason that scores predict risk in the general population would be because they act as a proxy for membership in different groups.

Second, the Commission analyzed whether average risk differed substantially by race, ethnicity, and income. If there were no substantial differences in the average risk across racial and ethnic groups, then there would be no underlying difference for which scores could act as a proxy. If there are substantial differences in risk across groups, scores may in part act as a proxy, even if scores also predict risk within groups (and are therefore not solely acting as a proxy for membership in different groups).

Third, the FTC created models that included controls for race, ethnicity, and income, along with credit-based insurance scores and the full range of other predictive variables. The Commission quantified the proxy effect of scores by measuring the impact of including these additional controls on the estimated relationship between scores and claims. To provide a basis for comparison, the FTC also conducted this analysis for several other variables that are predictive of risk.

1. Do Scores Act Solely as a Proxy for Race, Ethnicity, or Income?

Whether credit-based insurance scores predict risk within racial, ethnic, and income groups provides critical insight into whether scores are a proxy for membership in these groups. If scores did not predict claims within racial, ethnic, and income groups, the relationship between scores and claims must come from scores acting as a proxy for race, ethnicity, and income. On the other hand, if scores do predict risk within groups, then they do not serve solely as a proxy if used to assess risk for all consumers.

Therefore, the FTC analyzed whether scores predict risk within race, ethnicity, and income groups.

The results of the FTC's analysis are presented in Figure 14 for each racial and ethnic group for each type of automobile insurance coverage. If credit-based insurance scores predict the amount that insurance companies paid out in claims within each group, there should be a downward slope on each graph.[113] In other words, as scores increase for members of each group, the amount paid out on claims should be decreasing.

Although the relatively small sample size for the minority groups in the FTC database (which is a particular problem for bodily injury coverage, which has relatively few claims) leads to results that sometimes vary substantially from decile to decile, the overall pattern observed is that the amount paid out decreases as credit-based insurance scores increase for each group for each type of coverage.[114] With the exception of collision coverage, very few of the decile and coverage combinations have estimated risk for a given racial or ethnic group that is statistically significantly different from that of the overall sample.[115] Because they show that scores predict risk within groups, these results show that credit-based insurance scores do not predict risk solely by acting as a

[113] These were estimated by including interaction terms between the race/ethnicity variable and the scores variables. The coefficients on non-race/ethnicity non-score variables are therefore forced to be the same across groups. Entirely separate models cannot be estimated for many race/ethnicity/coverage combinations, because the small sample size of the minority groups often leads to the non-convergence of the estimation procedure.

[114] One cell that jumps out as being out of line with that pattern is the ninth decile for African Americans for comprehensive coverage. Further investigation showed that this result was affected by an outlier; a single individual with a very large claim, very low earned car years, and a very large nationally-representative weight had a large impact on the estimated risk for this decile. There are also few African Americans in the ninth decile. The difference between the estimated risk for African Americans in the ninth decile and the overall sample in the ninth decile was not statistically significant. When this outlier was dropped the risk estimate for this decile was similar to the surrounding deciles. The treatment of outliers is discussed in Appendix F.

[115] Statistical significance was determined using a bootstrap procedure with 500 replications. The bootstrap procedure is discussed in Appendix D.

proxy for membership in racial and ethnic groups.[116]

The FTC conducted the same analysis based on neighborhood income. These results are shown in Figure 15. These graphs show a consistent negative relationship between amount paid and credit-based insurance score for all neighborhood income groups. In other words, as scores increased, claims decreased for all income groups.

In short, because scores do predict risk within racial, ethnic, and income groups, they do not act solely as a proxy for these characteristics.

2. Differences in Average Risk by Race, Ethnicity, and Income

Even though scores do not act solely as a proxy for race, ethnicity, and income, there may still be some proxy effect. For such a partial proxy effect to occur, there must be differences in average risk among racial, ethnic, or income groups, *i.e.*, scores can only have a proxy effect if there is an underlying relationship for which scores can serve as a proxy. To determine whether such differences exist, the FTC created models that evaluated the relative amount paid on claims by race, ethnicity, and neighborhood income for the four main types of automobile insurance coverage. These models included other risk variables, but not scores. The results of this analysis are shown in Table 5. For purposes of comparisons in these tables, the FTC assigned a relative value of 1 to the amount of claims that would be expected to be paid to non-Hispanic white consumers and to consumers living in high income neighborhoods.

Column (a) shows that Asians and Hispanics had a higher amount of claims paid under property damage liability coverage than did African Americans and non-Hispanic

[116] We also did the same analysis for "foreign born" and "recent immigrants." The results were similar, and scores are correlated with risk for those groups.

whites, although the difference was not statistically significant for Hispanics. It also shows that there was very little relationship between the amount of property damage liability claims and whether a consumer lives in a neighborhood with a low, middle, or high income. While Asians did have more claims under property damage liability coverage, as discussed above, our analysis showed that they had scores that were similar to the scores of the overall distribution. Therefore, scores cannot act as proxy for being Asian, so it is unlikely that scores could act as a proxy for race or ethnicity in a model of property damage liability claims.

Columns (b) through (d) of Table 5 present results concerning the amount paid out for bodily injury, collision, and comprehensive coverage, respectively. After controlling for other risk factors, insurance companies paid out 48% more to African Americans than non-Hispanic whites for bodily injury, 43% more for collision, and 63% more for comprehensive coverage. Similarly, they paid out 25% more to Hispanics than non-Hispanic whites for bodily injury, 33% more for collision, and 45% more for comprehensive coverage. Insurance companies paid out 30% more to Asians than non-Hispanic whites for collision coverage. These differences were all statistically significant. The differences for bodily injury liability and comprehensive coverages between Asians and non-Hispanic whites were relatively small and not statistically significant. The large differences in average risk on comprehensive coverage for Hispanics and African Americans should be treated with some caution, as the geographic risk variable in the FTC database is not a very effective control for geographic variation in risk on comprehensive coverage.[117]

Table 5 shows that the differences among neighborhood income groups were much smaller than those among racial and ethnic groups. The one substantial difference in risk was that customers in low-income neighborhoods pose a 16% higher risk for comprehensive coverage. Again, this may in part be due to the lack of an effective geographic risk measure for comprehensive coverage.[118]

These results show that there were substantial differences in the average risk of consumers in different racial and ethnic groups for all four major automobile insurance coverages.[119] For property damage liability coverage, Asians were the only group with

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[117] The geographic risk measure in the FTC database is based on property damage liability claims, which result from accidents. The estimated effect of the geographic risk measure is much smaller in the comprehensive coverage risk models than in the models for the other coverages, suggesting that it is a poor control for geographic variation in comprehensive coverage risk. According to the Bureau of Justice Statistics, African Americans and Hispanics are much more likely to be victims of automobile theft (a risk covered by comprehensive coverage) than non-Hispanic whites. *See* Bureau of Justice Statistics file cv0516.csv, *available at* www.ojp.usdoj.gov/bjs/pub/sheets/cvus/2005/cv0516.csv; Bureau of Justice Statistics file cv0517.csv, *available at* www.ojp.usdoj.gov/bjs/pub/sheets/cvus/2005/cv0517.csv. In the absence of a good measure of the geographic variation in comprehensive coverage risk, race, ethnicity, and neighborhood income are likely picking up some of that variation in risk (*e.g.*, they may be acting as a proxy for other characteristics of neighborhoods that affect comprehensive coverage risk). Additional support for this hypothesis was found by estimating separate risk and severity models that included race, ethnicity, and income controls. In those models, race, ethnicity, and income affected only frequency in the property damage liability, bodily injury liability, and collision coverage models. In the comprehensive coverage model, race, ethnicity, and income were strongly related to claim severity. This is consistent with those variables being related to the likelihood of theft claims.

[118] *Id*.

[119] We found similar patterns when we used loss ratios as the measure of relative risk, instead of the direct results of the risk models. The loss ratio is the ratio of payments companies made on claims divided by premiums customers paid in. Using loss ratios, therefore, shows whether customers in different racial and ethnic groups generated greater or lesser total payouts on claims, on average, than predicted by the companies, as reflected in the premiums the customers were charged. Loss ratios were fairly similar across groups for property damage liability coverage, with Hispanics and Asians generating somewhat more claims relative to premiums than African Americans and non-Hispanic whites. For bodily injury liability coverage, collision coverage, and comprehensive coverage, African Americans and Hispanics generated higher claims relative to premiums than did non-Hispanic whites. The same was true for Asians for collision coverage, although Asians had a substantially smaller loss ratio for comprehensive coverage than did any other group. For example, the loss ratios of African Americans and Hispanics for collision coverage were 83.9% and 85.6%, respectively, for Asians 78.2%, and for non-Hispanic whites the loss ratio was 63.3%. Unlike in our risk models, the coverage with the largest differences across groups was bodily injury liability coverage, as opposed to comprehensive coverage. This again suggests that part of the reason we find such large differences in risk across groups for comprehensive coverage in our models is the lack of a geographic risk measure that is specific to risk on comprehensive coverage. For the four

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significantly higher risk. For the other three coverages, Hispanics and African Americans had substantially higher average payouts on claims than did non-Hispanic whites. Given that Hispanics and African Americans have much lower credit-based insurance scores, on average, than do non-Hispanic whites, there is the potential that scores could gain additional predictive power by acting as a proxy for race and ethnicity in models of claims under bodily injury, collision, and comprehensive coverages.

3. Controlling for Race, Ethnicity, and Income to Test for a Proxy Effect

a. Existence of a Proxy Effect

The FTC created models that evaluated the relative amount paid on claims by score decile with and without controls for membership in racial, ethnic, and income groups for the four main types of automobile insurance coverage. Table 6 shows the results.[120] For purposes of comparisons on this Table, the FTC assigned the relative value of 1 to: (1) the amount of claims that would be expected to be paid to consumers in the highest 10% of credit-based insurance scores; (2) non-Hispanic white consumers; and (3) consumers living in high-income Census tracts. For each coverage, the first column shows the predicted relative amount of claims for credit-based insurance score deciles for a model that does not include controls for race, ethnicity and income. The second column for each coverage shows the results from models that include scores and controls for the prohibited factors.

Comparing the two columns for property damage liability coverage (columns (a) and (b)) reveals that there was very little difference in the impact of credit-based

coverages combined, the loss ratios of the four groups were: for non-Hispanic whites, 62%; for African Americans, 80%; for Hispanics, 81%; and, for Asians, 67%.

[120] Again, the models used here are Tweedie GLMs. Modeling details are given in Appendix D.

insurance scores on predicted risk based on whether the model included controls for membership in a protected class. The only statistically significant difference was that the estimated relative risk for the lowest score decile was larger when protected class controls were included in the model.[121] This is opposite of the change that would occur if scores were acting as a proxy. This lack of a proxy effect is not surprising, given that the only statistically significant difference in risk by racial or ethnic group for this coverage was that Asians had higher average risk. As pointed out above, because Asians have similar scores, on average, as the population as a whole, scores cannot act as a proxy for being Asian. The lack of any proxy effect for property damage liability coverage is made very clear in Figure 16, which shows the estimated relationship between claims risk and credit-based insurance scores from Table 6.

Table 6 shows that the results were somewhat different for bodily injury liability, collision, and comprehensive coverage. These are the coverages for which African Americans and Hispanics had substantially higher average total payouts on claims than did non-Hispanic whites. The FTC's analysis revealed that including these controls did reduce somewhat the effect of scores on predicted risk for these three coverages. The results show, however, that scores do continue to predict claims strongly if controls for race, ethnicity, and income are included in the risk models, which means that scores do not predict risk primarily by acting as a proxy for these characteristics. In addition to Table 6, the results are presented in Figure 16, which shows the estimated relationship between scores and risk, with and without controls for race, ethnicity, and income. Controls for race, ethnicity, and income decreased the impact of scores on predicted risk

[121] A 95% confidence interval for the difference between the score decile parameter estimates from the two models was computed using a bootstrap procedure with 500 replications. Details of the bootstrap procedure are provided in Appendix C.

for these coverages most for the lowest credit-based insurance score deciles (where African Americans and Hispanics are disproportionately located), and these decreases were statistically significant. In short, the FTC's analysis indicates that credit-based insurance scores appear to have some proxy effect for three of the four coverages studied, but that this is not the primary source of their relationship with claims risk. In the next section, we address the magnitude of the proxy effect.

b. Magnitude of a Proxy Effect

The FTC also sought to determine the magnitude of any proxy effect from the use of credit-based insurance scores. Controlling for race and ethnicity had the largest impact on the predicted effect of scores on risk for comprehensive coverage. *See* columns (g) and (h) of Table 6. Without these controls, consumers in the lowest 10% of scores were estimated to pose 1.95 times more risk than consumers in the highest 10%. With the controls, consumers in the lowest 10% of scores were estimated to pose 1.74 times more risk than consumers in the highest 10%. As discussed above, this result should be treated with caution, because it could be affected by the lack of a good measure of the geographic variation in comprehensive coverage risk.

Controlling for race and ethnicity had a smaller effect on the predicted impact of scores on risk for bodily injury liability and collision coverage. For bodily injury liability coverage, without these controls, consumers who are in the lowest 10% of credit-based insurance scores were estimated to pose 2.20 times more risk than consumers in the highest 10% of scores, while with controls they were estimated to pose only 2.10 times more risk. *See* columns (c) and (d) of Table 6. For collision coverage, without controls, consumers who are in the lowest 10% of credit-based insurance scores were estimated to pose 2.03 times more risk than consumers in the highest 10% of scores, while with controls they posed only 1.93 times more risk. *See* columns (e) and (f) of Table 6.

It may be difficult to interpret the magnitudes of the proxy effects by examining changes in the predicted effects of scores on claims risk. An alternative way to measure the magnitude of the proxy effect is to examine how it affects the impact of scores on the predicted risk of different race and ethnicity groups. The information presented in Table 7 compares the impact of scores on predicted risk for different groups, with and without race, ethnicity, and income controls. The first column in Table 7 shows that if scores were used, then on average the predicted risk of African Americans increased by 10% and Hispanics increased by 4.2%, while the predicted risk of non-Hispanic whites dropped by 1.6% and Asians dropped 4.9%.[122] The second column shows the effects of scores on the average predicted risk of the different groups using the impact of scores on predicted risk that comes from models that include controls for race, ethnicity, and income. When these score effects were used, the average predicted risk of African Americans increased by 8.9% and Hispanics by 3.5%, while the predicted risk of non-Hispanic whites decreased by 1.4% and Asians by 4.8%.[123] The change in the impact of scores on predicted risk when race, ethnicity, and income controls were included was statistically significant for all racial and ethnic groups. However, given that the use of these controls when determining the effects of scores resulted in relatively small decreases in the effect of scores on predicted risk for African Americans (10% versus

[122] These are the same results that were presented in Table 4.

[123] The effects of other variables are held constant between the two models. This was done by using the estimated risk effects of non-credit risk variables from the models without race, ethnicity, and income controls, and the estimated risk effects of the score deciles from the models with the controls. The estimated risk effects of the race, ethnicity, and income controls were not used to predict risk. This hybrid risk estimate produced an overall average predicted claims payout that was lower than the actual average amount of claims payouts, so every individual's predicted risk was then inflated by the ratio of actual average claims over predicted average claims.

8.9%) and Hispanics (4.2% versus 3.5%), it is apparent that most of the effect of using scores on these groups is not because scores act as a proxy for race, ethnicity, and income.

To provide a basis for comparison in evaluating the importance of these proxy effects, the FTC conducted the same analysis for several other standard risk variables. This could only be done for a small set of the risk variables in the FTC database.[124] Variables that could be used were tenure (number of years the customer has been with the company), the model year of the car, and the vehicle identification number ("VIN"), which the FTC used to obtain information on vehicle characteristics like body type and safety systems.[125] In addition, there are two risk variables in the FTC database that did not come from the company policy-level database. These are the geographic risk measure and the CLUE prior-claims data.

Table 8 shows the results of applying the FTC's proxy-effect analysis to these variables. The proxy-effect analysis was applied to these other variables in the same way it was applied to scores.[126] These other variables have much smaller effects on the average predicted risk of different racial and ethnic groups than do scores.[127] For three of

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[124] Most of the standard risk variables that came from the companies' data had large numbers of missing values, which reflects the fact that some companies did not collect or store information on some of the variables. This means that evaluating these variables is complicated by the fact that when a group of policies has "missing" as the value of a given variable, that may mean that most of the policies came from the same company. When this is true, the effects of individual variables on risk may be confounded with differences across companies in the average risk of their customers.

[125] The VINs in the FTC database were truncated, so individual cars cannot be identified. While VIN is missing for a substantial number of cars, this is mainly for cars in earlier model years. Newer model years have relatively small numbers of missing values, roughly 12%, suggesting that the missing values are unlikely to be driven primarily by differences across companies in reporting VINs.

[126] The first column of Table 8 shows the difference in predicted risk between a model that does not include the variable being tested and a model that does. The second column shows the difference between a model that does not include the variable being tested and a model that does include the variable, where the impact of the variable comes from a model that includes controls for race, ethnicity, and income.

[127] There are several reasons that could explain why the impacts of these variables on the predicted risk of different groups are not as large. It may be because the differences in these variables across groups are not

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the four variables, adding race, ethnicity, and income controls reduced the magnitude of the impact that the variables had on the change in predicted risk for different groups. Adding the geographic risk measure increased average predicted risk 5.4% for African Americans, 3.3% for Hispanics, and 4.4% for Asians.[128] When controls were included for race, ethnicity, and income, the impact of the geographic risk measure decreased to 4.7% for African Americans, 2.2% for Hispanics, and 3.6% for Asians. The effect of tenure on predicted risk for different groups was also reduced by adding race, ethnicity, and income controls, from 0.4% to 0.1% for African Americans, from 2.4% to 1.9% for Hispanics, and from 2.1% to 1.7% for Asians. Finally, including race, ethnicity, and income controls reduced the impact of prior claims on predicted risk from 2.4% to 2.2% for African Americans, from 0.3% to 0.2% for Hispanics, and from 1.5% to 1.4% for Asians. While these effects are small in absolute value, they are of a similar proportion to the effects that these controls have on scores' impact on the predicted risk of different racial and ethnic groups. Thus, like scores, these other risk variables also gain some predictive power from acting as proxies for race, ethnicity, or income.

In summary, the FTC's analysis shows that credit-based insurance scores do predict risk within different racial, ethnic, and income groups. Thus, they do not act solely as a proxy for membership in these groups. Scores, however, do gain a small amount of additional predictive power because of a proxy effect. Controlling for race

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as large as the differences for scores, because the impacts of these variables on predicted risk are not as large as the impact of scores, and/or because the impact that the inclusion of the variable has on the risk associated with other variables is not as large as the impact that scores have.

[128] Note that this is not a geographic risk measure used by any company, but rather a variable created for the purpose of this study. In addition, the geographic risk measure is not a very effective control for risk on comprehensive coverage. A better geographic risk control for comprehensive risk would likely have a larger impact on the average predicted risk of African Americans and Hispanics, for comprehensive coverage, and thus overall, given the large risk differences between African Americans and Hispanics versus non-Hispanic whites for that coverage.

and ethnicity in estimating the relationship between scores and risk causes a small reduction in the extent to which scores increase the expected risk of African Americans and Hispanics. Finally, this small proxy effect is not limited to scores, but was found for three of four other risk variables studied.

VII. ALTERNATIVE SCORING MODELS

FACTA directed the Commission to determine whether credit-based insurance scoring models could be developed that would reduce the differences in scores for consumers in protected classes relative to other consumers, yet continue to be effective predictors of risk.[129] Because race and ethnicity account for the largest differences in credit-based insurance scores among groups of consumers in the FTC database, the agency focused on constructing an effective model that decreased differences among racial and ethnic groups. To the extent practicable, the Commission also sought to build an effective model that decreased differences among income groups.

As discussed above, credit-based insurance scores are calculated using models that assign values to credit history variables to calculate numerical scores. To develop a model that effectively predicts risk while reducing differences between racial and ethnic groups, the FTC first created a baseline scoring model using the information in its database. The Commission chose variables for its baseline model with regard only to their power to generate a score that predicts risk as accurately as possible. The FTC then used a number of different techniques to try to construct alternative scoring models that

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[129] FACTA § 215(a)(3) (2006); 15 U.S.C. § 1681 note (2006).

were as predictive as the FTC baseline model, yet had smaller differences in scores among racial and ethnic groups.

The FTC was not able to develop a credit-based insurance scoring model that met the dual objectives of maintaining predictive power and decreasing the differences in scores between racial, ethnic, and income groups. This does not necessarily mean that a model could not be constructed that meets these objectives. It does strongly suggest, however, that there is no readily available scoring model or score development methodology that would do so.

A. The FTC Baseline Model

Developing a baseline model to use for comparisons is the first step in determining whether a model can produce scores that continue to predict risk but have smaller differences by race and ethnicity.[130] The FTC used claims information in its database, the non-credit risk variables in the database, and credit history variables that were appended to the insurance policy data to build the model.[131] The FTC database includes 180 credit history variables for each consumer in the development sample. This is a set of variables that ChoicePoint developed over time for its own score-building, and they are intended to capture all relevant information in a credit report.[132]

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[130] Using either the ChoicePoint or FICO model as the base model would not be a useful test. Even a very simplistic model developed with the FTC database is likely to do better at predicting claims in the FTC database than either of those scores, because it is predicting "within sample." That is, the model is predicting the very claims that were used to develop it.

[131] The development sample was limited to consumers for whom there is race, ethnicity, and income information in the FTC database. This demographic information was used only to develop the alternative scoring models, not the baseline model. Appendix G contains a description of the methodologies used to produce this credit-based insurance score, as well as the other scoring models discussed in this section.

[132] No ChoicePoint model uses all 180 variables, and many of these variables are not used in any model.

The Commission selected variables for its baseline model that would produce credit-based insurance scores that were effective in predicting total dollars paid out on claims per year,[133] after controlling for other non-credit risk factors, such as age and driving history. This model was constructed without giving any consideration to race, ethnicity, or income. Insurance companies and other private firms that develop scoring models likewise build their models in a "race blind" fashion.

The variables that the FTC determined produced scores that were most predictive of the claims of the consumers in its development sample are presented in Table 9.[134] It shows the fifteen variables chosen and the scoring factor assigned to each of them.[135] To calculate a score for a consumer, the factors for his or her values of each variable are multiplied together.[136]

The first five variables that enter the model each represent different aspects of a credit report: (1) Delinquencies: presence of derogatory information on the file; (2) Credit utilization: number of accounts with balance greater than 75% of the credit limit or all-time high credit balance; (3) Age of accounts: average age of bank revolving (credit card) accounts; (4) Inquiries; and (5) Type of Credit: presence of an open auto finance account in the credit report.[137] The variables that entered the model later are all

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[133] The models are intended to be predictive of claims for all major types of coverage. For this reason, claims were summed across coverages into a single measure of losses. Claims under first-party medical coverage's, "Med Pay" and personal injury protection, are also included in the "total losses" variable.
[134] The variable descriptions are proprietary and confidential information of ChoicePoint. Some variable descriptions have been made public previously. For other variables, we include only a general description of the type of variable.
[135] The Table shows the variables in the order in which they were chosen by the score-building methodology. Variables chosen earlier are generally those that provide greater predictive power to the scoring model.
[136] The resulting score is the inverse of the relative predicted risk for the consumer. The inverse is used so that higher scores are associated with lower predicted risk.
[137] An auto finance account is an account with a lender associated with a car company, like GMAC or Ford Motor Credit.

variations on these categories, with the exception of a variable that measures what share of credit card accounts on the report are currently reported as "open." The category with the greatest impact on scores is delinquencies, which makes up six of the fifteen variables.[138]

The scores the FTC baseline model produces did predict risk. Figure 17 shows the relationship between total claims paid out and the FTC credit-based insurance score for the four major types of automobile coverage. Each graph shows three lines: (1) the average total amount paid on claims by score decile in the development sample; (2) the estimated relationship between scores and claims in the development sample from models controlling for other risk factors; and, (3) the average total amount paid on claims by score decile in CLUE data for the period June 2001 to December 2001, for people who were not in the development sample (an "out of sample" check).[139] If the model generated scores that effectively predicted risk, then the lines on the graph should slope downward to the right. The FTC baseline model produced results consistent with this expected pattern. For example, for bodily injury liability coverage, consumers in the lowest 10% of scores were more than three and a half times riskier than consumers in the highest 10% of scores. Even for property damage liability claims, which have the weakest relationship with the FTC score, consumers in the lowest 10% of scores of the

[138] In looking over the model, it is important to keep in mind that a piece of information in a credit report can be represented in multiple ways and affect multiple variables. This means that care must be taken when interpreting some of the results. For example, the score factors for variable C show that delinquencies on a particular kind of account actually lead to a better score, which seems very strange in isolation. But, it simply means that, in these data, a delinquency on that type of account is less indicative of risk than delinquencies on other kinds of accounts, since there is another variable in the model that is a broad measure of delinquencies and has a large negative impact on score.

[139] The development sample consists only of the sub-sample of the FTC database for which we obtained SSA race and ethnicity data. The development sub-sample includes everyone who had a claim in the company data, so there was no way to use the company data to look at claims outside of the development sample. Instead, we use CLUE data on claims for a different time period. We were able to use data on roughly 800,000 policies for these checks.

development sample were more than twice as risky as consumers in the highest 10% of scores. Consequently, the FTC baseline model is an effective predictor of risk. Figure 17 also shows that the FTC baseline model predicts risk for people outside the development sample. This result is important in that it shows the FTC baseline model scores do not simply predict the claims that were used to develop the model.

To establish a baseline for evaluating the results of other models, the FTC also measured the extent to which its model resulted in differences in scores among racial and ethnic groups. Figure 18 shows how the four groups were distributed across the range of FTC baseline-model scores. The horizontal axis shows score deciles, and the vertical axis shows the share of each group that fell in each decile. The deciles were defined using the overall distribution of scores, so if a given group had the same distribution of scores as the overall sample, 10% of that group's population would fall in each decile. Figure 18 shows that the FTC baseline model produced lower scores for African Americans and Hispanics than for non-Hispanic whites and Asians.[140]

Table 9 also shows the breakdown of the different racial and ethnic groups across the variables used in the FTC's baseline model. The variables that show large differences across racial and ethnic group are those relating to payment history (*e.g.*, delinquencies) and public records, and the variable for the share of accounts with high balances relative to credit limits. The inclusion of these variables in the FTC baseline model explains why African Americans and Hispanics had lower scores than non-Hispanic whites and Asians.

[140] Note that these differences across racial and ethnic groups for the FTC baseline model are very similar to those for the ChoicePoint scores discussed above, with the only substantial difference being that Asians were less well represented in the higher score categories for the FTC baseline model than for ChoicePoint scores.

B. Alternative Scoring Models

1. "Race Neutral" Scoring Models

The FTC credit-based insurance scoring model described in the previous section provides a baseline for evaluating alternative models. To construct a model that was "neutral" with respect to race, ethnicity, and income, the FTC created a model in which it controlled directly for these factors.[141] "Neutral" in this context means that while the scores produced by the model still may vary across groups, the variables used in the scoring model should not derive predictive power from a relationship with race, ethnicity, or income. Controls mitigate the impact of credit history variables that differ widely among different racial, ethnic, or income groups, if those variables derive a substantial portion of their power to predict losses from those differences. If controls are used for race, ethnicity, and income, these variables become less predictive of risk. With this loss in predictive power, these variables are either not selected for a scoring model at all, or, if selected, they are not given as much weight.

Table 10 shows the scoring model that was produced if controls for race, ethnicity, and income were used in the model building process. Most significantly, the variables selected in this model that controls for race (a race "neutral" model) are extremely similar to those in the FTC baseline model (a race "blind" model). Specifically, only two of the fifteen variables are different between these two models, and these two particular variables have a relatively weak effect on predicting risk. Despite controlling for race, ethnicity, and income, a very similar set of credit history variables

[141] Several authors have proposed this approach. *See* Elaine Fortowsky and Michael Lacour-Little, *Credit Scoring and Disparate Impact* (Dec. 31, 2001), *available at* http://fic.wharton.upenn.edu/fic/lacourpaper.pdf; Stephen L. Ross and John Yinger, THE COLOR OF CREDIT: MORTGAGE DISCRIMINATION, RESEARCH METHODOLOGY, AND FAIR LENDING ENFORCEMENT (2002).

thus were found to be most predictive of claims. Even though some of these variables have large differences across racial and ethnic groups, the variables were chosen not because they vary by race, ethnicity, or income.

The Commission tried another approach to developing a race "neutral" model to compare to the FTC baseline model. We constructed a credit-based insurance scoring model using a development sample that included only non-Hispanic whites. Because there were no other racial or ethnic groups in the sample used to construct such a model, the predictive power of the variables selected cannot be attributed to any relationship with race or ethnicity.

Table 11 shows the variables selected when a model was built using only non-Hispanic whites as the development sample. Upon first examination, the variables selected for this model appear quite different from the variables in the FTC baseline model. Eight of the fifteen variables are different, including the variable with the second greatest impact. However, there is an important similarity between the variables in these two models. The same *types* of variables were found to be the most important: delinquencies, inquiries, measures of high debt burden, age of the credit report, and type of credit.

Both race-neutral models that the FTC developed predict risk within the development sample about as well as the FTC baseline model. Figure 19 compares the results for each of these models for each of the four types of automobile insurance coverage.[142] These graphs show that the FTC baseline model (a race blind model) produced very similar results for each type of coverage as models that controlled for race

[142] Although only non-Hispanic whites were used to develop the "non-Hispanic whites" model, the results shown here are for the complete development sample.

and ethnicity or that were developed using only non-Hispanic whites (race neutral models). Given the similarity between the types of variables selected for use in these models, it is not surprising that these scores have comparable power in predicting risk.

Just as their risk prediction is comparable to that of the FTC baseline model, the race neutral models also display large differences in scores among racial and ethnic groups. Figure 20 shows the distribution of scores for the different racial and ethnic groups for the two race neutral models and the FTC baseline model. To facilitate comparisons, each graph shows the results for all three models for a single racial or ethnic group. For all groups except Asians, the distribution of people across deciles was nearly identical for the three scoring models. For Asians, the FTC baseline model and the model developed using controls for race, ethnicity, and income gave very similar results. The model built using only non-Hispanic whites, however, produced a distribution of scores for Asians that was more skewed towards lower scores.

In short, these comparisons show that, although the race neutral models that the FTC built accurately predict risk, they do not decrease the differences in credit-based insurance scores among racial and ethnic groups.

2. Model Discounting Variables with Large Differences by Race and Ethnicity

In addition to developing race neutral models as possible alternatives, the FTC also constructed alternative models that tried more directly to avoid selecting variables with large differences among racial and ethnic groups. In building such models, the FTC measured not just how well a given variable predicted claims, but how well it predicted race and ethnicity. The FTC then chose the variables that contributed the most to predicting risk and the least to predicting race and ethnicity.

Table 12 shows one of the models developed using this approach. It is very different from the models described in the previous two sections. Most significantly, there are no variables that relate directly to delinquencies, which Tables 9 – 11 showed varied a great deal among racial and ethnic groups. Most variables selected relate to the number and type of accounts that a consumer has. In addition, the discounted model includes variables that relate to the age of the credit account and total indebtedness.

Figure 21 shows that the discounted model is much less predictive of risk than the FTC baseline model for each of the four types of automobile insurance coverage. The discounted model does produce credit-based insurance scores that predict risk. However, each of these graphs shows that the relationship between the credit score and risk is much weaker (flatter) for the discounted model than for the FTC baseline model. This shows that this process of avoiding variables with large differences between groups resulted in a model that is substantially less effective as a predictor of risk than the FTC baseline model.

Figure 22 compares scores for each racial and ethnic group based on the results obtained from the discounted model and the FTC baseline model. The model that assigns consumers in a racial or ethnic group most closely to 10% in each decile (*i.e.*, a flat line at 10% on the vertical axis) shows the least differences based on race and ethnicity. Each of these graphs shows that the discounted model resulted in scores with smaller differences between members of racial and ethnic minority groups than did the FTC baseline model. These differences were most substantial for African Americans. While they were still slightly over-represented in the lower score categories, the scores from the discounted model showed 14% of African Americans are in the bottom 10% of scores. The scores from the FTC baseline model, in contrast, showed 27% of African Americans in the bottom 10% of scores. Although the discounted model did substantially reduce the differences in scores among members of racial and ethnic groups, as discussed above, it also provides far less effective risk prediction.

In summary, the FTC's inability to build a model that produces scores that continues to predict risk accurately at the same time as narrowing the differences in scores among racial and ethnic minority groups are by no means definitive. Perhaps someone could develop a model that meets both of these objectives. The FTC's inability to build to such a model, however, strongly suggests that there is no readily available approach for doing so.

VIII. CONCLUSION

The FTC's analysis demonstrates that credit-based insurance scores are effective predictors of risk under automobile insurance policies. Using scores is likely to make the price of insurance conform more closely to the risk of loss that consumers pose, resulting, on average, in higher-risk consumers paying higher premiums and lower-risk consumers paying lower premiums. It has not been clearly established why scores are predictive of risk.

Credit-based insurance scores may benefit consumers overall. Scores may permit insurance companies to evaluate risk with greater accuracy, which may make them more willing to offer insurance to higher-risk consumers. Scores also may make the process of granting and pricing insurance quicker and cheaper, cost savings that may be passed on to consumers in the form of lower premiums. However, little hard data was submitted or available to the FTC to quantify the magnitude of these potential benefits to consumers.

Credit-based insurance scores are distributed differently among racial and ethnic groups. The FTC's analysis revealed that the use of scores for consumers whose information was included in the FTC's database caused the average predicted risk for African Americans and Hispanics to increase by 10% and 4.2%, respectively, while it caused the average predicted risk for non-Hispanic whites and Asians to decrease by 1.6% and 4.9%, respectively. These changes in predicted risk are likely to have an effect on the insurance premiums that these groups on average pay.

Credit-based insurance scores predict risk within racial, ethnic, and income groups. Scores have only a small effect as a "proxy" for membership in racial and ethnic groups in estimating of insurance risk, remaining strong predictors of risk when controls for race, ethnicity and income are included in risk models. The FTC's analysis revealed that the use of scores for consumers whose information was included in the FTC's database caused the average predicted risk for African Americans and Hispanics to increase by 10% and 4.2%, respectively. The Commission's analysis also showed that using the effects of scores on predicted risk that come from models that include controls for race, ethnicity, and income caused scores to increase the average predicted risk for African Americans and Hispanics by 8.9% and 3.5%, respectively. The difference between these two predictions for these two groups (1.1% and 0.7%, respectively) shows that a relatively small portion of the impact of scores on these groups comes from scores acting as a proxy for race, ethnicity, and income.

Finally, the FTC was not able to develop an alternative credit-based insurance scoring model that would continue to predict risk effectively, yet decrease the differences in scores on average among racial and ethnic groups. This does not mean that a model could not be constructed that meets both of these objectives. It does strongly suggest, however, that there is no readily available scoring model that would do so.

TABLES

TABLE 1.
Typical Information Used in Credit-Based Insurance Scoring Models

Performance on Credit Obligations

- Late payments/Delinquencies (-)
- Collections (generally non-medical) (-)
- Public records (judgments or bankruptcies) (-)

Credit-Seeking Behavior

- Inquiries (generally non-insurance, non-medical) (-)
- New accounts (-)

Use of Credit

- Ratio of outstanding balances to available credit (-)

Length of Credit History

- Age of oldest account (+)
- Average age of all accounts (+)

Types of Credit Used

- Department store trade lines (-)
- Oil Company trade lines (-)
- Travel and Entertainment trade lines (-)
- Share of trade lines that are major bank credit cards or mortgages (+)

Note: (-) indicates that high values typically lead to a riskier score, and the converse for (+).

TABLE 2.
Claim Frequency, Claim Severity, and Average Total Amount Paid on Claims

Score Decile	Average Number of Claims Per Year of Coverage (per hundred) (a)	Average Cost per Claim (b)	Average Total Paid on Claims Per Year of Coverage [(a) x (b)] (c)
Property Damage Liability Coverage			
1	5.65	$2,100	$119
2	4.86	2,119	103
3	4.51	2,105	95
4	4.21	2,078	88
5	4.09	1,982	81
6	3.85	2,028	78
7	3.55	2,006	71
8	3.34	1,994	67
9	3.40	2,062	70
10	3.17	1,981	63
Overall	*4.06*	*$2,053*	*$83*
Bodily Injury Liablility Coverage			
1	1.79	$8,560	$153
2	1.59	10,002	159
3	1.39	7,798	109
4	1.39	7,993	111
5	1.19	7,940	95
6	1.01	8,892	89
7	0.91	8,538	78
8	0.89	8,760	78
9	0.85	9,127	78
10	0.77	8,372	64
Overall	*1.18*	*$8,609*	*$101*

(continued…)

TABLE 2.
Claim Frequency, Claim Severity, and Average Total Amount Paid on Claims (Continued)

	Score Decile	Average Number of Claims Per Year of Coverage (per hundred) (a)	Average Cost per Claim (b)	Average Total Paid on Claims Per Year of Coverage [(a) x (b)] (c)
Collision Coverage				
	1	11.80	$2,364	$279
	2	9.53	2,201	210
	3	8.57	2,174	186
	4	8.09	2,060	167
	5	7.45	2,014	150
	6	6.86	2,057	141
	7	6.47	2,006	130
	8	6.18	1,965	122
	9	6.11	2,003	122
	10	5.38	2,004	108
	Overall	*7.64*	*$2,112*	*$161*
Comprehensive Coverage				
	1	11.50	$1,032	$119
	2	9.69	879	85
	3	9.06	828	75
	4	9.06	773	70
	5	8.34	773	64
	6	8.07	752	61
	7	7.46	774	58
	8	7.42	718	53
	9	7.03	722	51
	10	6.95	688	48
	Overall	*8.44*	*$807*	*$68*

Note: All numbers on this table represent actual means (*i.e.* , not derived from any risk modelling procedure).

Source: Analysis of FTC Automobile Insurance Policy Database

TABLE 3.
Median Income and Age, and Gender Make-Up, by Race and Ethnicity

	Median Tract Income (a)	Median Age (b)	Percent Male (c)
African Americans	$34,876	46	48%
Hispanics	$38,475	42	60%
Asians	$50,953	42	72%
Non-Hispanic Whites	$44,356	48	68%

Note: Age and gender are measured at the individual level. See section VI.A.2 of the report for a discussion of how the age of the individual was determined. Neighborhood income is the median for the Census tract where the individual lives. See Appendix C for details on the data sources and the construction of the database.

Source: Analysis of FTC Automobile Insurance Policy Database

TABLE 4.
Change in Predicted Amount Paid on Claims from Using Credit-Based Insurance Scores, by Race and Ethnicity

	Share With a Decrease (a)	Share With an Increase (b)	Percent Change in Mean Predicted Risk (c)
African Americans	36%	64%	10.0%
Hispanics	47%	53%	4.2%
Asians	66%	34%	- 4.9%
Non-Hispanic Whites	62%	38%	- 1.6%
Overall	*59%*	*41%*	*0.0%*

Note: Predicted change in the amount paid on claims was estimated by comparing individuals' predicted total claims from risk models that include ChoicePoint Attract Standard Auto credit-based insurance scores with risk models that do not include scores. (By construction, the average of all changes for the sample is zero.) Both of these models include a standard set of risk variables as controls, and were run separately for property damage liability, bodily injury liability, collision, and comprehensive coverage. In the final step we sum the predicted dollar risks for all four types of insurance coverage with and without the use of credit-based insurance scores. See section VI.A.3 of the report for additional details on this analysis. Modeling details and a description of the variables included in the models are provided in Appendix D.

Source: Analysis of FTC Automobile Insurance Policy Database

TABLE 5.
Estimated Relative Amount Paid on Claims, by Race, Ethnicity, and Neighborhood Income

	Property Damage Liability Coverage (a)	Bodily Injury Liability Coverage (b)	Collision Coverage (c)	Comprehensive Coverage (d)
Race and Ethnicity				
African Americans	1.01	1.48 *	1.43 *	1.63 *
Hispanics	1.11	1.25 *	1.33 *	1.45 *
Asians	1.17 *	1.11	1.30 *	0.96
Non-Hispanic Whites	1.00	1.00	1.00	1.00
Neighborhood Income				
Low	0.97	1.01	1.05	1.16 *
Middle	0.95 *	1.02	0.99	1.06 *
High	1.00	1.00	1.00	1.00

Asterisks indicate statistically significantly different from base category at 5% level.

Notes:
1) For each variable – *i.e.* race and ethnicity, and neighborhood income – estimated amount paid on claims per year of coverage is measured relative to a base category. For race and ethnicity, the base category is non-Hispanic whites; and, for neighborhood income the base category is “high income” neighborhood.

2) Estimated relative amounts paid out on claims per year of coverage for each race, ethnicity and neighborhood income category in each column are derived from Tweedie GLMs (Generalized Linear Models); which here include a set of standard risk variables as controls, but not score. Since our GLM models are multiplicative, the relativities shown on this table are equivalent to the exponentiated regression coefficients of the indicator variables for these categories. Modeling details and a description of the variables included in the models are provided in Appendix D.

Source: Analysis of FTC Automobile Insurance Policy Database

TABLE 6.
Estimated Relative Amount Paid on Claims, by Score Decile, Race, Ethnicity, and Neighborhood Income

	Property Damage Liability Coverage		Bodily Injury Liability Coverage	
	(a)	(b)	(c)	(d)
Score Decile				
1	1.70 *	1.73 *	2.20 *	2.10 *
2	1.52 *	1.53 *	2.14 *	2.07 *
3	1.43 *	1.44 *	1.75 *	1.72 *
4	1.35 *	1.35 *	1.66 *	1.65 *
5	1.24 *	1.24 *	1.37 *	1.36 *
6	1.23 *	1.23 *	1.26 *	1.26 *
7	1.13 *	1.12 *	1.15	1.14
8	1.07	1.07	1.13	1.13
9	1.12 *	1.12 *	1.21	1.21
10	1.00	1.00	1.00	1.00
Race and Ethnicity				
African Americans	-	0.93	-	1.29 *
Hispanics	-	1.06	-	1.15
Asians	-	1.20 *	-	1.15
Non-Hispanic Whites	-	1.00	-	1.00
Neighborhood Income				
Low	-	0.96	-	0.98
Middle	-	0.94 *	-	1.00
High	-	1.00	-	1.00

Asterisks indicate statistically significantly different from base category at 5% level.

Coefficients in dashed boxes are statistically significantly different across models (within a given coverage type) at the 5% level.

(continued. . .)

TABLE 6.
Estimated Relative Amount Paid on Claims, by Score Decile, Race, Ethnicity, and Neighborhood Income (Continued)

	Collision Coverage		Comprehensive Coverage	
	(e)	(f)	(g)	(h)
Score Decile				
1	2.03 *	1.93 *	1.95 *	1.74 *
2	1.65 *	1.59 *	1.43 *	1.33 *
3	1.52 *	1.48 *	1.33 *	1.26 *
4	1.39 *	1.36 *	1.28 *	1.23 *
5	1.27 *	1.25 *	1.19 *	1.16 *
6	1.26 *	1.25 *	1.15 *	1.12 *
7	1.16 *	1.15 *	1.12 *	1.10 *
8	1.09	1.08	1.05	1.04
9	1.12 *	1.12 *	1.01	0.99
10	1.00	1.00	1.00	1.00
Race and Ethnicity				
African Americans	-	1.26 *	-	1.46 *
Hispanics	-	1.24 *	-	1.36 *
Asians	-	1.33 *	-	0.97
Non-Hispanic Whites	-	1.00	-	1.00
Neighborhood Income				
Low	-	1.01	-	1.13 *
Middle	-	0.97	-	1.04
High	-	1.00	-	1.00

Asterisks indicate statistically significantly different from base category at 5% level.

Coefficients in dashed boxes are statistically significantly different across models (within a given coverage type) at the 5% level.

Notes:
1) For each variable – score, race and ethnicity, and neighborhood income – estimated amount paid on claims per year of coverage is measured relative to a base category. For scores, the base category is the 10^{th} (highest) decile of scores; for race and ethnicity, the base category is non-Hispanic whites; and, for neighborhood income the base category is “high income” neighborhood.

2) Estimated relative amounts paid out on claims per year of coverage for each race, ethnicity and neighborhood income category in each column are derived from Tweedie GLMs (Generalized Linear Models); which here include a set of standard risk variables as controls, as well as score deciles. Since our GLM models are multiplicative, the relativities shown on this table are equivalent to the exponentiated regression coefficients of the indicator variables for these categories. Modeling details and a description of the variables included in the models are provided in Appendix D.

Source: Analysis of FTC Automobile Insurance Policy Database

TABLE 7.

Change in Predicted Amount Paid on Claims from Using Credit-Based Insurance Scores Without and With Controls for Race, Ethnicity, and Income, by Race and Ethnicity

	Average Score Effect From Model Without Race, Ethnicity, and Income Controls (a)	Average Score Effect from Model With Race, Ethnicity, and Income Controls (b)
African Americans	10.0%	8.9%
Hispanics	4.2%	3.5%
Asians	- 4.9%	-4.8%
Non-Hispanic Whites	- 1.6%	-1.4%

Numbers for all race and ethnicity groups are statistically significantly different across the models in columns (a) and (b) at the 5% level.

Notes:

Column (a): Results in this column come from the same analysis that was used to create Table 4. Predicted change in the amount paid on claims was estimated by comparing individual predicted risk from risk models that include ChoicePoint Attract Standard Auto credit-based insurance scores with risk models that do not include scores. All models include a standard set of risk variables as controls, and were run separately for property damage liability, bodily injury liability, collision, and comprehensive coverage (in the final step we sum the predicted dollar risks for all four types of insurance coverage); the same is true for column (b). This procedure is described in section VI.A.3 of the report. Modeling details and a description of the variables included in the models are provided in Appendix D.

Column (b): Results in this column are calculated by combining the estimated risk effects of the score deciles from models with controls for race, ethnicity, and income with the estimated risk effects of non-credit risk variables from the models used in column (a), which do not include these additional controls. The estimated risk effects of race, ethnicity, and income were not used to predict risk. This hybrid risk estimate produced an overall average predicted claims payout that was lower than the actual sample average amount of claims payouts, so every individual's predicted risk was then inflated by the ratio of actual average claims over predicted average claims.

Source: Analysis of FTC Automobile Insurance Policy Database

TABLE 8.
Change in Predicted Amount Paid on Claims from Using Other Risk Variables, Without and With Controls for Race, Ethnicity, and Income, by Race and Ethnicity

	Average Effect of Variable Without Race, Ethnicity, and Income Controls (a)	Average Effect of Variable With Race, Ethnicity, and Income Controls (b)
Geographic Risk		
African Americans	5.4%	4.7%
Hispanics	3.3%	2.2%
Asians	4.4%	3.6%
Non-Hispanic Whites	-1.3%	-1.0%
Tenure		
African Americans	0.4%	0.1%
Hispanics	2.4%	1.9%
Asians	2.1%	1.7%
Non-Hispanic Whites	-0.5%	-0.4%
Prior Claims		
African Americans	2.4%	2.2%
Hispanics	0.3%	0.2%
Asians	1.5%	1.4%
Non-Hispanic Whites	-0.3%	-0.3%

(continued…)

TABLE 8.
Change in Predicted Amount Paid on Claims from Using Other Risk Variables, Without and With Controls for Race, Ethnicity, and Income, by Race and Ethnicity (Continued)

	Average Effect of Variable Without Race, Ethnicity, and Income Controls (a)	Average Effect of Variable With Race, Ethnicity, and Income Controls (b)
Model Year & Other Car Attributes		
African Americans	-1.0%	-1.2%
Hispanics	0.5%	0.5%
Asians	2.8%	2.6%
Non-Hispanic Whites	0.0%	0.0%

Notes:

Column (a): Results in this column come from an analysis similar to that used to create Table 4 for score. Predicted change in the amount paid on claims was estimated by comparing individual predicted risk from risk models that included the particular variable being analyzed here with risk models that did not include the variable. All models include the standard set of risk controls (including score), and were run separately for property damage liability, bodily injury liability, collision, and comprehensive coverage (in the final step we sum the predicted dollar risks for all four types of insurance coverage); the same is true for column (b). This procedure is described in section VI.A.3 of the report. Modeling details and a description of the variables included in the models are provided in Appendix D.

Column (b): Results in this column are calculated by combining the estimated risk effects of the variable being analyzed from models with controls for race, ethnicity, and income with the estimated risk effects of all other risk variables from the models used in column (a), which do not include these additional controls. The estimated risk effects of race, ethnicity, and income were not used to predict risk. This hybrid risk estimate produced an overall average predicted claims payout that was lower than the actual sample average amount of claims payouts, so every individual's predicted risk was then inflated by the ratio of actual average claims over predicted average claims.

Source: Analysis of FTC Automobile Insurance Policy Database

TABLE 9.
Baseline Credit-Based Insurance Scoring Model Developed by the FTC

1) *Variable A: Presence of Certain Delinquencies or Adverse Public Records on the Credit File*

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.14	84.5%	56.0%	69.9%	83.0%
1 or more	1.00	15.5%	44.0%	30.1%	17.0%

2) Number of Accounts with Balance Greater than 75% of High Credit (Credit Limit)

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.25	43.2%	20.3%	28.9%	43.0%
1 - 2	1.16	24.9%	21.8%	24.6%	24.4%
2 - 3	1.09	13.1%	17.3%	15.9%	14.3%
3 - 6	1.04	14.0%	27.6%	23.3%	13.2%
6 or More	1.00	4.8%	13.0%	7.4%	5.1%

3) Average Number of Months Bank Revolving Accounts Have Been Open

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.16	3.2%	5.6%	5.5%	2.7%
0 - 24	0.67	3.6%	9.2%	10.0%	6.3%
24 - 51	0.80	10.4%	18.6%	18.6%	16.1%
51 - 64	0.83	9.4%	10.3%	12.0%	11.5%
64 - 99	0.84	34.8%	27.8%	31.3%	36.8%
99 - 205	0.87	36.2%	26.3%	21.5%	25.4%
205 or More	1.00	2.4%	2.1%	1.2%	1.3%

(continued. . .)

TABLE 9.
Baseline Credit-Based Insurance Scoring Model Developed by the FTC (Continued)

4) *Variable B: Relates to the Number of Inquiries on the File*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade lines	1.30	34.1%	21.6%	15.9%	19.8%
0	1.31	16.6%	13.9%	14.4%	16.2%
1 - 2	1.29	22.0%	22.8%	20.0%	21.3%
2 - 4	1.20	17.8%	23.2%	25.9%	23.6%
4 - 7	1.13	7.3%	12.6%	16.0%	12.7%
7 or more	1.00	2.4%	5.9%	7.8%	6.4%

5) Number of Open Auto Finance Accounts

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.13	90.0%	84.1%	88.0%	85.3%
0 or more	1.00	10.0%	15.9%	12.0%	14.7%

6) Number of Accounts 30 Days Late or Worse in the Last 12 Months

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.36	77.1%	47.4%	61.4%	75.8%
1 - 9	1.13	22.2%	50.3%	37.4%	23.6%
10 or more	1.00	0.7%	2.2%	1.2%	0.7%

7) *Variable C: Presence of Delinquencies on a Particular Kind of Account*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.99	25.1%	23.8%	20.0%	25.1%
0	0.78	71.8%	67.0%	72.5%	71.4%
1 or more	1.00	3.1%	9.2%	7.5%	3.5%

(continued. . .)

TABLE 9.
Baseline Credit-Based Insurance Scoring Model Developed by the FTC (Continued)

8) Number of Department Store Accounts

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.00	25.1%	23.8%	20.0%	25.1%
1 or more	1.17	72.3%	71.2%	74.4%	71.7%
6 or more	1.00	2.5%	5.0%	5.6%	3.2%

9) Share of all Bank Revolving Accounts that are Open

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.75	5.4%	9.8%	8.9%	4.8%
0 - .135	0.89	2.8%	4.3%	3.5%	2.8%
> .135	1.00	91.7%	85.8%	87.7%	92.3%

10) *Variable D: Presence of a Particular Kind of Delinquency on the Account*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.16	83.9%	54.1%	68.9%	82.3%
1 or more	1.00	16.1%	45.9%	31.1%	17.7%

11) Age of Youngest Account (Months)

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - 6	0.82	31.7%	37.2%	38.3%	37.4%
6 - 9	0.87	15.1%	18.0%	18.0%	15.6%
9 - 20	0.89	26.3%	26.7%	25.0%	26.0%
20 or more	1.00	26.9%	18.1%	18.7%	21.0%

(continued. . .)

TABLE 9.
Baseline Credit-Based Insurance Scoring Model Developed by the FTC (Continued)

12) *Variable E: Relates to the Number of Accounts in the Credit File*

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.89	0.2%	0.4%	0.5%	0.0%
0 - 3	0.82	3.7%	5.6%	4.6%	3.7%
3 or more	1.00	96.2%	94.1%	94.9%	96.3%

13) *Variable F: A Ratio Relating to Delinquencies*

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - .02	1.17	94.6%	80.7%	88.4%	93.8%
.02 - .14	1.20	2.7%	9.4%	6.0%	2.8%
> .14	1.00	2.8%	9.9%	5.6%	3.5%

14) Number of Bank Revolving Accounts Ever Bad Debt

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.62	3.0%	5.0%	5.2%	2.4%
0	0.90	90.1%	75.3%	81.8%	89.9%
1 or more	1.00	6.9%	19.8%	12.9%	7.7%

15) Number of Open Oil Accounts

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.92	91.6%	93.7%	88.7%	91.2%
0 or more	1.00	8.4%	6.3%	11.3%	8.8%

Notes:
1) Variables in italics have not been described publicly, and ChoicePoint considers the descriptions of those variables to be proprietary information.

2) This scoring model was developed to use credit history information to predict the relative risk posed by individuals, where risk is defined as expected total dollars that would be paid out on claims in a year. To calculate a score for a given individual with this model, the appropriate factors for each of the 15 variables are multiplied together. The resulting product is the inverse of the estimated relative riskiness of the individual, based on the individual's credit history. See Appendix E for a detailed discussion of the score-building process.

TABLE 10.
Credit-Based Insurance Scoring Model Developed by the FTC by Including Controls for Race, Ethnicity, and Neighborhood Income in the Score-Building Process

1) *Variable A: Presence of Certain Delinquencies or Adverse Public Records on the Credit File*

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.14	84.5%	56.0%	69.9%	83.0%
1 or more	1.00	15.5%	44.0%	30.1%	17.0%

2) Number of Accounts with Balance Greater than 75% of High Credit (Credit Limit)

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.26	43.2%	20.3%	28.9%	43.0%
1 - 2	1.17	24.9%	21.8%	24.6%	24.4%
2 - 3	1.11	13.1%	17.3%	15.9%	14.3%
3 - 6	1.05	14.0%	27.6%	23.3%	13.2%
6 or More	1.00	4.8%	13.0%	7.4%	5.1%

3) Average Number of Months Bank Revolving Accounts Have Been Open

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.13	3.2%	5.6%	5.5%	2.7%
0 - 24	0.67	3.6%	9.2%	10.0%	6.3%
24 - 51	0.80	10.4%	18.6%	18.6%	16.1%
51 - 64	0.82	9.4%	10.3%	12.0%	11.5%
64 - 99	0.84	34.8%	27.8%	31.3%	36.8%
99 - 205	0.87	36.2%	26.3%	21.5%	25.4%
205 or More	1.00	2.4%	2.1%	1.2%	1.3%

4) Number of Open Auto Finance Accounts

Category	Factor	Share in each category, by race or ethnicity			
		Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.12	90.0%	84.1%	88.0%	85.3%
0 or more	1.00	10.0%	15.9%	12.0%	14.7%

(continued. . .)

TABLE 10.
Credit-Based Insurance Scoring Model Developed by the FTC by Including Controls for Race, Ethnicity, and Neighborhood Income in the Score-Building Process (Continued)

5) *Variable B: Relates to the Number of Inquiries on the File*

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade lines	1.30	34.1%	21.6%	15.9%	19.8%
0	1.31	16.6%	13.9%	14.4%	16.2%
1 - 2	1.28	22.0%	22.8%	20.0%	21.3%
2 - 4	1.20	17.8%	23.2%	25.9%	23.6%
4 - 7	1.13	7.3%	12.6%	16.0%	12.7%
7 or more	1.00	2.4%	5.9%	7.8%	6.4%

6) Number of Accounts 30 Days Late or Worse in the Last 12 Months

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.35	77.1%	47.4%	61.4%	75.8%
1 - 9	1.14	22.2%	50.3%	37.4%	23.6%
10 or more	1.00	0.7%	2.2%	1.2%	0.7%

7) *Variable C: Presence of Delinquencies on a Particular Kind of Account*

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.97	25.1%	23.8%	20.0%	25.1%
0	0.78	71.8%	67.0%	72.5%	71.4%
1 or more	1.00	3.1%	9.2%	7.5%	3.5%

8) Share of all Bank Revolving Accounts that are Open

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.76	5.4%	9.8%	8.9%	4.8%
0 - .135	0.89	2.8%	4.3%	3.5%	2.8%
> .135	1.00	91.7%	85.8%	87.7%	92.3%

(continued. . .)

TABLE 10.
Credit-Based Insurance Scoring Model Developed by the FTC by Including Controls for Race, Ethnicity, and Neighborhood Income in the Score-Building Process (Continued)

9) Number of Department Store Accounts

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.00	25.1%	23.8%	20.0%	25.1%
1 or more	1.15	72.3%	71.2%	74.4%	71.7%
6 or more	1.00	2.5%	5.0%	5.6%	3.2%

10) Age of Youngest Account (Months)

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - 6	0.81	31.7%	37.2%	38.3%	37.4%
6 - 9	0.87	15.1%	18.0%	18.0%	15.6%
9 - 20	0.89	26.3%	26.7%	25.0%	26.0%
20 or more	1.00	26.9%	18.1%	18.7%	21.0%

11) *Variable G: Relates to the Number of Accounts in the Credit File*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - 2	0.89	5.0%	9.9%	6.6%	4.1%
2 or more	1.00	95.0%	90.1%	93.4%	95.9%

12) *Variable D: Presence of a Particular Kind of Delinquency on the Account*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.16	83.9%	54.1%	68.9%	82.3%
1 or more	1.00	16.1%	45.9%	31.1%	17.7%

(continued. . .)

TABLE 10.
Credit-Based Insurance Scoring Model Developed by the FTC by Including Controls for Race, Ethnicity, and Neighborhood Income in the Score-Building Process (Continued)

13) Number of Open Personal Finance Accounts

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.90	82.0%	66.4%	73.6%	82.9%
0 - 2	0.97	14.9%	24.6%	21.5%	14.2%
2 or more	1.00	3.1%	9.0%	4.9%	2.9%

14) *Variable F: A Ratio Relating to Delinquencies*

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - .02	1.17	94.6%	80.7%	88.4%	93.8%
.02 - .14	1.20	2.7%	9.4%	6.0%	2.8%
> .14	1.00	2.8%	9.9%	5.6%	3.5%

15) Number of Bank Revolving Accounts Ever Bad Debt

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.62	3.0%	5.0%	5.2%	2.4%
0	0.90	90.1%	75.3%	81.8%	89.9%
1 or more	1.00	6.9%	19.8%	12.9%	7.7%

Notes:
1) Variables in italics have not been described publicly, and ChoicePoint considers the descriptions of those variables to be proprietary information.

2) This scoring model was developed to use credit history information to predict the relative risk posed by individuals, where risk is defined as expected total dollars that would be paid out on claims in a year. To calculate a score for a given individual with this model, the appropriate factors for each of the 15 variables are multiplied together. The resulting product is the inverse of the estimated relative riskiness of the individual, based on the individual's credit history. This scoring model was developed by including controls for race, ethnicity, and neighborhood income during the process of selecting variables for the scoring model, and when estimating the final factors that are applied to the credit history variables. See Appendix E for a detailed discussion of the score-building process.

TABLE 11.
Credit-Based Insurance Scoring Model Developed by the FTC Using a Sample of Only Non-Hispanic White Insurance Customers

1) *Variable A: Presence of Certain Delinquencies or Adverse Public Records on the Credit File*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.23	84.5%	56.0%	69.9%	83.0%
1 or more	1.00	15.5%	44.0%	30.1%	17.0%

2) *Variable B: Relates to the Number of Inquiries on the File*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade lines	1.25	34.1%	21.6%	15.9%	19.8%
0 - 2	1.25	38.5%	36.7%	34.3%	37.5%
2 or more	1.14	21.5%	29.5%	32.0%	29.3%
5 or more	1.00	6.0%	12.3%	17.8%	13.4%

3) Total Average Debt Burden

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
Invalid past due amount	0.89	0.6%	0.8%	0.9%	0.7%
0 - .19	1.20	41.7%	18.4%	26.2%	44.0%
.19 - .46	1.13	25.5%	22.5%	25.5%	24.7%
.46 - .81	1.06	24.4%	38.8%	33.8%	23.7%
> .81	1.00	7.7%	19.4%	13.6%	6.8%

4) Age of Youngest Account (Months)

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - 6	0.84	31.7%	37.2%	38.3%	37.4%
6 - 14	0.90	30.3%	35.5%	34.4%	31.1%
14 or more	1.00	38.0%	27.3%	27.3%	31.4%

(continued. . .)

TABLE 11.
Credit-Based Insurance Scoring Model Developed by the FTC Using a Sample of Only Non-Hispanic White Insurance Customers (Continued)

5) Number of Accounts 30 Days Late in the Last 24 Months

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.15	83.9%	65.3%	73.9%	83.7%
1 or more	1.00	16.1%	34.7%	26.1%	16.3%

6) Share of all Bank Revolving Accounts that are Open

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.82	5.4%	9.8%	8.9%	4.8%
0 or more	1.00	94.6%	90.2%	91.1%	95.2%

7) Number of Open Auto Finance Accounts

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.10	90.0%	84.1%	88.0%	85.3%
0 or more	1.00	10.0%	15.9%	12.0%	14.7%

8) Average Number of Months Account have been Open

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - 32	0.68	3.8%	6.4%	9.8%	9.1%
32 - 75	0.90	30.5%	42.5%	45.2%	40.5%
75 - 118	0.95	41.7%	34.8%	32.7%	37.2%
118 or more	1.00	24.0%	16.4%	12.3%	13.2%

9) Number of Open Accounts

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - 12	1.10	81.3%	76.0%	76.8%	75.4%
12 or more	1.00	18.7%	24.0%	23.2%	24.6%

(continued. . .)

TABLE 11.
Credit-Based Insurance Scoring Model Developed by the FTC Using a Sample of Only Non-Hispanic White Insurance Customers (Continued)

10) *Variable H: Presence of a Particular Kind of Delinquency on the Account*

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.28	98.8%	95.4%	97.7%	98.7%
1 or more	1.00	1.2%	4.6%	2.3%	1.3%

11) Ratio of Open Personal Financial Accounts to Total Open Accounts

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.90	82.0%	66.4%	73.6%	82.9%
0 or more	1.00	18.0%	33.6%	26.4%	17.1%

12) *Variable D: Presence of a Particular Kind of Delinquency on the Account*

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.16	83.9%	54.1%	68.9%	82.3%
1 or more	1.00	16.1%	45.9%	31.1%	17.7%

13) *Variable C: Presence of Delinquencies on a Particular Kind of Account*

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.90	25.1%	23.8%	20.0%	25.1%
0	0.81	71.8%	67.0%	72.5%	71.4%
1 or more	1.00	3.1%	9.2%	7.5%	3.5%

(continued. . .)

TABLE 11.
Credit-Based Insurance Scoring Model Developed by the FTC Using a Sample of Only Non-Hispanic White Insurance Customers (Continued)

14) *Variable I: Relates to the Number of Accounts in the Credit File*

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
Disputed	1.41	0.2%	0.5%	0.5%	0.0%
0 - 2	0.85	2.2%	5.0%	3.3%	2.4%
2 or more	1.00	97.6%	94.6%	96.2%	97.5%

15) Number of Bank Installment Accounts Ever Bad Debt

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.37	44.0%	46.8%	48.0%	49.9%
0	1.37	54.7%	49.5%	49.6%	48.7%
1 or more	1.00	1.3%	3.7%	2.4%	1.3%

Notes:
1) Variables in italics have not been described publicly, and ChoicePoint considers the descriptions of those variables to be proprietary information.

2) This scoring model was developed to use credit history information to predict the relative risk posed by individuals, where risk is defined as expected total dollars that would be paid out on claims in a year. To calculate a score for a given individual with this model, the appropriate factors for each of the 15 variables are multiplied together. The resulting product is the inverse of the estimated relative riskiness of the individual, based on the individual's credit history. This scoring model was developed using a development sample of only non-Hispanic white insurance customers. See Appendix E for a detailed discussion of the score-building process.

TABLE 12.
Credit-Based Insurance Scoring Model Developed by the FTC by Discounting Variables with Large Differences Across Racial and Ethnic Groups

1) *Variable J: Indebtedness on Accounts of a Particular Type*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.22	5.6%	10.0%	8.9%	4.9%
$0 - $1,000	1.34	36.0%	28.6%	34.4%	38.1%
$1000 - $3,000	1.25	20.1%	18.0%	17.9%	20.8%
$3,000 - $14,000	1.14	27.4%	31.9%	29.5%	25.5%
$14,000 or more	1.00	10.9%	11.5%	9.2%	10.7%

2) *Variable E: Relates to the Number of Accounts in the Credit File*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.72	0.2%	0.4%	0.5%	0.0%
0 - 3	0.80	3.7%	5.6%	4.6%	3.7%
3 or more	1.00	96.2%	94.1%	94.9%	96.3%

3) Share of all Accounts that are Open

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - .14	0.83	2.1%	2.6%	2.3%	1.6%
.14 - .27	0.89	8.3%	9.1%	8.1%	8.7%
.27 or more	1.00	89.6%	88.4%	89.6%	89.7%

4) Number of Open Auto Finance Accounts

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.26	90.0%	84.1%	88.0%	85.3%
0 or more	1.00	10.0%	15.9%	12.0%	14.7%

(continued. . .)

TABLE 12.
Credit-Based Insurance Scoring Model Developed by the FTC by Discounting Variables with Large Differences Across Racial and Ethnic Groups (Continued)

5) Number of Open Bank Installment Accounts

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.13	68.5%	68.5%	67.9%	69.4%
0 or more	1.00	31.5%	31.5%	32.1%	30.6%

6) Number of Open Oil Accounts

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.85	91.6%	93.7%	88.7%	91.2%
0 or more	1.00	8.4%	6.3%	11.3%	8.8%

7) Ratio of Open Oil Accounts to Total Open Accounts

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.00	91.6%	93.7%	88.7%	91.2%
0 - .0741	0.86	4.6%	4.3%	6.2%	5.3%
.0741 or more	1.00	3.8%	2.1%	5.2%	3.5%

8) Number of Accounts Opened in the Last 3 Months

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0	1.15	79.3%	75.6%	74.7%	74.5%
1 or more	1.00	20.7%	24.4%	25.3%	25.5%

(continued. . .)

TABLE 12.
Credit-Based Insurance Scoring Model Developed by the FTC by Discounting Variables with Large Differences Across Racial and Ethnic Groups (Continued)

9) Number of Credit Union Accounts

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.06	36.1%	37.2%	34.0%	31.7%
1 - 5	1.06	51.5%	49.0%	52.3%	56.0%
5 or more	1.00	12.4%	13.7%	13.6%	12.3%

10) Age of Last Activity

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
0 - 2	0.88	98.3%	97.8%	98.5%	98.5%
2 or more	1.00	1.7%	2.2%	1.5%	1.5%

11) *Variable K: Number of Accounts of a Particular Type*

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.77	5.4%	9.8%	8.9%	4.8%
0 - 6	0.96	77.8%	75.2%	74.6%	68.3%
6 or more	1.00	16.8%	15.0%	16.6%	26.9%

12) Ratio of Open Department Store Accounts to Total Open Accounts

Category	Factor	Share in each category, by race or ethnicity: Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.99	32.0%	31.7%	28.1%	33.2%
0 - .36	0.93	58.9%	59.0%	61.6%	60.0%
.36 or more	1.00	9.1%	9.3%	10.3%	6.8%

(continued. . .)

TABLE 12.
Credit-Based Insurance Scoring Model Developed by the FTC by Discounting Variables with Large Differences Across Racial and Ethnic Groups (Continued)

13) Ratio of Open Bank Installment Accounts to Total Open Accounts

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	1.00	68.5%	68.5%	67.9%	69.4%
0 - .2917	1.10	27.5%	28.3%	28.6%	27.2%
.2917 or more	1.00	4.0%	3.2%	3.5%	3.4%

14) *Variable L: Based on Total Available Credit*

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
$0 - $3,000	0.91	4.7%	6.8%	6.7%	4.6%
$3,000 or more	1.00	95.3%	93.2%	93.3%	95.4%

15) Ratio of Open Credit Union Accounts to Total Open Accounts

		Share in each category, by race or ethnicity			
Category	Factor	Non-Hispanic Whites	African Americans	Hispanics	Asians
No trade line of this type	0.97	49.8%	48.9%	46.3%	45.1%
0 - .0789	0.95	7.4%	8.9%	8.6%	8.6%
.0789 or more	1.00	42.8%	42.2%	45.1%	46.3%

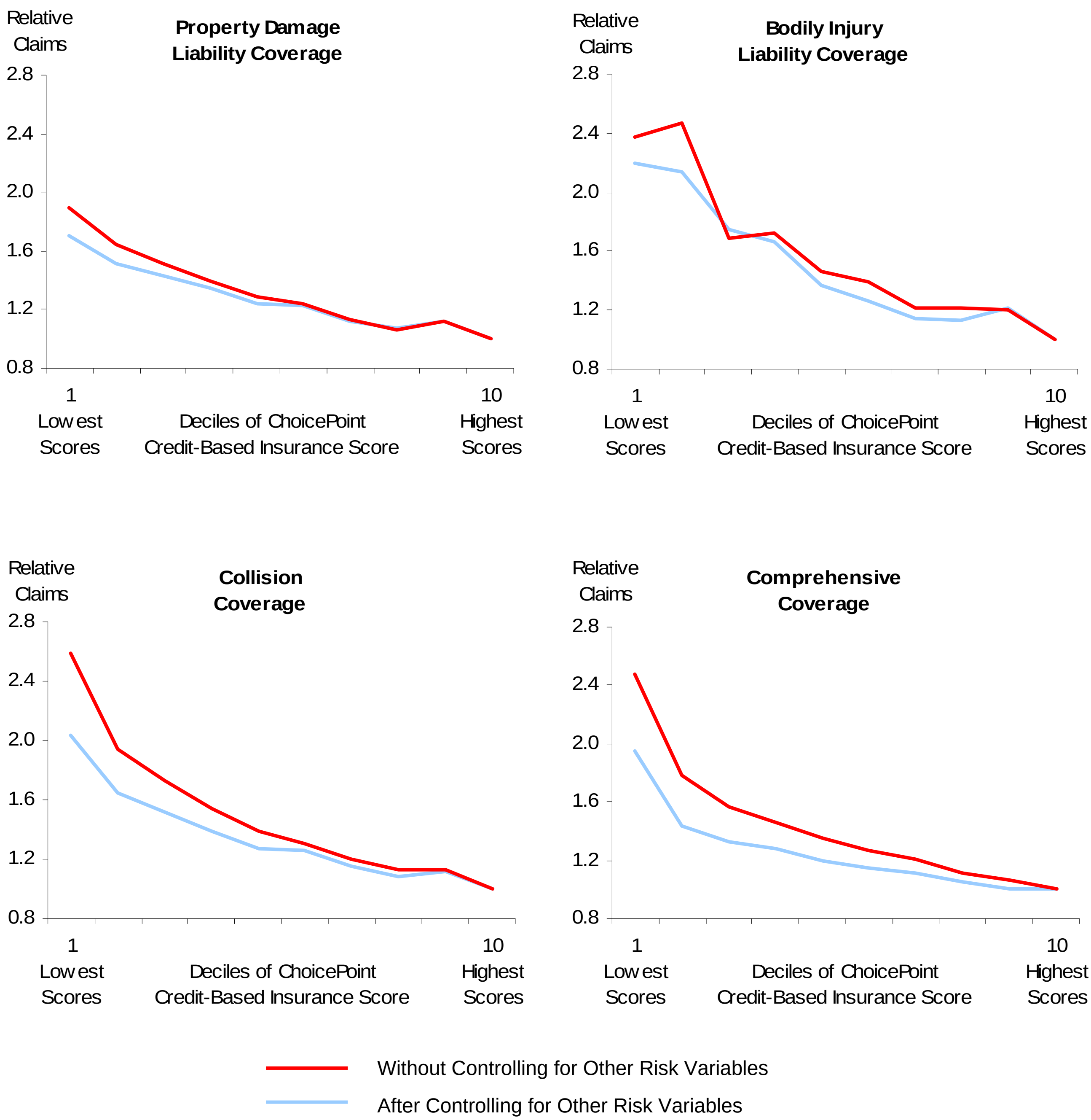
Notes:
1) Variables in italics have not been described publicly, and ChoicePoint considers the descriptions of those variables to be proprietary information.

2) This scoring model was developed to use credit history information to predict the relative risk posed by individuals, where risk is defined as expected total dollars that would be paid out on claims in a year. To calculate a score for a given individual with this model, the appropriate factors for each of the 15 variables are multiplied together. The resulting product is the inverse of the estimated relative riskiness of the individual, based on the individual's credit history. This scoring model was developed by discounting the predictive power of variables that had large differences across racial and ethnic groups, so that those variables would be less likely to be chosen by the score-building procedure. See Appendix E for a detailed discussion of the score-building process.

FIGURES

FIGURE 1.

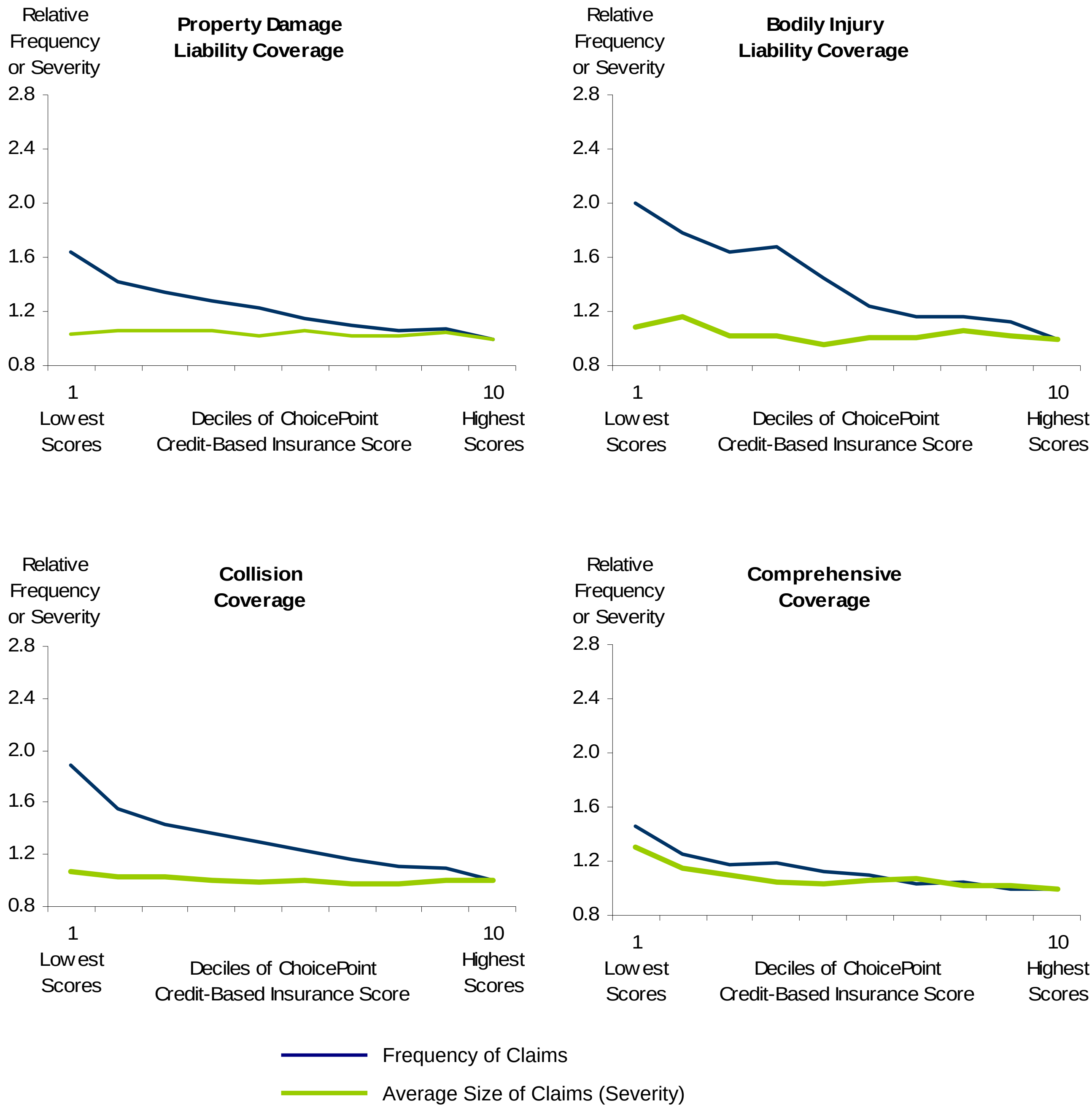
Estimated Average Amount Paid Out on Claims, Relative to Highest Score Decile



See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 2.

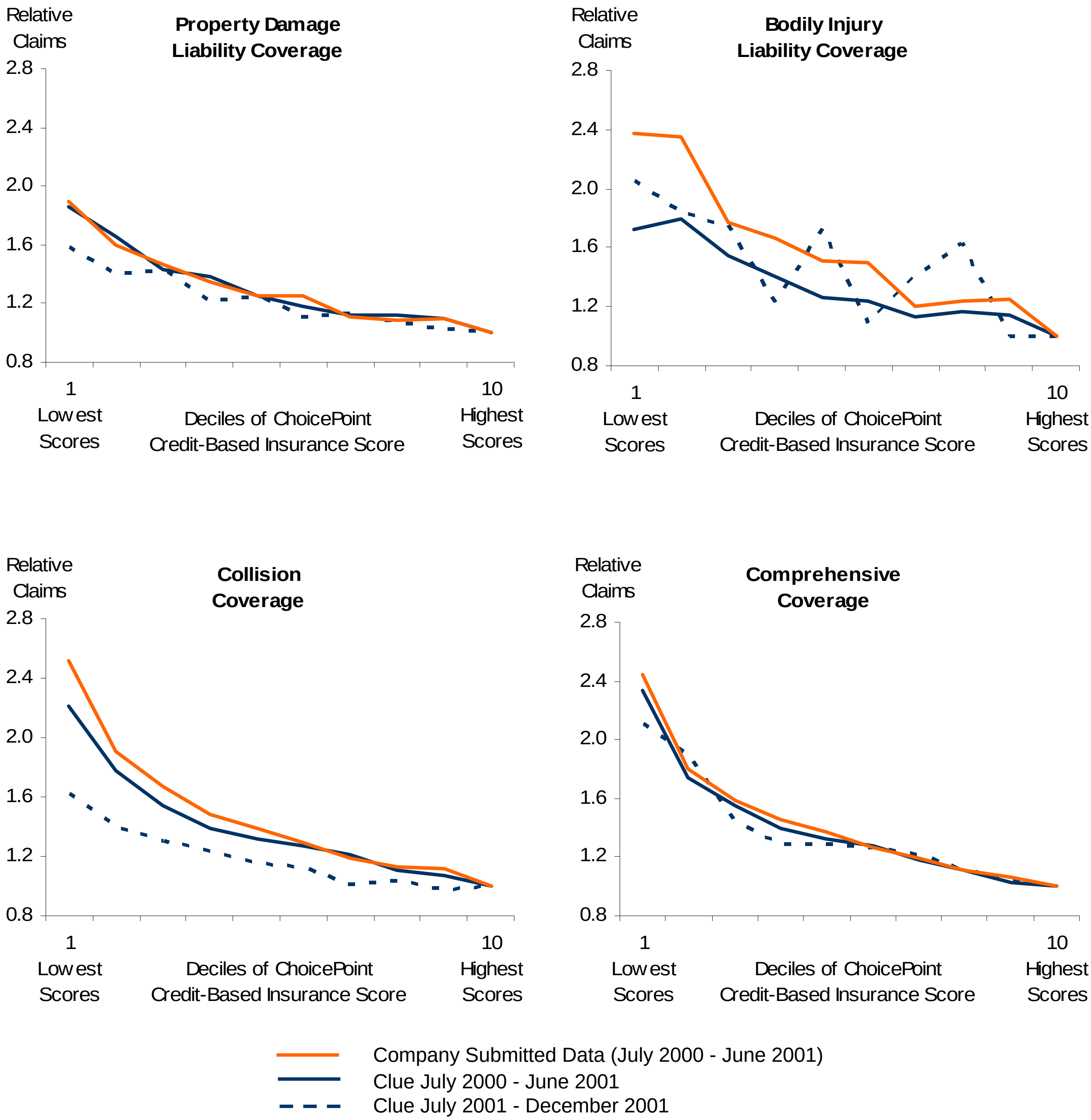
Frequency and Average Size (Severity) of Claims,
Relative to Highest Score Decile



See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 3.

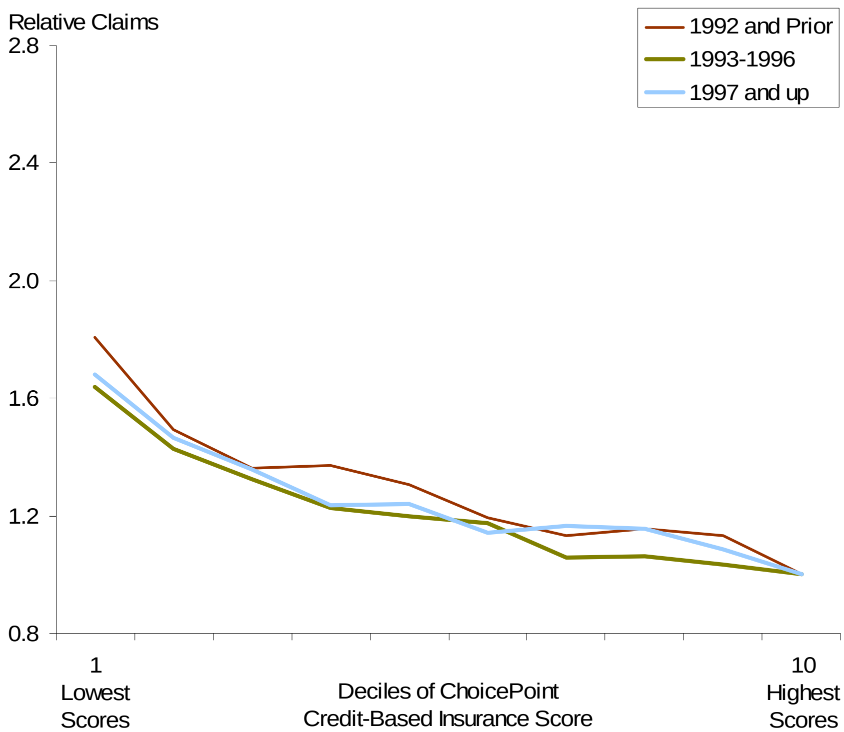
"CLUE" Claims Data:
Average Amount Paid Out on Claims,
Relative to Highest Score Decile



See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 4.

**By Model Year of Car:
Estimated Average Amount Paid Out on Claims,
Relative to Highest Score Decile
(Property Damage Liability Coverage)**

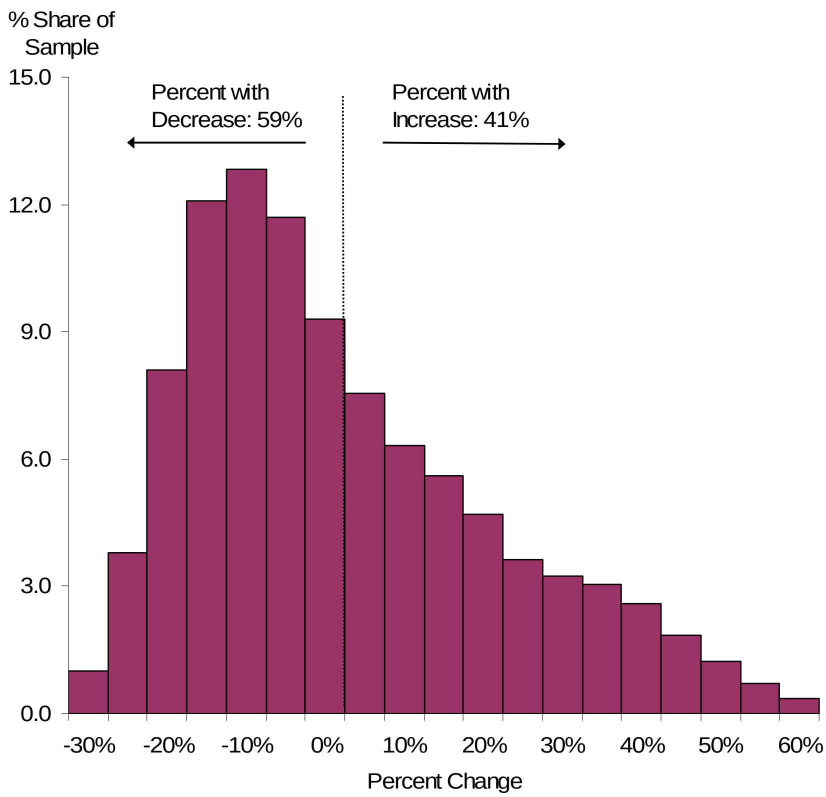


See notes on Figures at the end of this section.

Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 5.

Change in Predicted Amount Paid on Claims from Using Scores

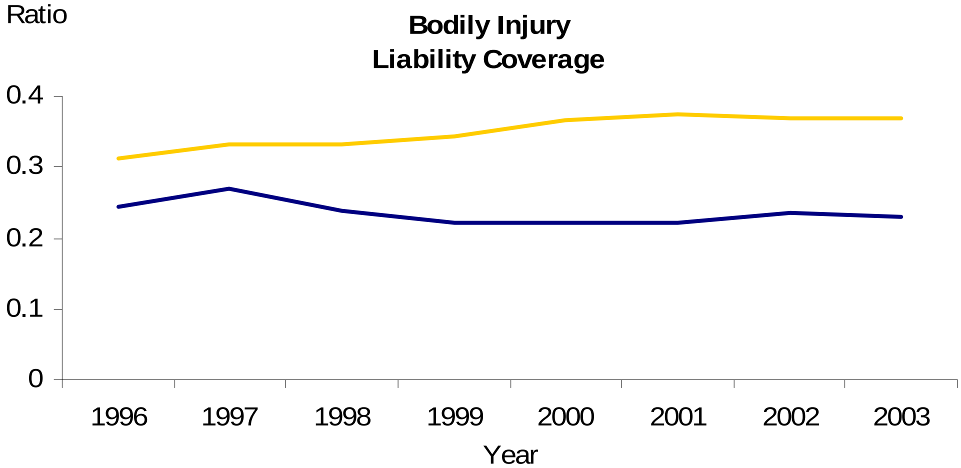


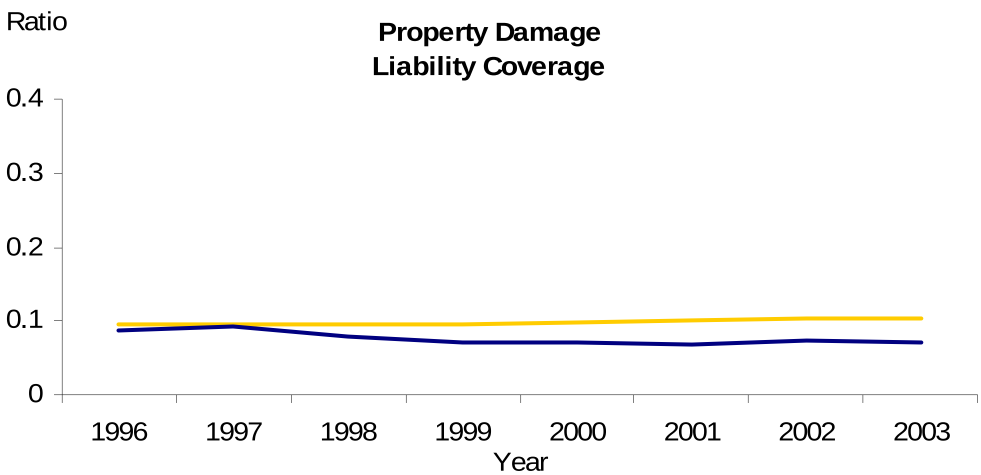
See notes on Figures at the end of this section.

Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 6.

The Ratio of Uninsured Motorist Claims to Liability Coverage Claims (1996-2003)





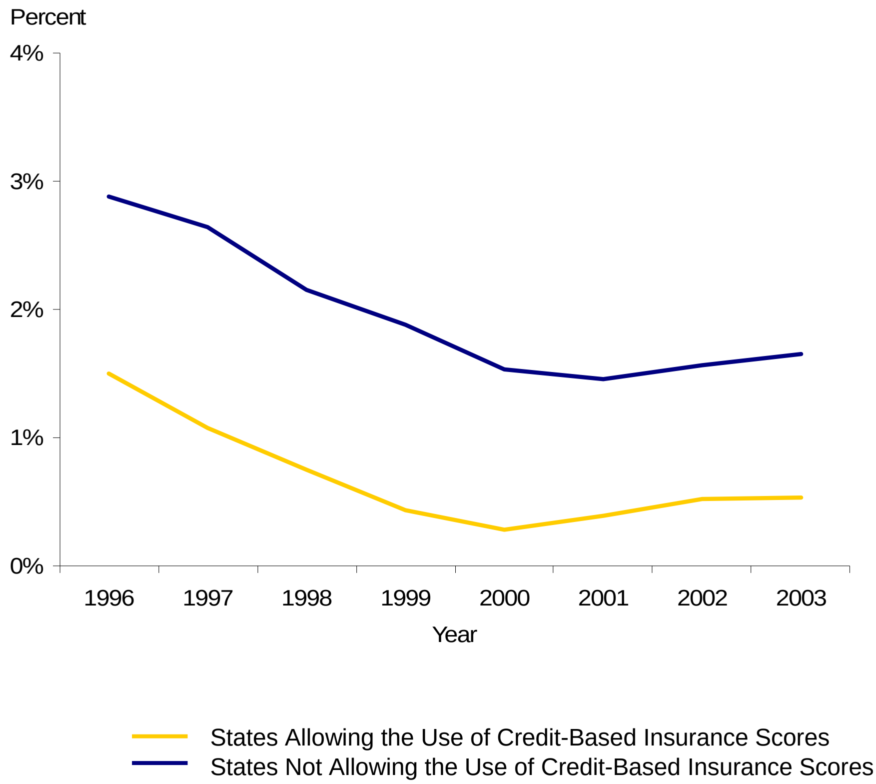
States Allowing the Use of Credit-Based Insurance Scores
States Not Allowing the Use of Credit-Based Insurance Scores

See notes on Figures at the end of this section.

Source: Analysis of data from several National Association of Insurance Commissioners Database Reports.

FIGURE 7.

Share of Cars Insured through States' "Residual Market" Insurance Programs (1996-2003)



See notes on Figures at the end of this section.

Source: Analysis of data from several National Association of Insurance Commissioners Database Reports.

FIGURE 8.

Distribution of Scores, by Race and Ethnicity

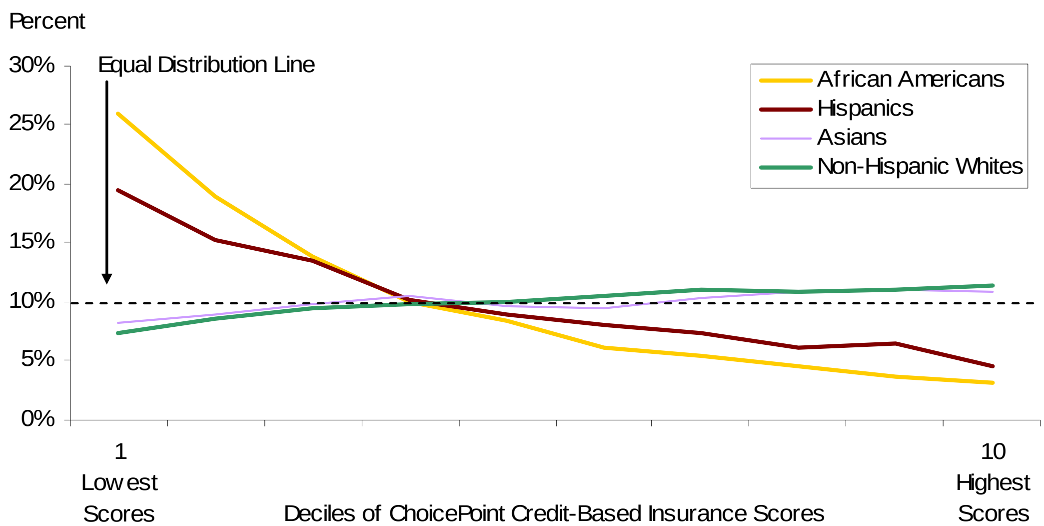
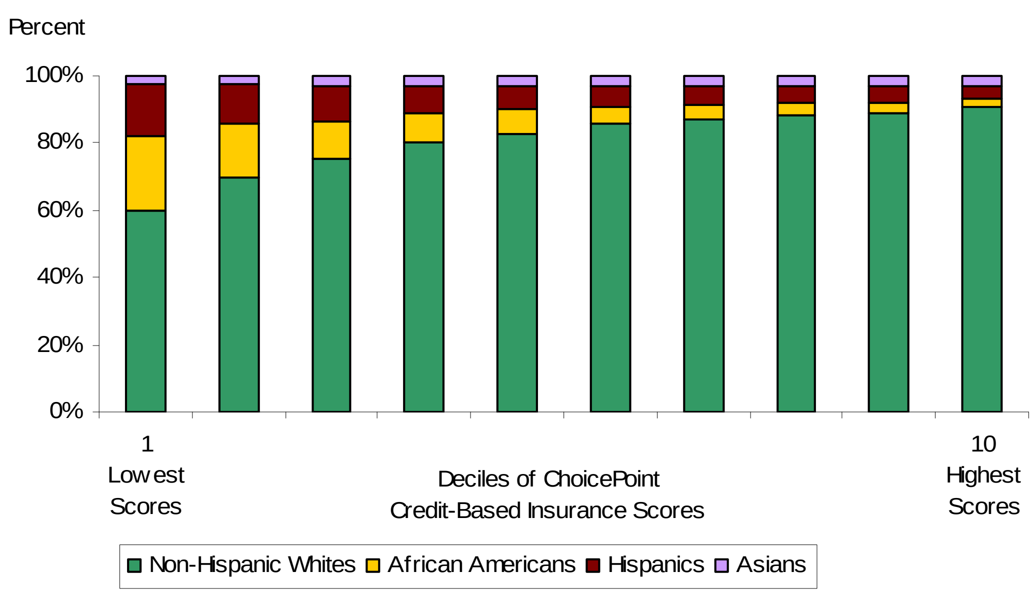


FIGURE 9.

Distribution of Race and Ethnicity, by Score Decile



See notes on Figures at the end of this section.

Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 10.

Distribution of Scores, by Neighborhood Income

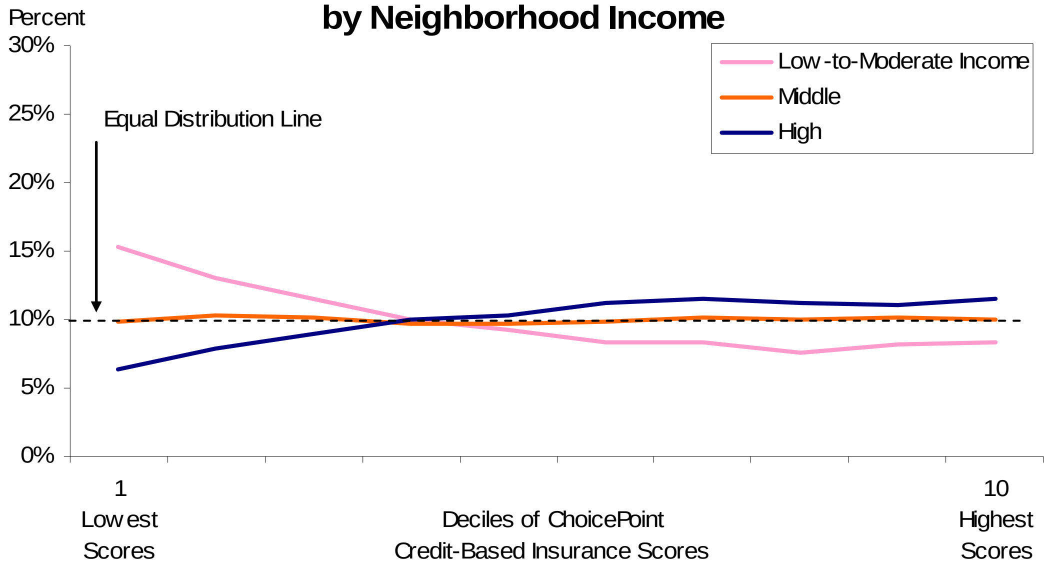
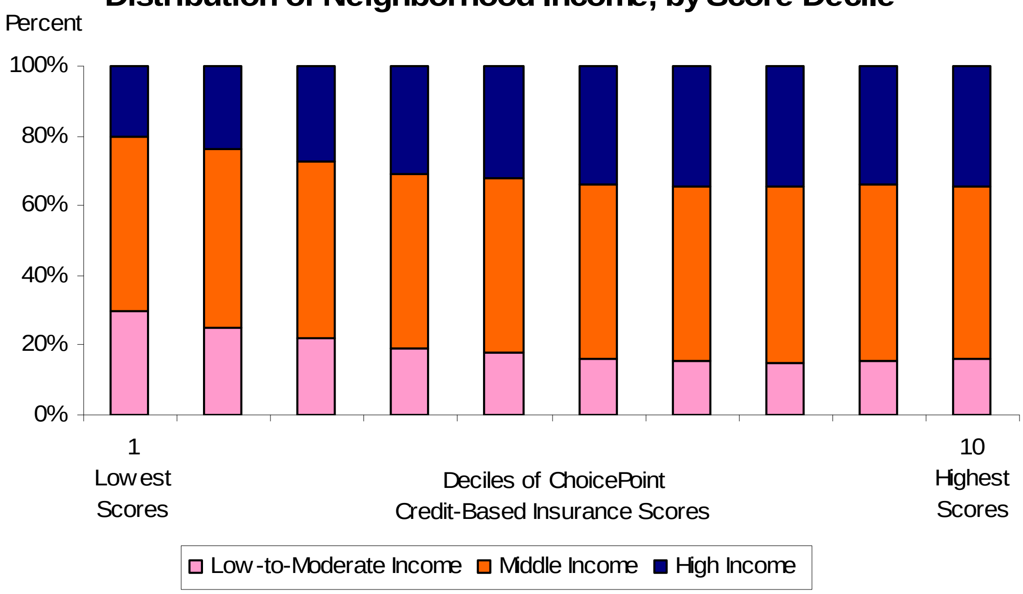


FIGURE 11.

Distribution of Neighborhood Income, by Score Decile

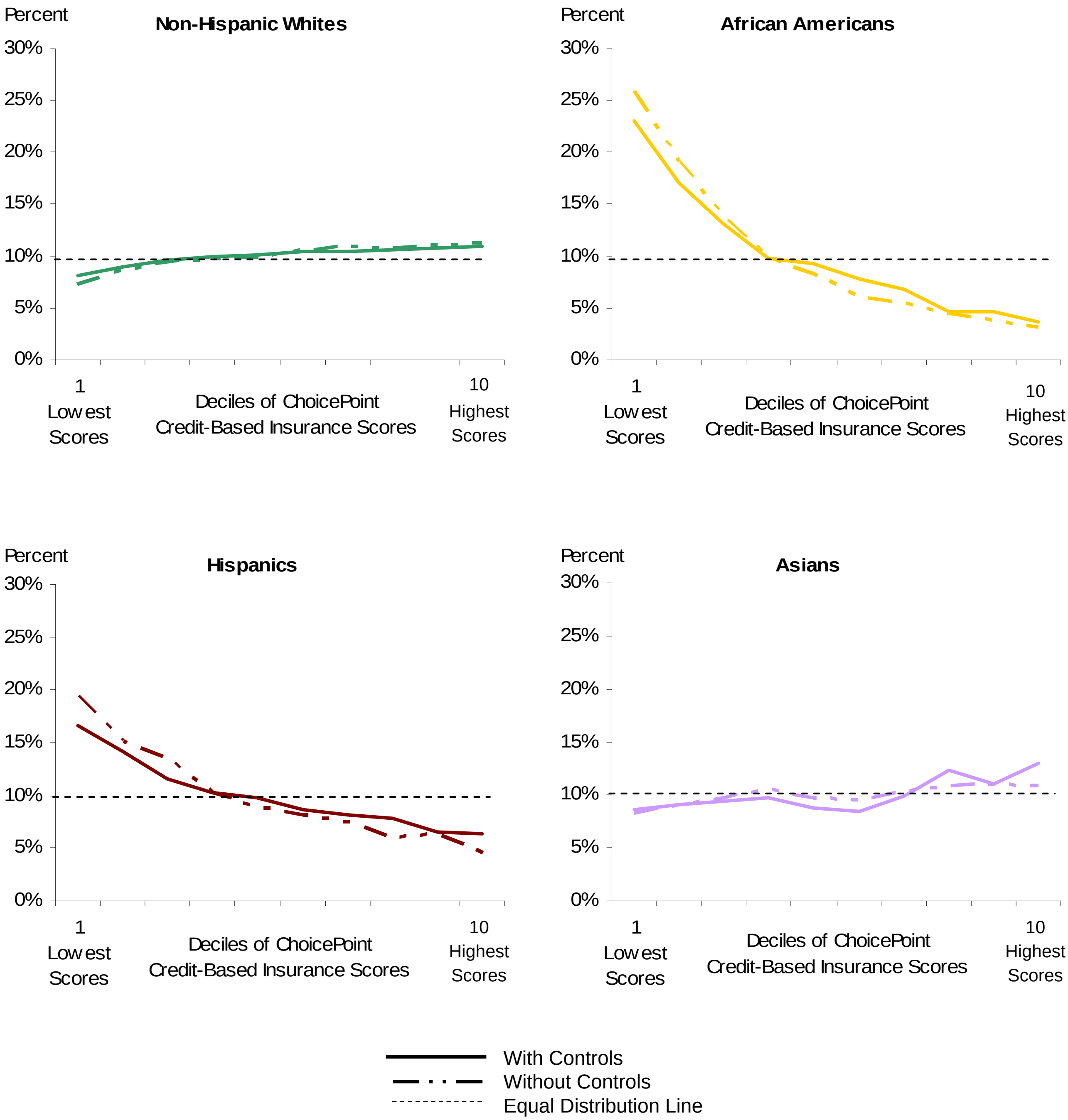


See notes on Figures at the end of this section.

Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 12.

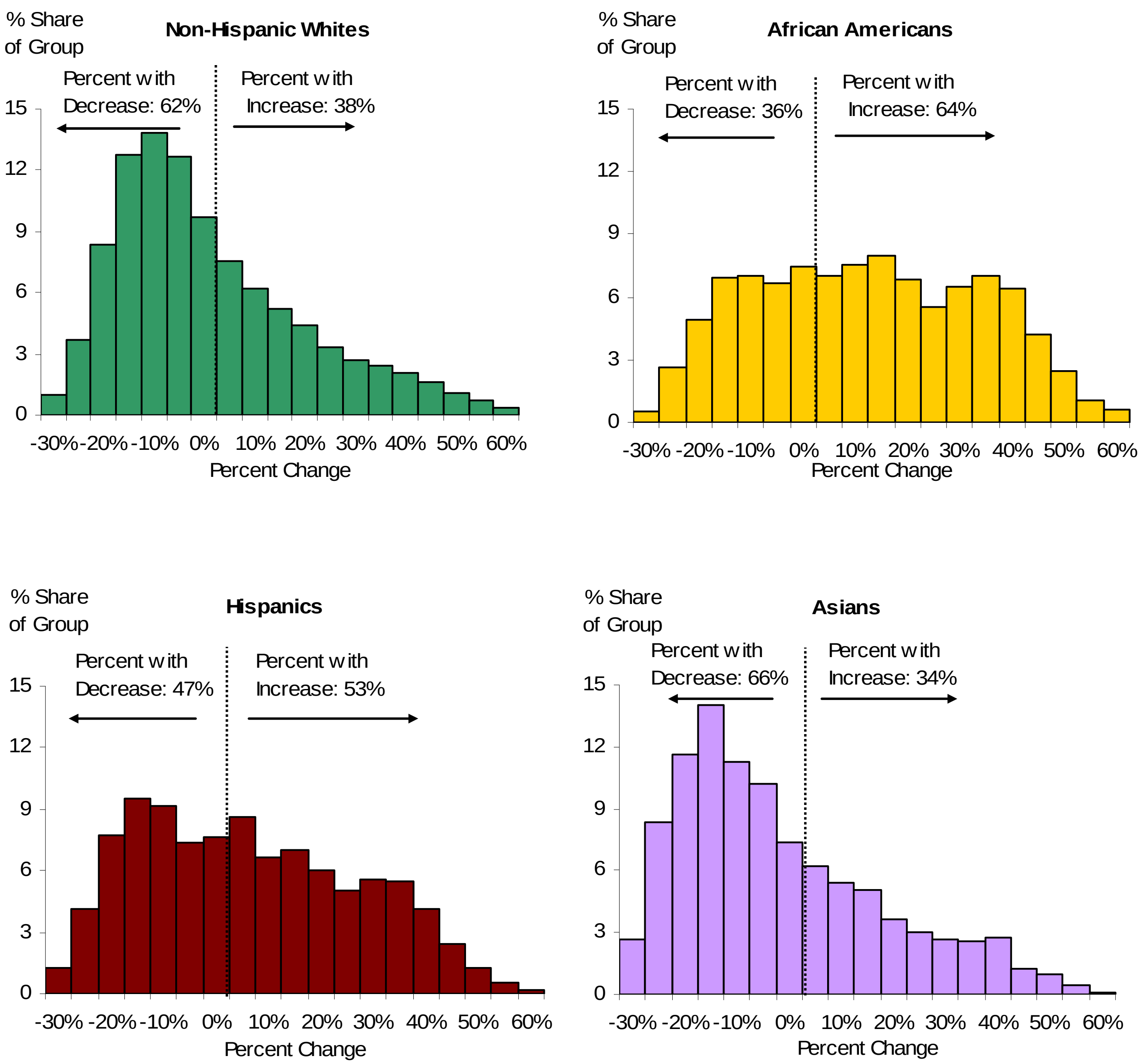
**Distribution of Scores by Race and Ethnicity,
After Controlling for Age, Gender, and Neighborhood Income**



See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 13.

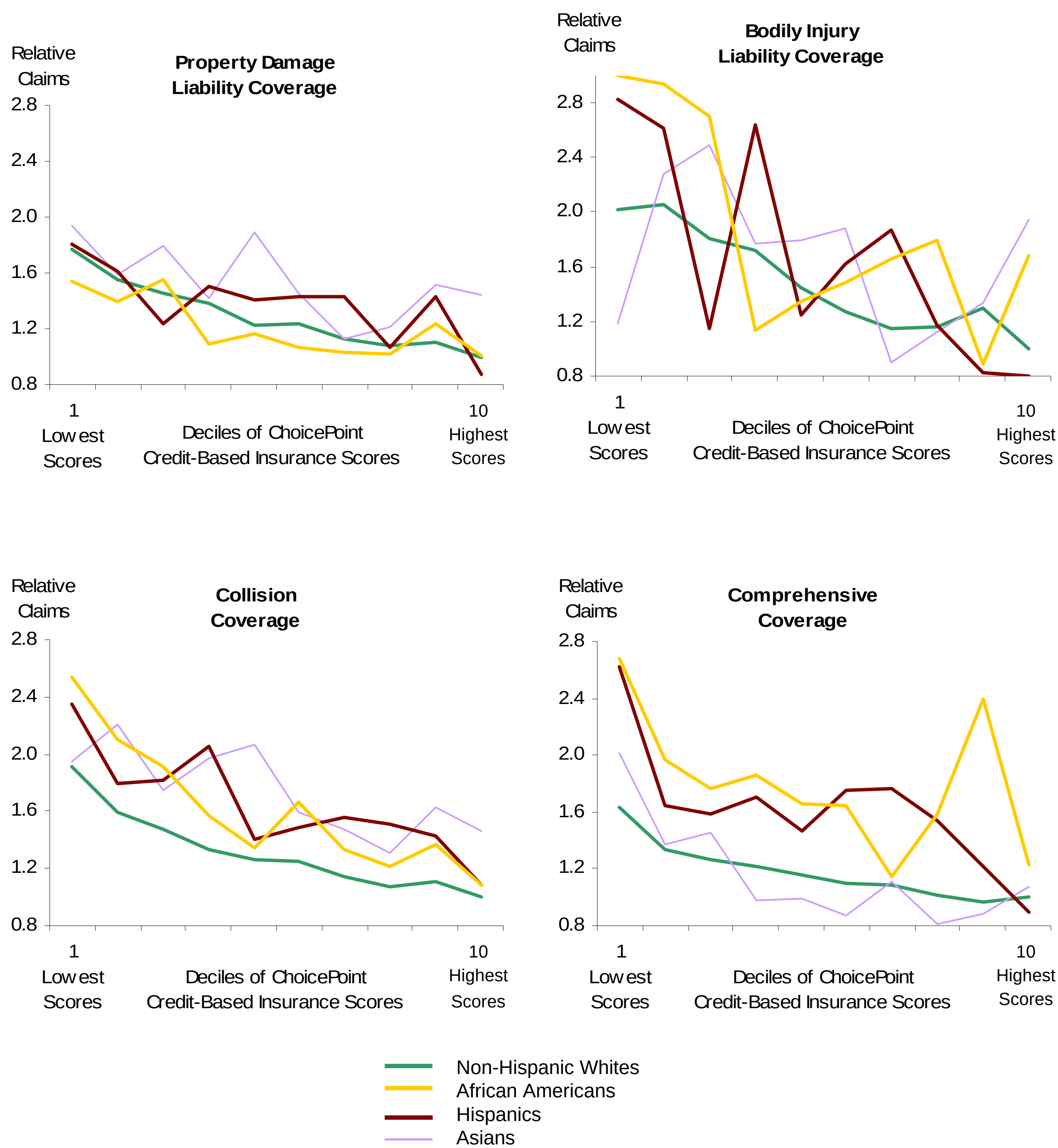
By Race and Ethnicity: Change in Predicted Amount Paid on Claims from Using Scores



See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 14.

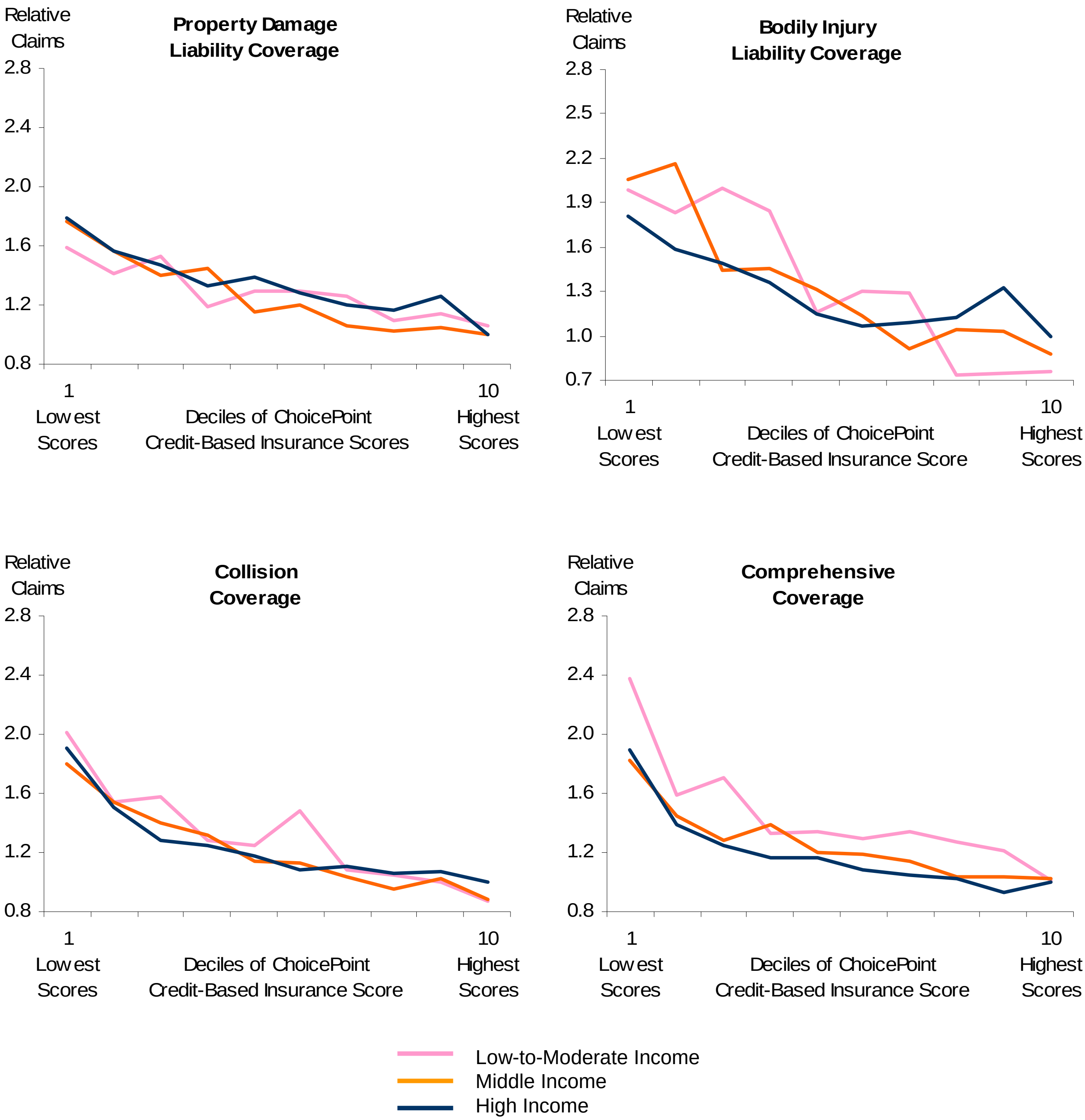
By Race and Ethnicity:
Estimated Average Amount Paid Out on Claims,
Relative to Non-Hispanic Whites in Highest Score Decile



See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 15.

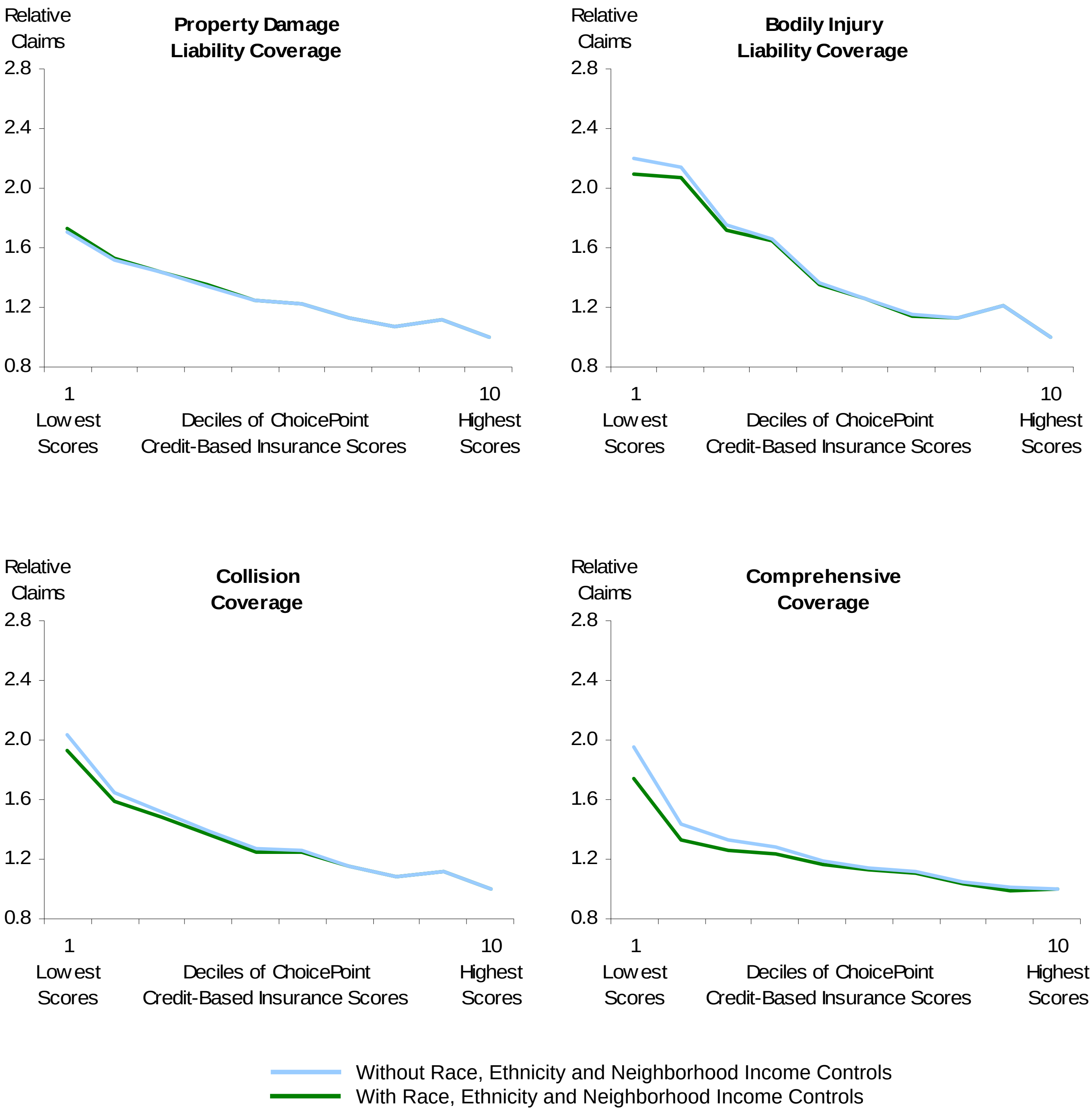
**By Neighborhood Income:
Estimated Average Amount Paid Out on Claims,
Relative to People in Highest Score Decile in High Income Areas**



See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 16.

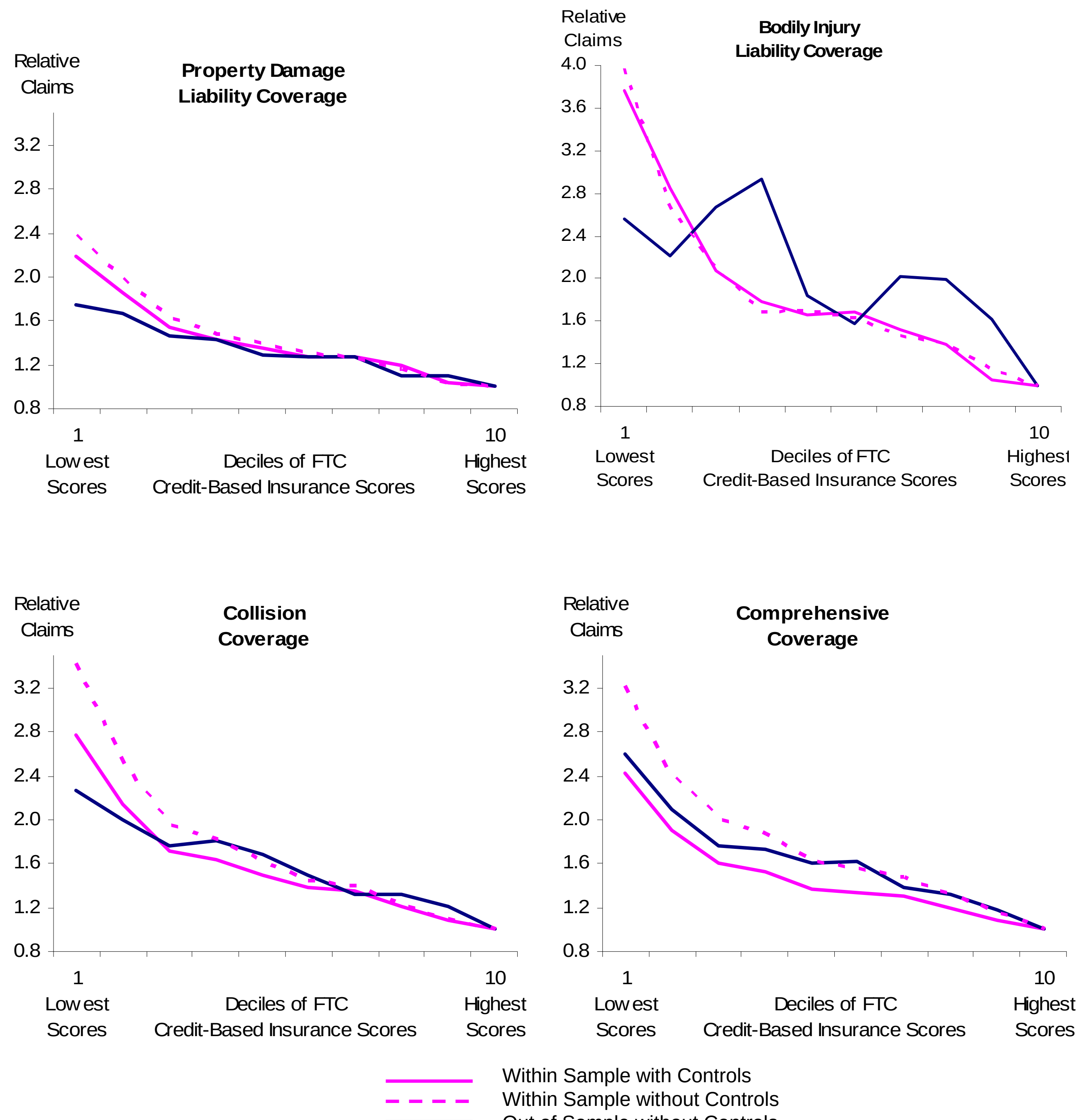
Estimated Average Amount Paid Out on Claims, Relative to Highest Score Decile, with and without Controls for Race, Ethnicity, and Neighborhood Income



See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 17.

FTC Baseline Model -
Estimated Average Amount Paid Out on Claims,
Relative to Highest Score Decile

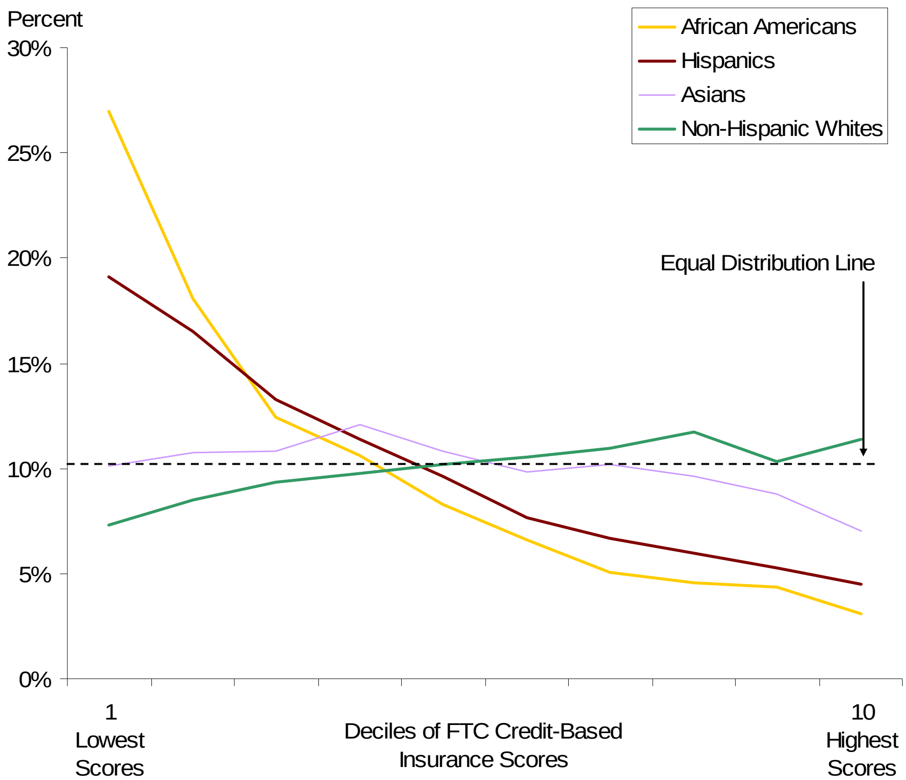


Note that the vertical scale on these graphs is different than for previous graphs of relative claims and score deciles.

See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 18.

Distribution of FTC Baseline Model Credit-Based Insurance Scores, by Race and Ethnicity

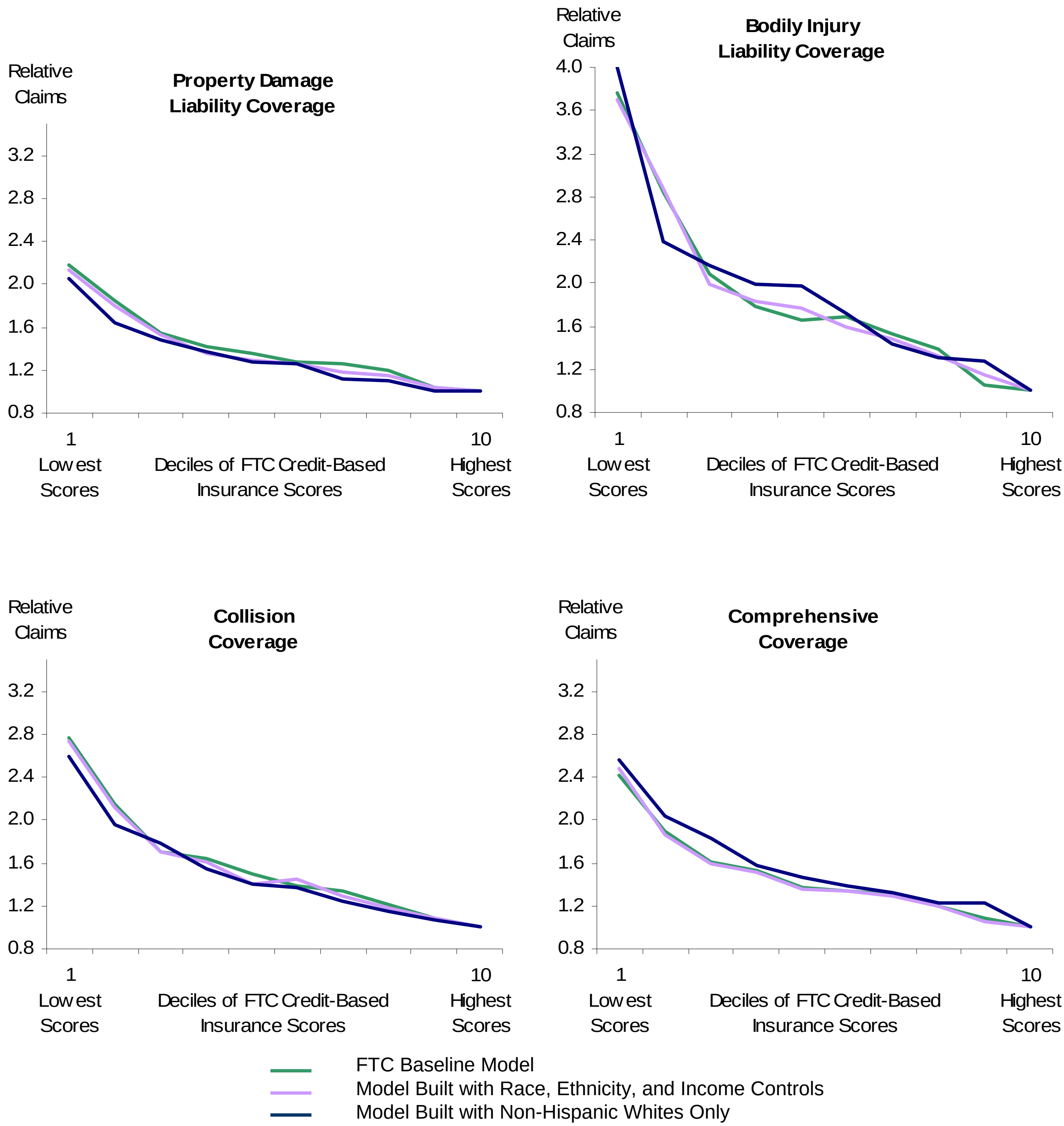


See notes on Figures at the end of this section.

Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 19.

**FTC Score Models
Built Controlling for Race, Ethnicity, and Neighborhood Income:
Estimated Average Amount Paid Out on Claims,
Relative to Highest Score Decile**

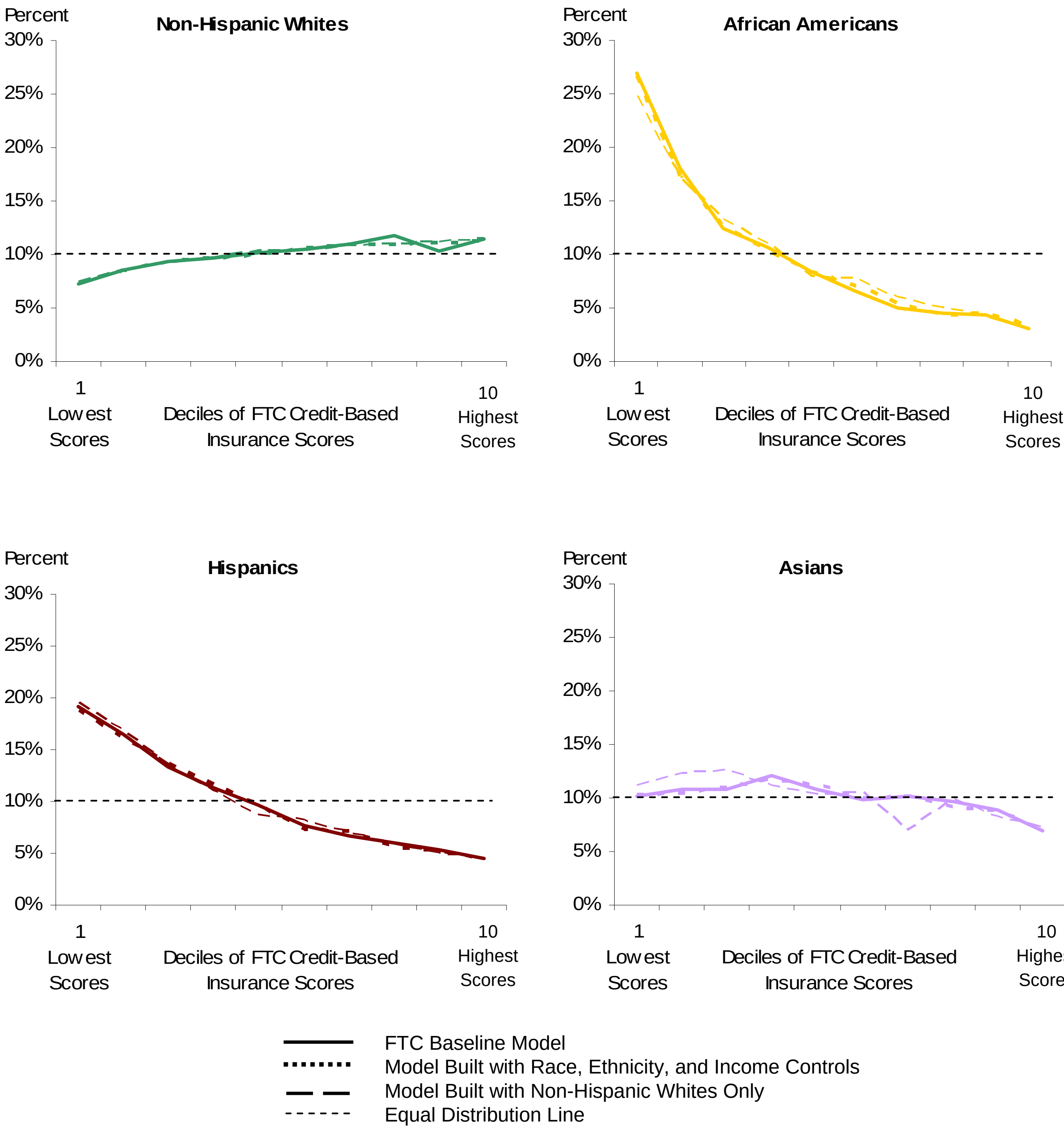


Note that the vertical scale on these graphs is different than for some previous graphs of relative claims and score deciles.

See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 20.

Distribution of FTC Credit-Based Insurance Scores, by Race and Ethnicity (A)

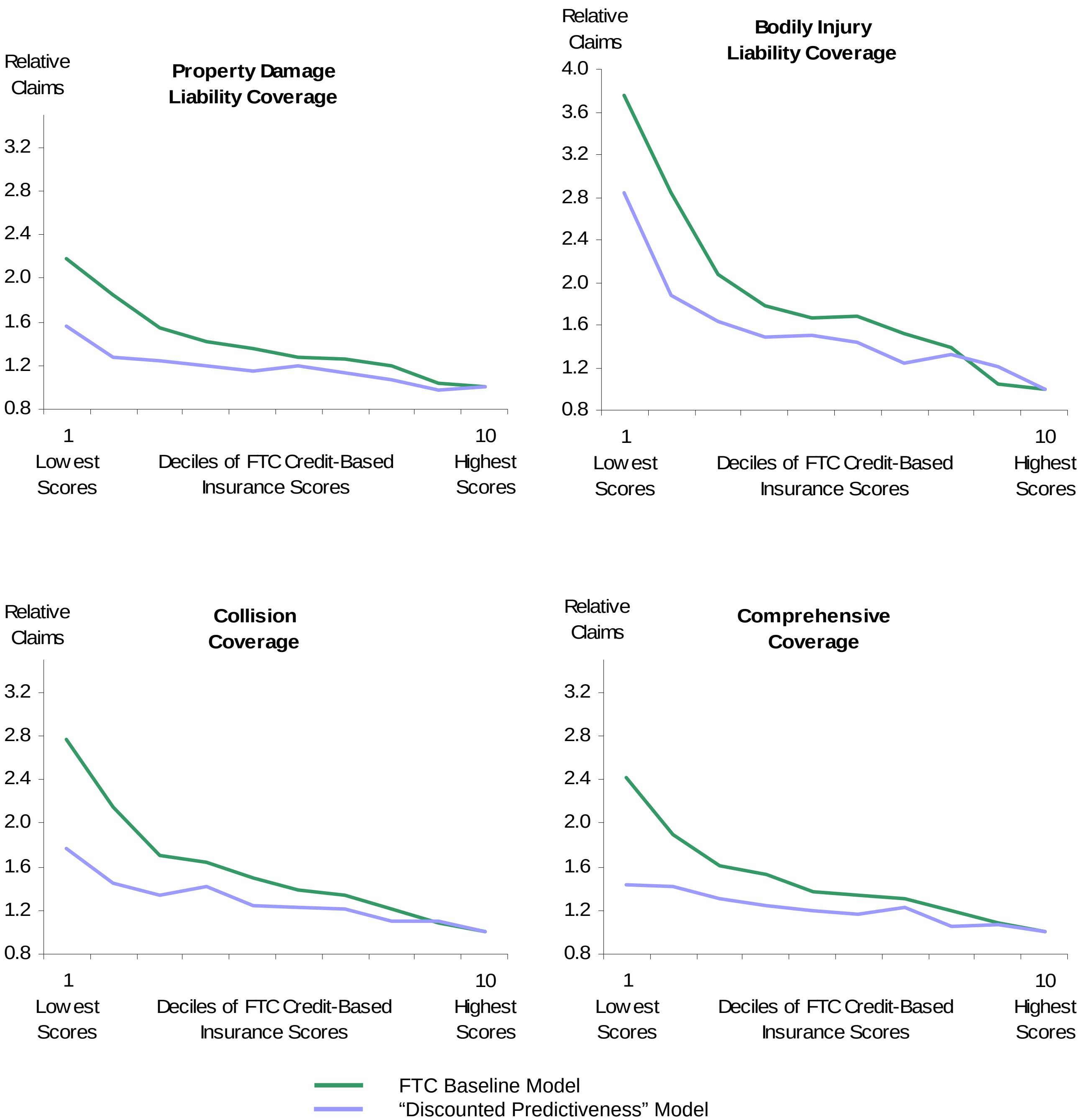


See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 21.

An Additional FTC Credit-Based Insurance Scoring Model: The "Discounted Predictiveness" Model

Estimated Average Amount Paid Out on Claims, Relative to Highest Score Decile



Note that the vertical scale on these graphs is different than for some previous graphs of relative claims and score deciles.

See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

FIGURE 22.

Distribution of FTC Credit-Based Insurance Scores, by Race and Ethnicity (B)

See notes on Figures at the end of this section.
Source: Analysis of FTC Automobile Insurance Policy Database

Notes on Figures

Figure 1:

The lines labeled "without controlling for other variables" show the actual average amount paid out on claims per year of coverage for each score decile, relative to the highest score decile. These are derived from the information in Table 2. For example, the relativity for the lowest decile on the PD graph has a value of 1.89. This number is calculated from column (c) on Table 2; by taking the average total paid on PD claims per year of coverage for the 1^{st} decile ($118.73) and dividing it by the respective value for the 10^{th} decile ($62.70).

The lines labeled "after controlling for other variables" show the predicted amount paid out on claims per year of coverage for each score decile, relative to the highest score decile, from Tweedie GLMs (Generalized Linear Models) of claims risk that included score and a set of standard risk variables as controls. Since our GLM models are multiplicative, the relativities shown by these lines are equivalent to the exponentiated coefficients of the score decile indicator variables. Modeling details and a description of the variables in the models are provided in Appendix D.

Figure 2:

The lines labeled "frequency of claims" show the predicted number of claims per year of coverage for each score decile, relative to the highest score decile, from Poisson GLM models ("Poisson Regressions") that included score and a set of standard risk variables as controls. Since our GLM models are multiplicative, the relativities shown by these lines are equivalent to the exponentiated coefficients of the score decile indicator variables. Modeling details and a description of the variables in the models are provided in Appendix D.

The lines labeled "average size of claims" show the predicted average size of claims for each score decile, relative to the highest score decile, from Gamma GLM models that included score and a set of standard risk variables as controls. Since our GLM model is multiplicative, the relativities shown by these lines are equivalent to the exponentiated coefficients of the score decile indicator variables. Modeling details and a description of the variables in the models are provided in Appendix D.

Figure 3:

"CLUE" stands for Comprehensive Loss Underwriting Exchange. This informational/ database exchange service is run by ChoicePoint, which collects data on claims from most major automobile insurance firms in the United States. These data allow firms to determine whether a potential new customer has filed a claim under a previous policy with another firm, and use that information in underwriting and rating.
Each line on this graph shows the average total amount paid out on claims per year of coverage for each score decile, relative to the highest decile. These results do not include controls for other risk variables because reliable non-credit risk variables are not available for the CLUE claims data. For this figure we use the full sample of 1.4 million

policies, as opposed to the set of policies within the sub-sample of 400,000 normally used. This is because the latter would have proved a very limited sub-sample for the CLUE analysis for the half a year period moving forward, *i.e.*, for July 2001 to December 2001. See Appendix C for a description of the company-provided claims data and the CLUE database and claims data.

Figure 4:

Each line shows the predicted amount paid out on claims per year of coverage for each score decile, relative to the highest score decile, for each of three ranges of car model years from a Tweedie GLM risk model of claims that included score and a set of standard risk variables as controls. The different lines for the three groups of model years were estimated by interacting three model year range indicator variables with the score decile indicator variables. Modeling details and a description of the variables included in the models are provided in Appendix D.

Figure 5:

Predicted change in premium was estimated by comparing individuals' predicted total claims from risk models that included ChoicePoint Attract Standard Auto credit-based insurance score decile indicator variables with risk models that did not include scores. (By construction, the average of all changes is zero.) Both of these models were run separately for property damage liability, bodily injury liability, collision, and comprehensive coverage. In the final step we summed the predicted dollar risks for all four types of insurance coverage with and without the use of credit-based insurance scores. See section V.A. of the report for additional details on this analysis. Modeling details and a description of the variables included in the models are provided in Appendix D.

Figure 6:

Analysis based on data from several National Association of Insurance Commissioners Database Reports. (*e.g.*, National Association of Insurance Commissioners, "Auto Insurance Database Report 2003/2004" (2006)) The states included in the category "states not allowing the use of credit-based insurance scores" are California, New Jersey, Massachusetts, and Hawaii. The category "states allowing the use of credit-based insurance scores" includes all other states, except South Carolina and Texas (for which complete information was not provided in the NAIC reports).

Credit-based insurance scores for use in automobile insurance were first commercially available in 1995, and were widely adopted by insurance companies (in states that allowed their use) during the late 1990s.

Figure 7:

The "residual market" consists of state-sponsored programs to sell insurance to drivers who are unable to purchase insurance in the normal "voluntary" market. Analysis based on data from several National Association of Insurance Commissioners Database Reports. (*e.g.*, National Association of Insurance Commissioners, "Auto Insurance

Database Report 2003/2004" (2006)) The states included in the category "states not allowing the use of credit-based insurance scores" are California, New Jersey, Massachusetts, and Hawaii. The category "states allowing the use of credit-based insurance scores" includes all other states, except South Carolina and Texas (for which information was not provided in the NAIC report).

Credit-based insurance scores for use in automobile insurance were first commercially available in 1995, and were widely adopted by insurance companies (in states that allowed their use) during the late 1990s.

Figure 8:

Each line shows the share of each racial and ethnic group that is in each of the ten deciles of the ChoicePoint Attract Standard Auto credit-based insurance score. If each racial and ethnic group had the same distribution of scores, 10% of each group would be in each decile.

Figure 9:

[No Notes]

Figure 10:

Each line shows the share of each neighborhood income group that is in each of the ten deciles of the ChoicePoint Attract Standard Auto credit-based insurance score. If each neighborhood income group had the same distribution of scores, 10% of each group would be in each decile.

Figure 11:

[No Notes]

Figure 12:

Each line shows the share of each racial and ethnic group that is in each of the ten deciles of the ChoicePoint Attract Standard Auto credit-based insurance score *after controlling* for age, gender, and neighborhood income. This was calculated based on the residuals from an Ordinary Least Squares regression of ChoicePoint Attract Standard Auto credit-based insurance scores on age, gender, and neighborhood income. If each racial and ethnic group had the same distribution of scores, after controlling for age, gender, and neighborhood income, 10% of each group would be in each decile.

Figure 13:

Predicted change in premium was estimated by comparing individuals' predicted total claims from risk models that included ChoicePoint Attract Standard Auto credit-based insurance scores with risk models that did not include scores. By construction, the average of all changes for the entire sample is zero as in Figure 5, but the changes by race or ethnic group are not. See note for Figure 5 above or section V.A. of the report for additional details on this analysis. Modeling details and a description of the variables included in the models are provided in Appendix D.

Figure 14:

Each line shows the predicted amount paid out on claims per year of coverage for each score decile, relative to non-Hispanic whites in the highest score decile, from a Tweedie GLM risk model of claims that included score and a set of standard risk variables as controls. These values were generated by interacting the race and ethnicity indicator variables with the score decile indicator variables. The score decile cut-points used are the same across all race and ethnicity groups (these are the same deciles used for all previous Figures). Thus, given the race and ethnicity distributions across score deciles observed in Figure 8, there are relatively few African Americans and Hispanics in each of the higher score deciles intervals (*i.e.*, fewer than 10% of their group). Modeling details and a description of the variables included in the models are provided in Appendix D.

The differences in the estimates of the amount paid out in claims in higher score deciles versus the bottom score decile, within each race group, are generally statistically significant (at the 5% level), except for Asians (where they are only significant for comprehensive coverage). We also estimated the slope for each race and ethnicity group using a continuous score (as opposed to deciles), and found a statistically significant downward sloping relationship between score and the amount paid out in claims within each group, with the exception of bodily injury and property damage for Asians. Property damage for Asians did have a downward slope but was significant only at the 10% level. Note that Asians are the smallest race or ethnic group in our sample.

Figure 15:

Each line shows the predicted amount paid out on claims per year of coverage for each score decile, relative to the residents of high-income neighborhoods in the highest score decile, from a Tweedie GLM risk model of claims that included score and a set of standard risk variables as controls. These values were generated by interacting the neighborhood income category indicator variables with the score decile indicator variables. Modeling details and a description of the variables included in the models are provided in Appendix D.

Figure 16:

Each line shows the predicted amount paid out on claims per year of coverage for each score decile, relative to the highest score decile, from a Tweedie GLM risk model of claims that included score and a set of standard risk variables as controls. Since our GLM model is multiplicative, the relativities shown by this line are the exponentiated coefficients of the score decile indicator variables. The lines labeled "with race, ethnicity, and neighborhood controls" come from a model that also included indicator variables for race, ethnicity, and Census tract median income category. Modeling details and a description of the variables included in the models are provided in Appendix D.

Figure 17:

The line labeled "Within Sample" shows the predicted amount paid out on claims per year of coverage for each score decile relative to the highest score decile, *of the FTC baseline model*, from Tweedie GLM risk models of claims that included score and a set of standard risk variables as controls. Modeling details and a description of the variables included in the models are provided in Appendix D. Details on the score building process are provided in Appendix E.

The line labeled “Within Sample without Controls” shows the average total amount paid out on claims per year of coverage for each score decile relative to the highest decile, *of the FTC baseline model*, without controlling for any other risk variables. (This line is shown for comparison with the “Out of Sample” values below, for which we do not have controls.)

The “Out of Sample” line is based on CLUE claims data and shows the average total amount paid out on claims per year of coverage for each score decile relative to the highest decile, *of the FTC baseline model*, without controlling for any other risk variables (since reliable non-credit risk variables are not available in CLUE). This “Out of Sample” line is for the period July 2001 to December 2001, and uses CLUE claims data only for individuals who were not in the score development sample.

The development sample consisted only of the sub-sample of the FTC database for which we obtained SSA race and ethnicity data, which includes everyone who had a claim in the company data, so there is no way to use the company data to look at claims outside of the development sample. Therefore, we use CLUE data on claims for a different time period and for a different set of people instead (we were able to use data on roughly 800,000 policies for this from the original 1.4 million dataset). See Appendix C for a description of the CLUE database and claims data. Details on the score building process are provided in Appendix E.

(Note that the vertical scale on the graphs in this Figure rises higher than it does for previous graphs of relative claims and score deciles in Figures 1-4 and Figures 14-16)

Figure 18:

Each line shows the share of each racial and ethnic group that is in each of the ten deciles of the scores produced by the FTC’s baseline credit-based insurance scoring model. If each racial and ethnic group had the same distribution of scores, 10% of each group would be in each decile.

Figure 19:

Each line shows the predicted amount paid out on claims per year of coverage for each score decile, relative to the highest score decile, from Tweedie GLM risk models of claims that included score and a set of standard risk variables as controls. Since our GLM models are multiplicative, the relativities shown by these lines are equivalent to the exponentiated coefficients of the score decile indicator variables. The lines labeled “baseline model” use scores from the FTC baseline scoring model. The lines labeled “race, ethnicity, and income controls model” use scores from a model built by controlling for those variables during the score building process. The lines labeled “Non-Hispanic whites model" come from a scoring model built using a development sample made up exclusively of non-Hispanic white insurance customers. Modeling details and a description of the variables included in the models are provided in Appendix D. Details on the score building process are provided in Appendix E.

(Note that the vertical scale on the graphs in this Figure rises higher than it does for previous graphs of relative claims and score deciles in Figures 1-4 and Figures 14-16)

Figure 20:

Each line shows the share of each racial and ethnic group that is in each of the ten deciles of three FTC credit-based insurance scoring models. The lines labeled "baseline model" use scores from the FTC baseline scoring model. The lines labeled "race, ethnicity, and income controls model" use scores from a model built by controlling for those variables during the score building process. The lines labeled "Non-Hispanic whites model" come from a scoring model built using a development sample made up exclusively of non-Hispanic white insurance customers. If each racial and ethnic group had the same distribution of scores, 10% of each group would be in each decile. Details on the score building process are provided in Appendix E.

Figure 21:

Each line shows the predicted relative amount paid out on claims per year of coverage for each score decile, relative to the highest score decile, from Tweedie GLM risk models of claims that included score and a set of standard risk variables as controls. Since our GLM models are multiplicative, the relativities shown by these lines are equivalent to the exponentiated coefficients of the score decile indicator variables. The lines labeled "baseline model" use scores from the FTC baseline scoring model. The lines labeled "discounted predictiveness model" use scores from a model built by discounting the power of a variable to predict risk based on how different the variable was across racial and ethnic groups. Modeling details and a description of the variables included in the models are provided in Appendix D. Details on the score building process are provided in Appendix E.

(Note that the vertical scale on the graphs in this Figure rises higher than it does for previous graphs of relative claims and score deciles in Figures 1-4 and Figures 14-16)

Figure 22:

Each line shows the share of each racial and ethnic group that is in each of the ten deciles of two FTC credit-based insurance scoring models. The lines labeled "baseline model" use scores from the FTC baseline scoring model. The lines labeled "discounted predictiveness model" use scores from a model built by discounting the power of a variable to predict risk based on how different the variable was across racial and ethnic groups. If each racial and ethnic group had the same distribution of scores, 10% of each group would be in each decile. Details on the score building process are provided in Appendix E.

APPENDIX A

TEXT OF SECTION 215 OF THE FACT ACT

SEC. 215. STUDY OF EFFECTS OF CREDIT SCORES AND CREDIT-BASEDINSURANCE SCORES ON AVAILABILITY AND AFFORDABILITYOF FINANCIAL PRODUCTS.

(a) STUDY REQUIRED.—The Commission and the Board, in consultation with the Office of Fair Housing and Equal Opportunity of the Department of Housing and Urban Development, shall conduct a study of—

(1) the effects of the use of credit scores and credit-based insurance scores on the availability and affordability of financial products and services, including credit cards, mortgages, auto loans, and property and casualty insurance;

(2) the statistical relationship, utilizing a multivariate analysis that controls for prohibited factors under the Equal Credit Opportunity Act and other known risk factors, between credit scores and credit-based insurance scores and the quantifiable risks and actual losses experienced by businesses;

(3) the extent to which, if any, the use of credit scoring models, credit scores, and credit-based insurance scores impact on the availability and affordability of credit and insurance to the extent information is currently available or is available through proxies, by geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, and creed, including the extent to which the consideration or lack of consideration of certain factors by credit scoring systems could result in negative or differential treatment of protected classes under the Equal Credit Opportunity Act, and the extent to which, if any, the use of underwriting systems relying on these models could achieve comparable results through the use of factors with less negative impact; and

(4) the extent to which credit scoring systems are used by businesses, the factors considered by such systems, and the effects of variables which are not considered by such systems.

(b) PUBLIC PARTICIPATION.—The Commission shall seek public input about the prescribed methodology and research design of the study described in subsection (a), including from relevant Federal regulators, State insurance regulators, community, civil rights, consumer, and housing groups.

(c) REPORT REQUIRED.—

(1) IN GENERAL.—Before the end of the 24-month period beginning on the date of enactment of this Act, the Commission shall submit a detailed report on the study conducted pursuant to subsection (a) to the Committee on Financial Services of the House of Representatives and the Committee on Banking, Housing, and Urban Affairs of the Senate.

(2) CONTENTS OF REPORT.—The report submitted under paragraph (1) shall

include the findings and conclusions of the Commission, recommendations to address specific areas of concerns addressed in the study, and recommendations for legislative or administrative action that the Commission may determine to be necessary to ensure that credit and credit-based insurance scores are used appropriately and fairly to avoid negative effects.

APPENDIX B

REQUESTS FOR PUBLIC COMMENT

[Billing Code 6750-01-P]

FEDERAL TRADE COMMISSION
RIN 3084- [AA94]

Public Comment on Methodology and Research Design for Conducting a Study of the Effects of Credit Scores and Credit-Based Insurance Scores on Availability and Affordability of Financial Products

AGENCY: Federal Trade Commission
ACTION: Notice and request for public comment.

SUMMARY: The Fair and Accurate Credit Transactions Act of 2003 ("FACT Act" or "Act") requires the Federal Trade Commission ("FTC" or "Commission") and the Federal Reserve Board ("Board") to conduct a study on the effects of credit scores and credit-based insurance scores on the availability and affordability of financial products. These products include credit cards, mortgages, auto loans, and property and casualty insurance. The Act requires the FTC to seek public input about "the prescribed methodology and research design of the study." As part of its efforts to fulfill its obligations under the Act, the FTC seeks public comment on how the FTC and the Board should conduct the study.

DATES: Comments must be received by August 16, 2004.

ADDRESSES: Public comments are invited, and may be filed with the Commission in either paper or electronic form. Comments should refer to "FACT Act Scores Study, Matter No. P044804," to facilitate their organization. A comment filed in paper form should include this reference both in the text and on the envelope, and should be mailed or delivered to: Federal Trade Commission/Office of the Secretary, Room H-159 (Annex N), 600 Pennsylvania Avenue, N.W., Washington, D.C. 20580. The FTC urges that any comment filed in paper form be sent by courier or overnight service, if possible, because

U.S. postal mail in the Washington area and at the Commission is subject to delay due to heightened security precautions.

Comments that do not contain any nonpublic information may be filed in electronic form (in ASCII format, WordPerfect, or Microsoft Word) as a part of or as an attachment to email messages directed to: FACTAscoringstudy@ftc.gov. If a comment contains nonpublic information, it must be filed in paper (rather than electronic) form, and the first page of the document must be clearly labeled "Confidential."[143]

The FTC Act and other laws the Commission administers permit the collection of public comments to consider and use in this proceeding as appropriate. All timely and responsive public comments, whether filed in paper or electronic form, will be considered by the Commission, and will be available to the public on the FTC Web site, to the extent practicable, at www.ftc.gov. As a matter of discretion, the FTC makes every effort to remove home contact information for individuals from the public comments it receives before placing those comments on the FTC Web site. More information, including routine uses permitted by the Privacy Act, may be found in the FTC's privacy policy, at http://www.ftc.gov/ftc/privacy.htm.

FOR FURTHER INFORMATION CONTACT: Jesse Leary, Deputy Assistant Director, (202) 326-3480, Division of Consumer Protection, Bureau of Economics, Federal Trade Commission, 600 Pennsylvania Avenue, N.W., Washington, DC 20580.

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143 1 Commission Rule 4.2(d), 16 CFR 4.2(d). The comment must also be accompanied by an explicit request for confidential treatment, including the factual and legal basis for the request, and must identify the specific portions of the comment to be withheld from the public record. The request will be granted or denied by the Commission's General Counsel, consistent with applicable law and the public interest. See Commission Rule 4.9(c), 16 CFR 4.9(c).

SUPPLEMENTARY INFORMATION:

I. Background

The FACT Act was signed into law on December 4, 2003. Fair and Accurate Credit Transactions Act of 2003, Pub. L. No. 108-159 (2003). In general, the Act amends the Fair Credit Reporting Act ("FCRA") to enhance the accuracy of consumer reports and to allow consumers to exercise greater control regarding the type and amount of marketing solicitations they receive. To promote increasingly efficient national credit markets, the FACT Act also establishes uniform national standards in key areas of regulation regarding consumer report information. The Act contains a number of provisions intended to combat consumer fraud and related crimes, including identity theft, and to assist its victims. Finally, the Act requires a number of studies be conducted on credit reporting and related issues.

Section 215 of the FACT Act requires the FTC and the Board, in consultation with the Office of Fair Housing and Equal Opportunity of the Department of Housing and Urban Development, to conduct a study on the effects of credit scores and credit-based insurance scores on the availability and affordability of financial products. These products include mortgages, auto loans, credit cards, and property and casualty insurance. Section 215 further requires the FTC and the Board to study: 1) "the statistical relationship, utilizing a multivariate analysis that controls for prohibited factors under the Equal Credit Opportunity Act and other known risk factors, between credit scores and credit-based insurance scores and the quantifiable risks and actual losses;" and 2) "the extent to which, if any, the use of credit scoring models, credit scores, and credit-based insurance scores impact on the availability and affordability of credit to the extent information is currently available or is available through proxies, by geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, and creed, including the extent to which the consideration or lack of consideration of certain factors by credit scoring systems could result in negative or differential treatment of the protected classes, under the Equal Credit Opportunity Act, and the extent to which, if any, the use of underwriting systems relying on these models could achieve comparable results through the use of factors with less negative impact."

The study is due December 4, 2005.

II. Request for Comments

The Act requires the FTC to seek public input about "the prescribed methodology and research design of the study." As part of its efforts to fulfill its obligations under the Act, the FTC seeks public comment on how the FTC and the Board should conduct the study. Public comment is requested on all aspects of the study. In addition, the FTC seeks comment on the following questions:

1. How should the effects of credit scores and credit based insurance scores on the price and availability of mortgages, auto loans, credit cards, other credit products, and property and casualty insurance be studied? What is a reasonable methodology for measuring the price and availability of mortgages, auto loans, credit cards, other credit. Products, and property and casualty insurance, and the impact of credit scores and credit based insurance scores on those prices and availability?

2. An effect can often only be measured relative to a counterfactual (that is, relative to some hypothetical alternative situation). To determine the effects of credit scores on the price and availability of credit products, what is a reasonable counterfactual

to the current use of credit scores? To determine the effects of credit-based insurance scores on the price and availability of property and casualty insurance, what is a reasonable counterfactual to the current use of credit-based insurance scores?

3. Paragraph (a)(2) of Section 215 requires a study of "the statistical relationship, utilizing a multivariate analysis that controls for prohibited factors under the (ECOA) and other known risk factors, between credit scores and credit-based insurance scores and the quantifiable risks and actual losses experienced by businesses." (The ECOA "prohibited factors" are race, color, religion, national origin, sex or marital status, and age.) What is an appropriate multivariate technique for studying this relationship? What data would be required to undertake such an analysis? What data are available to undertake such an analysis?

4. What is an appropriate methodology to determine whether the use of credit scores or credit based insurance scores results in "negative or differential treatment" of ECOA-protected classes?

5. What is an appropriate methodology to determine whether the use of specific factors in credit scores or credit based insurance scores results in "negative or differential treatment" of ECOA protected classes?

6. What is an appropriate methodology to determine whether there are factors that are not considered by credit scores or credit based insurance scores that result in "negative or differential treatment" of ECOA protected classes?

7. In order to address paragraphs (a)(2) and (a)(3) of Section 215, data are needed on the geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, or creed of borrowers, potential borrowers, insurance customers, or

potential insurance customers. Are these data available, and if so, where?

8. If the data discussed in question 7 are not available, what proxies are available for the geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, or creed of borrowers, potential borrowers, insurance customers, or potential insurance customers?

9. If there are proxies for the geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, or creed of borrowers, potential borrowers, insurance customers, or potential insurance customers, what type of analysis would allow inferences to be drawn using the proxies instead of actual data on individual characteristics? What limitations are there to the inferences that can be drawn using proxies in place of data on individual characteristics?

10. One potential proxy for individual characteristics may be Census data about the location where a borrower or insurance customer resides. What type of analysis would allow inferences to be drawn using data about the characteristics of the location where a borrower or insurance customer resides instead of data on individual characteristics? What limitations are there to the inferences that can be drawn using data about the characteristics of the location where a borrower or insurance customer resides in place of data on individual characteristics?

Authority: Sec. 112(b), Pub. L. 108-159, 117 Stat. 1956 (15 U.S.C. 1681c-1).

By direction of the Commission.

Donald S. Clark

Secretary

[Billing Code 6750-01-P]

FEDERAL TRADE COMMISSION
RIN [3084-AA94]

Public Comment on Data, Studies, or Other Evidence Related to the Effects of Credit Scores and Credit-Based Insurance Scores on the Availability and Affordability of Financial Products

AGENCY: Federal Trade Commission
ACTION: Notice and request for public comment.

SUMMARY: The Fair and Accurate Credit Transactions Act of 2003 ("FACT Act" or "Act") requires the Federal Trade Commission ("FTC" or "Commission") and the Federal Reserve Board ("Board") to conduct a study on the effects of credit scores and credit-based insurance scores on the availability and affordability of financial products. These products include credit cards, mortgages, auto loans, and property and casualty insurance. As part of its efforts to fulfill its obligations under the Act, the FTC seeks public comment on any evidence the FTC and the Board should consider in conducting the study.

DATES: Comments must be received by April 25, 2005.

ADDRESSES: Public comments are invited, and may be filed with the Commission in either paper or electronic form. Comments filed in paper form should refer to "FACT Act Scores Study" both in the text and on the envelope, to facilitate their organization, and should be mailed or delivered to: Federal Trade Commission/Office of the Secretary, Room H-159 (Annex Z), 600 Pennsylvania Avenue, N.W., Washington, D.C. 20580. The FTC requests that any comment filed in paper form be sent by courier or overnight service, if possible, because U.S. postal mail in the Washington area and at the Commission is subject to delay due to heightened security precautions. Comments may be filed in electronic form by clicking on the following: https://secure.commentworks.com/FTCCreditScoreStudy/ and following the instructions on the web-based form. If a comment contains confidential information, it must be filed in paper (rather than electronic) form, and the first page of the document must be clearly labeled "Confidential."[144]

To ensure that the Commission considers an electronic comment, you must file it on the web-based form at https://secure.commentworks.com/FTCCreditScoreStudy/. You also may visit http://www.regulations.gov to read this Notice, and may file an electronic comment through that website. The Commission will consider all comments that regulations.gov forwards to it.

The FTC Act and other laws the Commission administers permit the collection of public comments to consider and use in this proceeding as appropriate. All timely and responsive public comments, whether filed in paper or electronic form, will be considered by the Commission, and will be available to the public on the FTC Web site, to the extent practicable, at www.ftc.gov. As a matter of discretion, the FTC makes every effort to remove home contact information for individuals from the public comments it receives before placing those comments on the FTC Web site. More Information, including routine uses permitted by the Privacy Act, may be found in the FTC's privacy policy, at http://www.ftc.gov/ftc/privacy.htm.

FOR FURTHER INFORMATION CONTACT:

[144] Commission Rule 4.2(d), 16 CFR 4.2(d). The comment must also be accompanied by an explicit request for confidential treatment, including the factual and legal basis for the request, and must identify the specific portions of the comment to be withheld from the public record. The request will be granted or denied by the Commission's General Counsel, consistent with applicable law and the public interest. See Commission Rule 4.9(c), 16 CFR 4.9(c).

Jesse Leary, Deputy Assistant Director, (202) 326-3480, Division of Consumer Protection, Bureau of Economics, Federal Trade Commission, 600 Pennsylvania Avenue, N.W., Washington, DC 20580.

SUPPLEMENTARY INFORMATION:

I. Background

The FACT Act was signed into law on December 4, 2003. Fair and Accurate Credit Transactions Act of 2003, Pub. L. No. 108-159 (2003). In general, the Act amends the Fair Credit Reporting Act ("FCRA") to enhance the accuracy of consumer reports and to allow consumers to exercise greater control regarding the type and amount of marketing solicitations they receive. The Act contains a number of provisions intended to combat consumer fraud and related crimes, including identity theft, and to assist its victims. Finally, the Act requires that a number of studies be conducted on credit reporting and related issues.

Section 215 of the FACT Act requires the FTC and the Board, in consultation with the Office of Fair Housing and Equal Opportunity of the Department of Housing and Urban Development, to conduct a study on the effects of credit scores and credit based insurance scores on the availability and affordability of financial products. These products include mortgages, auto loans, credit cards, and property and casualty insurance. Section 215 further requires the FTC and the Board to study: 1) "the statistical relationship, utilizing a multivariate analysis that controls for prohibited factors under the Equal Credit Opportunity Act and other known risk factors, between credit scores and credit-based insurance scores and the quantifiable risks and actual losses;" and 2) "the extent to which, if any, the use of credit scoring models, credit scores, and credit-based insurance scores impact on the availability and affordability of credit to the extent information is currently available or is available through proxies, by geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, and creed, including the extent to which the consideration or lack of consideration of certain factors by credit scoring systems could result in negative or differential treatment of the protected classes, under the Equal Credit Opportunity Act, and the extent to which, if any, the use of underwriting systems relying on these models could achieve comparable results through the use of factors with less negative impact."

The study is due on December 4, 2005.

II. Request for Comments

The Act requires the FTC to seek public input about "the prescribed methodology and research design of the study." As part of its efforts to fulfill its obligations under the Act, the FTC, (in a *Federal Register* notice dated June 18, 2004, see 69 FR 34167) sought public comment on methodological aspects of the study. The FTC received comments in response to that notice, and the FTC and the Board are considering them as they conduct the study. In the present request, the FTC seeks comment on specific studies, data, or other evidence that might be useful for the study. Although we enumerate a set of questions below, we encourage commenters to provide information on any aspects of credit scores, credit-based insurance scores, and the effects of scores on the relevant markets that would be useful to the study. In particular, the FTC seeks information that bears on the following questions:

<u>A. Credit Scores and Credit:</u>

1. Specifically, how are credit scoring models developed? Who develops credit

scoring models? What data and methodologies are used to develop credit scoring models? What factors are used in credit scoring models? Why are those factors used?
What other factors have been considered for use in credit scoring models, but are not used? Why are those other factors not used? Are there benefits or disadvantages, either to creditors or consumers, from the use of particular factors by credit scoring models?

2. How many different credit scoring models are in use today? What different types of general purpose or specialized credit scoring models are available?
Who offers credit scores?

3. How are credit scores used? Who uses credit scores, and how widely are they used? How do they fit into the underwriting process for mortgages, auto loans, credit cards, and other credit products? For what purposes are credit scores used, other than the initial underwriting or pricing decision?

4. How has the use of credit scores changed over time? When were they first used for each type of financial product (credit cards, mortgages, auto loans, etc.)? How has their use expanded to encompass different groups of borrowers (*e.g.*, lower income borrowers, urban/rural borrowers, borrowers with poor credit histories, borrowers with non-traditional credit histories)? If the use of credit scores has expanded to encompass Different groups of borrowers, how has this affected the price or availability of credit to those borrowers?

5. Has the use of credit scores affected the price and availability of mortgages, auto loans, credit cards, or other credit products? If so, are there estimates of the type and size of such changes? Have some groups of consumers experienced cost reductions while others have experienced cost increases? Have some groups of consumers experienced

greater access to credit while others have experienced reduced access?

6. Has the use of credit scores affected the amount of credit made available to consumers? Has it affected initial loan-to-value ratios at which auto loans or mortgages (first- or second-lien) are originated to different groups of borrowers? Has it affected credit limits on credit cards and home equity lines of credit for different groups of borrowers?

7. How has the use of credit scores affected the costs of underwriting and/or the time needed to underwrite?

8. What impact has the use of credit scores had on the accuracy of underwriting decisions? What impact has the use of credit scores had on the share of applicants that are approved for mortgages, auto loans, credit cards, or other credit products? What impact has the use of credit scores had on the default rates of mortgages, auto loans, credit cards, or other credit products? Have the sizes of such changes or effects been estimated and reported?

9. Has the use of credit scores affected the cost and availability of credit to consumers with poor credit histories? If so, how? What effect has it had on the use of credit by consumers with poor credit histories?

10. How has the use of credit scores affected the cost and availability of credit to consumers with no credit history? What effect has it had on the use of credit by consumers with no credit history?

11. How has the use of credit scores affected refinancing behavior for mortgage, auto, or student loans? How has it affected the average life of revolving lines of credit (including credit cards)?

12. Has the use of credit scores and credit scoring models impacted the availability or cost of credit to consumers by geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, or creed? If so, how has it impacted each such category? What are the estimated sizes of any such changes for each of the above categories?

13. To what extent does consideration or lack of consideration of certain factors by credit scoring systems result in negative or differential treatment of those categories of consumers who are protected under the Equal Credit Opportunity Act ("ECOA") (*e.g.*, race, color, religion, national origin, sex, age, and marital status)?

14. To what extent, if any, could the use of underwriting systems that rely on scoring models achieve comparable results through the use of factors with less negative impact on those categories of consumers who are protected under the ECOA?

15. What steps, if any, do score developers, lenders, or other users of credit scores take to ensure that the use of credit scores does not result in negative or differential treatment of protected categories of consumers under the ECOA? Have score developers, lenders, or other users of credit scores changed the way credit scores are developed or used in order to avoid negative or differential treatment of protected categories of consumers under the ECOA? Are any particular credit history factors not used because of actual or potential negative or differential treatment of protected categories of consumers under the ECOA? If so, what are they?

16. Has the use of credit scores caused a change in the rate of home ownership? What is the estimated size of such a change?

17. Has the use of credit scores caused a change in the method and amount of pre-

screening consumers for credit offers? What effects has this had on the terms offered to consumers?

18. What specific role do credit scores play in granting "instant credit?" What impact have credit scores had on the availability and use of instant credit?

19. How has the use of credit scores affected companies' ability to enter new lines of business or expand activities in the various credit industries?

20. What role does credit scoring play in secondary market activities? In what ways has the availability of credit scores affected the development of the secondary market for credit products? Has the use of credit scoring increased or decreased creditors' access to capital? In what ways?

21. How are credit scores used to manage existing credit accounts, such as credit card accounts? How has the use of credit scores affected the way credit accounts are managed? How are credit scores used in the servicing of mortgages, and how has the use of credit scores affected the way mortgages are serviced?

22. How are records of inquiries used by credit scoring systems? Does concern about the possible effects on their credit scores affect consumers' credit shopping behavior? If so, what impact does this have on the consumers or on competition in the various credit markets?

23. How does the use of credit scores affect consumers with inaccurate information on their credit reports? How does the use of credit scores affect consumers who have been the victims of identity theft?

24. Are there particular forms of inaccuracy or incompleteness in the credit reporting system, such as incomplete reporting by creditors, that affect either the

usefulness of credit scores to lenders or the benefits or disadvantages of scoring to consumers? What are those types of inaccuracies or incompleteness? How do they affect the usefulness of credit scores to lenders or the benefits or disadvantages of scoring to consumers?

B. Credit-Based Insurance Scores and Property and Casualty Insurance:

1. Specifically, how are credit-based insurance scoring models developed? Who develops credit-based insurance scoring models? What data and methodologies are used to develop credit-based insurance scoring models? What factors are used in credit based insurance scoring models? Why are those factors used? What other factors have been considered for use in credit-based insurance scoring models, but are not used? Why are those other factors not used? Are there benefits or disadvantages, either to insurers or consumers, from the use of particular factors by credit-based insurance scoring models?

2. How many different credit-based insurance scoring models are in use today? Who offers credit-based insurance scores?

3. How are credit-based insurance scores used? Who uses credit-based insurance scores, and how widely are they used? How do they fit into the underwriting and rating process for automobile and homeowners insurance?

4. Has the use of credit-based insurance scores affected the price and availability of automobile and homeowners insurance? We are especially interested in evidence containing estimates of the size of such changes. Have some groups of consumers experienced cost reductions while others have experienced cost increases? If so, which consumers have experienced reductions and which have experienced increases, and what are the magnitudes of those changes? Have some consumers experienced dramatic

increases in their insurance premiums, solely as the result of the introduction of credit-based insurance scoring? If so, what has been the impact of this rise in premiums on these consumers?

5. How has the use of credit-based insurance scores affected the costs of underwriting and rating and/or the time needed to underwrite and rate?

6. How has the use of credit-based insurance scores affected the accuracy of underwriting and rating decisions? Have the sizes of such changes been estimated and reported?

7. Has the use of credit-based insurance scores affected the amount of automobile or homeowners insurance purchased by consumers? Has it affected the limits or deductibles that consumers select when purchasing automobile or homeowners insurance? Has it affected the number of drivers who drive without insurance? Has it affected the number of homeowners that have no homeowners insurance? What are the estimated sizes of such changes?

8. How has the use of credit-based insurance scores affected the cost and availability of automobile or homeowners insurance to consumers with poor credit histories? What effect has it had on the purchasing of automobile or homeowners insurance by consumers with poor credit histories?

9. Has the use of credit-based insurance scores affected the cost and availability of automobile or homeowners insurance to consumers with no credit history? If so, how? What effect has it had on the purchasing of automobile or homeowners insurance by consumers with no credit histories?

10. How has the use of credit-based insurance scores impacted the availability or

cost of insurance to consumers by geography, income, ethnicity, race, color, religion, national origin, age, sex, marital status, or creed? What are the estimated sizes of such changes for each of the above categories?

11. To what extent does consideration or lack of consideration of certain factors by credit-based insurance scoring systems result in negative or differential treatment of protected classes of consumers, that is, the same categories of consumers against whom discrimination is prohibited under the ECOA (*e.g.* race, color, religion, national origin, sex, age, and marital status)?

12. To what extent, if any, could the use of underwriting systems relying on credit-based insurance scoring models achieve comparable results through the use of factors with less negative impact on consumers in the ECOA protected categories?

13. What steps, if any, do score developers or insurance companies take to ensure that the use of credit-based insurance scores does not result in negative or differential treatment of protected categories of consumers listed in the ECOA? Have score developers or insurance companies changed the way credit-based insurance scores are developed or used in order to avoid negative or differential treatment of protected categories of consumers listed in the ECOA? Are any particular credit history factors not used because of actual or potential negative or differential treatment of protected categories of consumers listed in the ECOA? If so, what are they?

14. Has the use of credit-based insurance scores caused a change in the method and amount of pre-screening consumers for insurance offers? What effects has this had on the terms offered to consumers?

15. How has the use of credit-based insurance scores affected companies' ability

to enter new lines of the automobile or home- owners insurance business?

16. If the use of credit-based insurance scores has affected the costs individual consumers pay for insurance, has it (i) caused a change in the overall average cost of insurance for consumers?; (ii) changed the distribution of individual costs?; or (iii) Caused any other change in the costs to consumers? What are the magnitudes of any such changes?

17. Would an analysis of the share or number of consumers that purchase automobile or homeowners insurance from "involuntary," "pooled risk," "assigned risk," or other types of insurance other than insurance offered on a voluntary basis by private insurers, be informative about the price and/or availability of automobile or homeowners insurance? Would an analysis of the share of drivers that drive without automobile insurance be informative about the price and/or availability of automobile insurance?

18. What impact, if any, does banning or limiting the use of particular underwriting or rating factors, such as gender, territory, or credit-based insurance score, have on the price or availability of automobile or homeowners insurance? Has the prohibition on the use of credit-based scores for insurance in particular states had any impact on the price or availability of automobile or homeowners insurance for consumers in those states? If so, what has that impact been? If the use of credit-based insurance scores was not allowed in additional states, what impact would this have on the price or availability of automobile or homeowners insurance? Are there, or would there be, any specific effects on those insurance consumers who are within protected categories listed in the ECOA?

19. How are records of inquiries used by credit-based insurance scoring systems?

Does concern about the possible effects on their credit-based insurance scores affect consumers' insurance-shopping behavior? If so, what impact does this have on competition in the insurance markets?

20. How does the use of credit-based insurance scores affect consumers with inaccurate information on their credit reports? How does the use of credit-based insurance scores affect consumers who have been the victims of identity theft?

21. Are there particular forms of inaccuracy or incompleteness in the credit reporting system, such as incomplete reporting by creditors, that affect either the usefulness of credit-based insurance scores to insurers or the benefits or disadvantages of scoring to consumers? What are those types of inaccuracies or incompleteness? How do they affect the usefulness of credit-based insurance scores to insurers or the benefits or disadvantages of scoring to consumers?

Authority: Sec. 112(b), Pub. L. 108-159, 117 Stat. 1956 (15 U.S.C. 1681c-1).

By direction of the Commission.

Donald S. Clark

Secretary

APPENDIX C

THE AUTOMOBILE POLICY DATABASE

APPENDIX C. The Automobile Policy Database

The FTC constructed the database of automobile policies used to do the analysis for this report by combining policy data from five large auto insurance firms submitted with data from a range of additional sources. This Appendix describes that process.

C.1. The EPIC Database

The automobile policy data in the FTC database were originally collected for a study conducted by EPIC, a firm of consulting actuaries, that was released in 2003.[145] The EPIC database was constructed by randomly sampling from the policies in place at the participating firms between July 1, 2000 and June 30, 2001. Data on policies that were in place throughout the sample year were collected for the entire year. Data on policies of customers that left a firm during the year were collected until the policy ended, and data on the policies of customers that joined were collected from the date the policy began until the end of the year. While the EPIC report did not include information on the number of cars in their database, it did provide information on the total "earned car years." An "earned car year" is equivalent to one year of insurance coverage for one car. The EPIC database contained roughly 2.7 million earned car years.

The sampling of policies was done in a way that produced roughly the same number of records from each firm. This means that the larger firms in the database are under-represented, relative to their market share. All cars covered by a sampled policy were included in the sample. The samples were drawn to ensure that some minimum number of policies would be available for each state. This means that drivers in small

[145] Michael J. Miller and Richard A. Smith, *The Relationship of Credit-Based Insurance Scores to Private Passenger Automobile Insurance Loss Propensity: An Actuarial Study by EPIC Actuaries, LLC* (June 2003) [hereinafter EPIC Study], *available at* http://www.progressive.com/shop/EPIC_CreditScores.pdf.

states were over-represented in the sample.[146]

EPIC received data on the cars and drivers covered by each policy. Car information included vehicle identification number (VIN), miles driven, coverages, limits, deductibles, premiums, and claims paid. Driver information included most standard risk variables, including age, gender, marital status, and driving history (*e.g.*, violations). Important risk variables missing from the data were prior claims (on accidents at companies other than the customer's current company) and territory. EPIC did attempt to control for territory in their analysis by using the population density of each ZIP code, based on Census data.

Claims were included in the data if they were for events that occurred between July 1, 2000 and June 30, 2001. The samples were drawn in the second half of 2002, and information on claims is as of June 30, 2002. For some claims, especially bodily injury liability claims, the reported amount paid out on the claim may not reflect the actual ultimate cost of the claim. This is because the process of determining the final cost of a claim can take a very long time, especially if the claim goes to litigation. For claims that were not yet resolved, any reserves for the claims were included as an amount paid.

Credit-based insurance scores had never been calculated for many of the policies in the database. For those that had been scored, different companies may have used different models, and the models may have varied by state. The credit scores EPIC obtained for the study were ChoicePoint Attract Standard Auto scores. Scores were only calculated for one person, the first named insured, for each policy. This means that the same score was assigned to each car covered by a policy, even if a different person was

[146] All of the analysis presented in the body of the report uses data that have been weighted to be geographically representative.

the primary driver of that car.[147] Credit history data used by ChoicePoint to calculate scores came from the June 2000 archives of Experian (just before the beginning of the sample period). There were three possible outcomes for each individual submitted for scoring: a score, a "no-hit," meaning a credit report for the person could not be located in Experian's records, and a "thin-file," meaning a credit report for the person could be located, but it did not contain enough information to calculate a score.

High-risk drivers are likely under-represented in the database. None of the firms provided data on "residual market" policies. These are policies purchased through state-run plans that offer access to insurance for customers who are unable to purchase insurance in the normal "voluntary" market. They make up less than 2% of the total market for automobile insurance. In addition, while four of the five firms that submitted data to the FTC did sell policies to high-risk drivers, two of them did so through subsidiaries that did not use the same data systems, and therefore policies from the high-risk subsidiaries were not included in the sample. These subsidiaries represented less than 5% of the total business of any one firm, and less than 2% of the total business of the five firms. Although these are small portions of these firms' total customers, it is quite possible that the sample under-represents the highest-risk portion of the insurance market. For this reason, we conducted an analysis that focused on the highest-risk portion of the sample that was collected. This analysis is described in Appendix F.

C.2 The FTC Database

The database analyzed by the FTC is a subset of the original EPIC database. Not all of the firms that contributed data to the EPIC database agreed to have their data

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[147] This is a form of measurement error that should have the effect of understating the relationship between credit score and claims.

forwarded to the FTC for this study. Data from five firms were submitted to the FTC. These five firms together represented 27% of the U.S. market of automobile insurance in 2000 (the time period covered by the data).

The database submitted by the five firms includes over 2.5 million records. Each record has data on one car for up to one year. Many records cover only part of the year, either because customers commenced or discontinued coverage during the year, or because the company generated a separate record each time a policy was renewed or modified. Adjusting for the period of time covered by each record, the total number of "car-years" in the database is just over 1.8 million. Many of the policies in the database cover more than one car; the total number of policies in the database is 1.4 million.

The FTC combined the information the insurance firms submitted with data from a number of other sources. The agency obtained additional information to broaden the range of credit history variables analyzed; to improve the set of other risk controls in the analysis; to provide an independent measure of claims; and to analyze issues relating to race, ethnicity, income, and national origin. In constructing the database, the FTC never took possession of any personally identifying information. The following describes the data that were collected and the process by which they were collected.

C.2.1 Additional Information Obtained for the Full Sample

Core Policy Data and ChoicePoint Credit Scores

The participating firms submitted their samples of policy data to EPIC.[148] EPIC forwarded the data to ChoicePoint. ChoicePoint calculated and appended the Attract

[148] During the course of this project, EPIC was purchased by Tillinghast/Towers Perrin Consulting. For simplicity, we refer to "EPIC" throughout this appendix, even though some of the steps in the data collection and preparation process took place after the change in ownership.

Standard Auto credit-based insurance scores, stripped off the names and addresses, and created a new anonymous unique identifier. ChoicePoint then returned the database to EPIC.

EPIC standardized the coding of the data and combined the data from the five firms into a single database. When a particular variable was always missing for a particular company, a small portion (5%) of records of that variable for other companies were chosen at random and changed to missing. This was done to mask which policies came from the same company. The combined database was then forwarded to the FTC.

Territorial Risk Variable

The five firms also submitted to EPIC data on earned car years and claims on property damage liability policies by ZIP code for a three-year period from 2000 to 2002, for their full book of business. EPIC combined the data from the five firms to calculate ZIP-code level average property damage liability pure premiums (*i.e.*, average dollars paid out per year of coverage per car).[149] This is an improvement over the original Census-based population density measure that EPIC used in its report. The new ZIP code risk variable was included in the policy database EPIC forwarded to the FTC.

Geographic Location Information and Census Data

ChoicePoint used commercial mapping software to match the addresses of the drivers in the database to Census location information (a process commonly referred to as "geo-coding"). These data were sent to EPIC, and forwarded to the FTC with the core policy database. ChoicePoint was able to determine the Census block location for 95% of the overall sample, and 98% of the sub-sample for which Social Security

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[149] For ZIP codes with fewer than 3,000 property damage liability claims, data from surrounding ZIP codes were also used to calculate average pure premiums.

Administration race and ethnicity data were obtained (see below for a discussion of the Social Security Administration data). FTC staff used the Census location information to append data on race, ethnicity, vehicle ownership, and income from the 2000 Census.

ChoicePoint Credit History Variables

In the process of calculating the ChoicePoint credit scores, ChoicePoint generated and maintained 180 credit history variables for each person for whom Experian was able to locate a credit report. These are a set of variables that ChoicePoint has developed over time for its score-building research that are intended to capture all important information contained in a credit report. These 180 credit history variables are from the June 2000 Experian credit report archive. ChoicePoint forwarded the credit history variables directly to the FTC.

CLUE Data

ChoicePoint collects data on claims from most major automobile insurance firms in the United States. These data allow firms to determine whether a potential new customer has filed a claim under a previous policy with another firm, and use that information in underwriting and rating. The database is referred to as the Comprehensive Loss Underwriting Exchange ("CLUE").

Pursuant to two 6(b) orders, the FTC obtained the CLUE records for everyone in our database for the period July 1995 – June 2003:[150] five years prior to the year covered by the firm-submitted data, the year covered by the firm data, and two years after.

[150] The CLUE database maintains records on individual claims, with name and address and other identifying information about the policy on which the claim was filed. The CLUE records that the FTC obtained were found by matching the names and addresses in the company-submitted data to the CLUE database. Claims, therefore, were only located for people who had the same address in the company data and the CLUE database, and the claims of people who had moved were not located.

ChoicePoint sent the CLUE data directly to the FTC.

Hispanic Surname Match

ChoicePoint forwarded to Experian a database containing the names and addresses of the individuals in the sample, along with the anonymous unique identifier created by ChoicePoint. The FTC forwarded to Experian a file containing a list of Hispanic surnames created by the Census Department following the 1990 Census.[151] Experian matched the last names of all of the drivers in the database against the list of Hispanic surnames. Experian then forwarded directly to the FTC a database containing only the anonymous unique identifier for each record in the database, and an indicator for whether the surname of the person associated with that record was on the Census list of Hispanic surnames.

Vehicle Characteristics

Included with the database EPIC forwarded to the FTC was a 10-digit Vehicle Identification Number (VIN). These are not enough digits to identify a particular vehicle, but enough to identify make and model. The 10-digit VINs were matched to Edmunds data on a range of vehicle characteristics, including vehicle body type (*e.g.*, sedan, pickup truck, etc.), engine displacement, and safety features.

C.2.2 Additional Information Obtained for a Sub-Sample of 400,000

Some data were obtained for only a sub-sample of the records. A sub-sample was used for budgetary reasons. The sub-sample consisted of 400,000 of the 1.4 million policies in the FTC database. Using a smaller sample can reduce the power of statistical tests. To minimize that effect, the sub-sample was drawn using stratification: all policies

[151] The list and a paper that describes how it was developed are available at: http://www.census.gov/population/documentation/twpno13.pdf

with claims were included in the sub-sample, and policies without claims were sampled at a rate sufficient to bring the total to 400,000.[152] This results in a much smaller reduction in statistical power than simple, un-stratified random sampling. ChoicePoint conducted the sampling following directions from the FTC.

FICO Scores

ChoicePoint arranged for Experian to match the names and addresses of the first named insureds of the 400,000 policy sub-sample against the June 2000 credit history archive, and calculate a FICO “Standard Auto, Greater than Minimum Limits” credit-based insurance score. Experian forwarded the FICO scores (or an indicator for why a score could not be calculated – either “no-hit” or “thin file”) directly to the FTC.

SSA Data on Race, Ethnicity, National Origin, and Gender

Whenever someone applies for a Social Security card, the Social Security Administration (SSA) attempts to collect information on race, ethnicity, national origin, and gender. That information is recorded in the SSA’s “Numident” file. Experian attempted to locate Social Security Numbers (SSNs) and dates of birth (DOBs) for the 400,000-person sub-sample in Experian’s consumer credit history files. DOBs were only used when an actual day, month, and year could be found. Experian located an SSN or valid DOB for 324,563 individuals. The name, SSN, DOB, and the anonymous identifier for those individuals were forwarded to the SSA. The SSA matched name, SSN, and DOB against the Numident file, and was able to locate information for 308,746 individuals. The SSA then deleted the names, SSNs, and DOBs, and forwarded to the

[152] Of the 400,000, 56% had a claim in at least one coverage, and 44% had no claim. We used the sampling probabilities to construct sampling weights, which are used throughout the analysis to keep the sub-sample representative of the overall sample.

FTC the anonymous unique identifier and data on race, ethnicity, national origin, and gender.

APPENDIX D

MODELING AND ANALYSIS DETAILS

APPENDIX D Analysis and Modeling Details

D.1 Intermediate Analysis and Data Preparation

The process of preparing and analyzing the FTC database included several intermediate analyses and data preparation steps that require further explanation. First, the race and ethnicity data in the database were from several imperfect sources, and were combined in a way to take advantage of the strengths of each. Second, the sample likely was not representative of the national population of automobile insurance customers, and so was weighted to be representative by geography, and race and ethnicity. Finally, the risk models were not run on the full sample, mainly because race and ethnicity data are only present for a sub-set of the policies. The process of creating the modeling sample is described below.

D.1.1 Using Race and Ethnicity Data

The data on race and ethnicity in the FTC database come from three sources: SSA data, a Hispanic surname match, and Census information about the racial and ethnic makeup of the location where each individual lives. The SSA data have the two most important attributes of race/ethnicity data: they are at the individual level, and they are self-reported. The Hispanic surname match is at the individual level, but is not self-reported. (Comparing the SSA data and the Hispanic surname match shows that there are many people who have a Hispanic surname who do not report themselves to be Hispanic, and vice-versa.) The Census data come from self-reports, but they are only available for geographic areas, not for individuals.

The SSA data do have an important limitation. Prior to 1981, the only available answers to the race/ethnicity question were: “White,” “Black,” or “Other.” After 1981, the choices were expanded to include “Hispanic,” “Asian, Asian-American, or Pacific Islander,” and “North American Indian or Native Alaskan,” and the “White” and “Black” categories were specifically labeled “non-Hispanic.”[153] The “Other” option was dropped. Our only option for identifying Hispanics, Asians, and Native Americans among people for whom we only had pre-1981 responses was to make inferences using the information we did have.

The SSA was able to locate the records of 308,746 people, out of the 324,563 for whom Experian was able to locate an SSN or a valid date of birth. Of those, 10,661 did not have a valid response to a race/ethnicity question. Of the 298,085 people for whom we had valid race/ethnicity data, 162,755 had only a pre-1981 response. These are the people for whom we only had answers for the limited race/ethnicity options. We did, however, have pre- *and* post-1981 responses for 91,519 people. This allows us to evaluate how people identified themselves when given the limited set of race/ethnicity choices, and how they subsequently identified themselves when given the broader set of choices. Based on those patterns, we determined that very few people who answered “Black” pre-1981 chose some other option post-1981, and very few people who answered “White” pre-1981 chose “Black” post-1981. For this reason, anyone who answered “Black” pre-1981 was identified as African American, and no one who answered “White” pre-1981 was identified as African American.

The remaining challenge was to try to determine how someone who answered

[153] The post-1981 options raise other concerns. In particular, “Hispanic” is presented as a mutually exclusive alternative to the other options. In recent Census questionnaires, “Hispanic/Non-Hispanic” information is collected separately from race information. In our data, we find a lower number of people with Hispanic surnames self-identifying as Hispanic, post-1981, than does the Census. This is likely due to the fact that the Census questionnaire, unlike the SSA questionnaire, collects race and ethnicity data separately.

"White" or "Other" pre-1981 would have answered if given the broader post-1981 set of choices. We did that using a statistical analysis of individuals for whom we have pre- and post-1981 responses. The analysis was based on the following factors: the pre-1981 response ("White" or "Other"); whether someone had a Hispanic surname (from the surname match); country of birth (from the SSA data); gender (from the SSA data), and the racial/ethnic makeup of the Census block where the person lived.

We split the group of people who have both a pre-1981 and a post-1981 SSA race/ethnicity answer into cells using the following characteristics:

- Pre-1981 SSA race/ethnicity answer (*i.e.*, "white" or "other") (2 categories)
- Gender (2 categories)
- Region of Birth, based on Country of Birth from SSA data (4 categories):
  - U.S. born.
  - "Hispanic" Countries: Countries of birth where more than half of the people born in that country identified themselves as Hispanic in their post-1981 SSA race/ethnicity response.
  - "Asian" Countries: Countries of birth where more than half of the people born in that country identified themselves as Asian in their post-1981 SSA race/ethnicity response.
  - All Other Countries: Countries of birth that were not included in the three prior categories (these are mainly countries in Europe, the Middle East, and Africa).
- Hispanic surname match flag (2 categories)

This generated 32 cells (*i.e.*, 2x2x4x2). Within each cell, we ran a simple logit model to predict the probabilities that someone would answer "Hispanic" vs. "white", "Asian" vs. "white", or "Black" vs. "white" (the latter only for people who answered "Other" pre-1981) using the relative Census block race/ethnicity concentration for that race/ethnic group vs. non-Hispanic whites as the explanatory variable.[154]

We then imputed the probability of being of each race for the individuals in each cell for whom we only have a pre-1981 race/ethnicity answer. This was a two-step process. We first estimated the probability of being of a given race/ethnicity relative to the probability of being non-Hispanic white, and then used a log-odds ratio calculation to determine the probability of being of a given race or ethnicity.[155]

To use the predicted probabilities that come out of this process, we generated a record for each race/ethnicity that was estimated to have a positive probability for each person. Each of these records was identical, except for the race/ethnicity variable. We included the multiple records in the analysis, giving each record a weight equal to the predicted probability. For example, someone who is predicted to be non-Hispanic white with 85% probability, Asian with 10% probability, and Hispanic with 5% probability will have three records in the database. One record will have "non-Hispanic white" as the race/ethnicity, and a weight of .85; one record will have "Asian" as the race/ethnicity, and a weight of .1; and one record will have "Hispanic" as the race/ethnicity, and a weight of .05.[156]

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[154] For several cells where everyone, or nearly everyone, gave the same post-1981 answer we simply assigned everyone in that cell to that category with probability one. For example, all men who answered "other" pre-1981, were born in a Hispanic country, and had a Hispanic surname were considered to be Hispanic.

[155] The predicted values from a logit are bounded between zero and one, and therefore a logit model gives every person for whom we predicted race/ethnicity a positive predicted probability of being each race or ethnicity. This is true even for people who lived on blocks with no residents of that race or ethnicity, according to the 2000 Census. We therefore reset the predicted probabilities of being of a given race or ethnicity to zero if someone lived on a block with no residents of that race or ethnicity and had a predicted probability from the logit model of being of that race or ethnicity that was less than 1%. As discussed in Appendix F, we also ran the analysis without that restriction and the results were unaffected.

[156] We also estimated the probability of being Native American, but there were so few Native Americans in the sample that we did not include them in the analysis.

D.1.2 Nationally Representative Weighting

One limitation of the database is that it was a random sample of policies of customers of five insurance firms, not a random sample of all insurance customers in the nation. We did not have sufficient information about the automobile insurance market as a whole to know exactly how well our sample represented the entire market.[157] Because much of the analysis presented in this report focuses on the relationship between race, ethnicity, income and credit history and insurance risk, the racial, ethnic, and income mix of the sample could have affected the results.

We did not know the racial, ethnic, and neighborhood-income makeup of car insurance customers nationwide. We did, however, observe the racial, ethnic, and income breakdowns of car ownership, using the 2000 Census. This is shown in column (a) of Table A.1.[158] Column (b) shows the same breakdowns in our sample.[159] Comparing our sample with Census data on car owners, we see that our sample under-represented minorities and residents of low-to-moderate income tracts, and over-represented non-Hispanic whites and residents of upper-income tracts. We did not know how much of this difference is due to differences between the customers of the companies in the sample relative to the market as a whole, versus differences between the racial, ethnic and income make-up of the general population of car owners relative to the

[157] We do know that the sample likely under-represents the highest-risk portion of the market. As described in Appendix F, the robustness checks appendix, we also estimated risk models for the riskiest segment of the sample.

[158] The distribution of race and ethnicity for vehicle owners in the overall Census data, which was used as the "target" for the weighting, was adjusted using Census race and ethnicity data for the full sample of 1.4 million policies and the sub-sample for which we obtained SSA race and ethnicity data. This was done so that if the weights developed on the sub-sample were applied to the full sample (which would require obtaining SSA race and ethnicity data for the full sample), that full sample would have the correct distribution of race and ethnicity.

[159] The racial and ethnic makeup of the FTC sample is based on the SSA race and ethnicity data, including the imputed results for people for whom we only have pre-1981 data.

population of car owners with insurance.

To make our sample close to nationally representative, we weighted the sample using a two-step process. We first created a geographic weight at the Census tract level. Our database contained cars from most Census tracts in the country. There were 64,946 tracts with cars in the 2000 Census, and our database contains records from 62,964 of those tracts.[160] We therefore could make our sample almost perfectly geographically representative of the entire country by applying a weight that was the ratio of the share of all cars in the country that are in a tract over the share of cars in our sample that are in that tract.[161] Column (c) of Table A.1 shows the racial, ethnic and income breakdown after weighting the sample in this way. The weighted sample was now almost perfectly nationally representative by income group, because income is measured at the tract level, but minorities were still under-represented. We therefore applied a second weight, which was the ratio of the share of cars owned by each racial or ethnic group in the country over the share of cars owned by each racial or ethnic group in the sample after applying the tract weights. Column (d) of Table A.1 shows the racial, ethnic, and income breakdowns after applying those weights.[162] The racial and ethnic proportions were now the same as those for the nation as a whole, by construction. Adding this second weight did make the weighted sample slightly over-representative of residents of low-to-moderate income

[160] The 62,964 tracts are in the full database. Tract weights are applied to the full database, and the second step – the race-weight step – is done with the sub-sample for whom we have SSA race and ethnicity data.
[161] To be precise, the measure in the FTC database is the share of property damage liability earned car years by tract. There were a small number of tracts with very small number of earned car years (for example, someone may have only had a week of coverage) that resulted in very large tract weights. We capped the tract weights at the 99.95 percentile of their distribution. Even with that cap, there were some outliers once claims paid were adjusted for earned car years. Removing these outliers did not affect the results of the analysis. These results are discussed in Appendix F, the robustness check appendix.
[162] Because individuals with imputed race and ethnicity are represented by multiple records in the database, each record received the appropriate nationally representative weight associated with the race or ethnicity of that record.

tracts, but it was very close to the national numbers. We used these weights throughout the analysis, except where noted.

CLUE data were analyzed using the full sample of 1.4 million policies. Because the main weights were developed to apply to SSA race and ethnicity data, and we only have SSA race and ethnicity data for a sub-sample, we cannot generate those weights for the full sample of 1.4 million. Instead, we first developed a set of weights to make the sample geographically representative at the tract level, and then calculated race and ethnicity weights based on Census block-level race data.

D.1.3 The Modeling Sample

Most of the analysis presented in the report was conducted using a sub-sample of the original database. As discussed in Appendix C, which describes the construction of the database, the FTC only obtained SSA race and ethnicity data for a stratified sub-sample of the database. Although not all of the analysis required the use of race/ethnicity data, the sub-sample with that information was used throughout the report for the sake of consistency.[163]

For a record to be included in the modeling sample, the following conditions had to be met:

- It had to have valid SSA race/ethnicity data.
- It had to have a Census block location.
- The combination of coverages on the policy had to be "plausible," meaning the policy had to have one of the following combinations:
    - All four main coverages, or
    - Liability coverages and comprehensive, or
    - Liability coverages only.

[163] All of the analyses that did not require race or ethnicity data were also run on the full sample, and all results were very similar. These results are discussed in Appendix F.

- For the ChoicePoint score and FICO score risk models, the sample was limited to policies with a score. This was done because there were very few policies with a "no hit" or "thin file" that had SSA race and ethnicity data.[164]

In addition to the overall analysis sub-sample restrictions, there were additional restrictions for the individual coverage risk models:

- The earned car years for each record for the coverage being modeled had to be greater than zero and not greater than one.

- Total claims count had to be less than six. (This eliminated only a handful of records).

Table A.2 shows summary statistics for the database we analyzed. Column (a) shows statistics for the full sample of 1.4 million policies and 2.3 million vehicles. Column (b) shows the characteristics of the modeling sub-sample, and column (c) shows the characteristics of the modeling sub-sample when weights were applied to make the sub-sample nationally representative by geography, race, ethnicity, and income.

Comparing columns (a) and (b) shows that the sub-sample used for most of the analysis did not differ in any dramatic way from the full sample. This similarity is reassuring, especially given that some of the steps that produced the sub-sample could be quite non-random; in particular, the process of locating Social Security Numbers at Experian, which eliminated roughly ¼ of the original sub-sample of 400,000.

Comparing columns (b) and (c) shows that applying the nationally representative weights did affect some of the characteristics of the sub-sample. In particular, the share of people with missing values for many of the characteristics was quite different once nationally representative weights are applied. The likelihood that a characteristic is

[164] We did a separate analysis of "no hits" and "thin files" using Census race/ethnicity data. Those results are presented in part V of the report.

"missing" is determined by the information that the data providing firms collected and maintained. So, we reasoned that the change in the shares of many of the characteristics with unknown values reflected an effect of the nationally representative weights on the relative mix of the companies in the sample. As noted in Appendix F, all of the analyses were also run without the nationally representative weights, and this had very little effect on any of the results.

D.2 The Risk Models

The statistical models that the FTC constructed and used throughout the report are forms of Generalized Linear Models. These are fairly standard modeling techniques in the insurance industry. This section describes those techniques, and the specifics of how they were used to analyze the FTC database.

To better understand insurance claims risk, it helps to think of that risk as being made up of two components. The first component of risk is the probability that someone will file a claim. This is usually called "frequency." The second component of risk is the size of a claim, usually called "severity." Any risk factor, such as driver experience, geography, or credit history, could be correlated with either or both components of risk.[165] Because claims are generated in this way, claims data have certain distinct features. The data consist of a mix of a large number of zeros (policies with no claims) and a smaller number of positive dollar amounts. The mass of claims is centered around a relatively low number – the hundreds or low thousands of dollars – but claims can

[165] Some factors might affect both types of risk in the same direction. For example, someone who drives especially fast might be more likely to get into an accident, and any accident would probably be more severe than average. Other factors might affect the two types of risk in off-setting ways. For instance, someone with a very expensive car might be especially cautious and unlikely to have an accident, but face very high repair costs in the event of an accident.

range into the tens or even hundreds of thousands of dollars. Both of these features – the many zeros and the long "tail" in the distribution of claims size – require the use of specialized statistical techniques.

There are two approaches to modeling risk. Either frequency and severity can be modeled separately, and the results combined, or total claims cost can be modeled in one step. Most of the analysis in the body of the report is concerned only with the total effects on risk of given variables, such as credit based insurance scores, so most of the analysis is done with total claims estimated in a single step. In the discussion of the predictive power of scores, however, separate results for frequency and severity are presented, as this may provide insights into how scores are predictive of risk. Whether risk is modeled in a single step or the two components of risk are modeled separately, the standard approaches are all built around Generalized Linear Models (GLMs).

D.2.1 Generalized Linear Models[166]

"Generalized Linear Models" are, as the name suggests, a class of statistical models that are generalized forms of standard linear models. GLMs generalize from linear models by allowing for the dependent variable to be distributed according to any member of the exponential family of distributions. GLMs also allow for the variance of the error term to vary with the mean of the distribution. Finally, GLMs allow the effects of explanatory variables to be a transformation of a linear function. The transformation is referred to as the "link function." A specific GLM model is defined by the link function and by the assumption made about the distribution of the dependent variable. The

[166] An excellent source for GLMs, especially in the context of modeling insurance claims, is Duncan Anderson, *et al*., A Practitioner's Guide To Generalized Linear Models, *CAS 2004 Discussion Paper* 1 – 116 (May 2005) (presented at Program CAS – Arlington).

standard Ordinary Least Squares regression model is a special case of the GLM, with an identity link function and normally distributed errors.

D.2.1.1 Modeling "Frequency"

The standard approach to modeling frequency is called "Poisson regression," because it is a Generalized Linear Model (GLM) that uses the Poisson distribution. The Poisson distribution gives the likelihood that a certain number of events will occur in a given period of time, such as how many claims will be filed on an insurance policy during a year. The link function we used in our Poisson regression models was the natural log, so the regressions provided estimates of the multiplicative effects of the variables on risk. That is, the estimates show the effects of variables on relative risk, so an estimated effect of "2" means "predicted claims double when the variable takes this value."[167]

To implement a Poisson regression with the FTC database for a given coverage, the dependent variable was the number of claims for that coverage divided by the earned car years of that coverage.[168] To limit the effects of outliers, we dropped records that had more than six claims on a given coverage in a year.[169] Earned car years were also used as weights, because records with higher earned car years (that is, records that cover longer periods of time) contain more information about risk. Other weights were the sampling weights (which are necessary because the modeling sample was a stratified sub-sample of

[167] The value "2" here would be the exponentiated coefficient estimate from the regression.

[168] Records with a positive count for a coverage but zero dollars paid out on claims for that coverage had the count set to zero. It is fairly common for a customer to file a claim that never results in a payment. For records with multiple claims and positive dollars paid on claims on a coverage, we cannot determine whether all of the claims resulted in payments, as we have only one variable on the total dollars paid on claims for each coverage. So, those records may overstate the number of claims that resulted in payments.

[169] This restriction caused very few records to be dropped, and it did not affect the results. Appendix F includes a discussion of the treatment of outliers.

the original sample), the nationally-representative weights,[170] and, where necessary, the weights used to implement the race/ethnicity imputation. The explanatory variables in the model are listed below.

D.2.1.2 Modeling "Severity"

The standard approach to modeling the severity of claims is to use a GLM with a Gamma distribution. The Gamma distribution is used because it has the features of the observed distribution of claims, all positive values with a relatively low central mass and a long tail of larger values. As with the Poisson regressions, we used a natural log link function for the Gamma GLM models, so the estimated effects from the model are multiplicative.

To implement a Gamma GLM for a given coverage in the FTC database, the sample was first limited to those records with claims on that coverage that resulted in payouts. The dependent variable for the severity regression was dollars paid out on claims for that coverage divided by the claim count for that coverage.[171] The size of claims was capped at the 99th percentile to mitigate the effects of outliers. The weights were the claim count, the sampling weight, the nationally representative weight, and the race-imputation weight, where needed. The explanatory variables were the same as for the frequency models, and are described below.

D.2.1.2 Modeling Total Claims Cost ("Pure Premiums")

[170] All of the analyses were also run without the nationally representative weights. As described in Appendix F, this had very little effect on any of the results.

[171] This may be affected by the problem of people with multiple claims on a single coverage, where we could not determine if all of the claims resulted in payments. For records with multiple claims and positive dollars paid on claims on a coverage, we cannot determine whether all of the claims resulted in payments, as we have only one variable on the total dollars paid on claims on a coverage. So, those records may overstate the number of claims that resulted in payments, which, in turn, will understate the average claim size for that record.

When frequency and severity are modeled separately, the results of the two models can be combined and the overall effect of a particular factor on expected dollars of claims can be calculated. It is also possible to model claims risk in a single step. This can be done by using a GLM with a "Tweedie" distribution.[172] The Tweedie distribution is a compound distribution of the Poisson and Gamma.[173] In essence, the Tweedie GLM approach addresses both the frequency effect and severity effect of risk factors in a single model. That is, it estimates the effect of a given factor on the total dollars of claims paid out per year of coverage.

To implement the Tweedie GLM with the FTC database for a given coverage, the dependent variable is dollars paid out on that coverage divided by earned car years. The same restrictions were placed on the dependent variable to limit outliers as were used in the frequency and severity models.[174] The weights in the pure premiums regressions were the same as for the frequency model: earned car years, the sampling weight, the nationally representative weight, and, where necessary, the race imputation weight. The explanatory variables were the same as those used in the frequency and severity models.

D.2.2 Bootstrapping Significance Tests

In several places in the analysis, we report the results of statistical significance

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[172] The distribution is named for M. C. K. Tweedie, who first introduced it in 1984. Tweedie MCK (1984). "An index which distinguishes between some important exponential families." In 'Statistics Applications and New Directions', Proceedings of the Indian Statistical Institute Golden Jubilee International Conference. (Ed. JK Ghosh and J Roy) pp. 579-604. (Indian Statistical Institute: Calcutta).

[173] Estimating the Tweedie GLM models required choosing the value of a parameter of the distribution, P, that relates to the shape of the distribution and can vary between one and two. A standard approach is to use P=1.5, and that was used to produce the results presented in the report. We also tested values of P across the range from one to two, and the results of the models were not affected in any meaningful way.

[174] Using the same restrictions to avoid outliers did not eliminate all outliers from the pure premium models. Even though claim size and the nationally representative weights were capped, several claims became outliers when claim size, earned car years, and nationally geographic weights were combined. These were not excluded from the results reported in the body of the report. As discussed in Appendix F removing those records had no qualitative effects on the results, with one minor exception.

tests. In each case, these tests were done using an approach known as "bootstrapping."[175] A bootstrap works by repeatedly drawing random samples, with replacement, from the analysis sample that are the same size as the analysis sample. Because these "pseudo-samples" are drawn with replacement, a record in the analysis sample may appear repeatedly, or not at all, in a given pseudo-sample. The parameter of interest is estimated for each pseudo-sample, and this is repeated many times. The confidence interval for the parameter can then be estimated simply by measuring the observed distribution of parameter estimates from all of the pseudo-samples.

For example, bootstrapping was used to determine whether including race, ethnicity, and income controls had a statistically significant impact on the estimated risk impact of each score decile. This was done by first generating 500 pseudo-samples by drawing samples, with replacement, from the modeling sample.[176] The pseudo-samples were drawn at the policy level, so that any correlation in the unobserved risk across cars on the same policy would be accounted for in the bootstrapped confidence intervals. Once the pseudo-samples were generated, the risk models were estimated for each pseudo-sample, with and without controls for race, ethnicity, and income. The difference between the estimated risk for each score decile for the models with and without the controls was computed. Those differences are collected, and form the estimated distribution of the difference for each score decile. The 95% confidence interval for the difference for a given score decile can then be determined simply by measuring the value of the 2.5 percentile and 97.5 percentile of that distribution of estimated differences.

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[175] A standard reference for the bootstrap is B. Efron and R. Tibshihanit, *An Introduction to the Bootstrap*, 1993, Chapman and Hall, Monographs on Statistics and Applied Probability (1993), at 57.

[176] The number of pseudo-samples is arbitrary. We found that our confidence intervals converged after 200 to 300 replications.

We also calculated robust standard errors for the parameter estimates of the GLM Tweedie models that took account of the fact that many records come from the same policies (*i.e.*,“clustering”). The resulting standard errors for the parameters of the models were very similar to those produced by the bootstrapping procedure. We rely on the bootstrap procedure, however, because statistical significance tests on the parameter estimates across different models cannot be done using the standard errors from those models (*e.g.*, comparing score decile parameter estimates across models with and without controls for race, ethnicity, and income).

D.2.3 Variables Used in the Risk Models

The following variables were used in the risk models. All variables were included in all models, except where otherwise indicated. All variables entered the models as indicator (“dummy”) variables. A number of variables have “missing” as one of the categories, and this category was included in the models. Whether a variable was missing for a record was determined by whether the company that provided that record had collected and maintained the information, and therefore when multiple records are missing the same variable it may mean they came from the same company. This complicates the interpretation of some variables, but may have the benefit of acting like an indicator variable for a particular company.

Credit-Based Insurance Score Decile

The credit-based insurance score decile of the score on the policy. Deciles were determined using property damage liability coverage earned car years as a weight, so each decile contains 10% of the property damage liability earned car years. The nationally representative weights were used when the score deciles were determined, and the same decile cut-points were used throughout the analysis.

Race/Ethnicity

Race and ethnicity category – from the SSA data, census data, and Hispanic surname match. As discussed above, this is a simple indicator variable for people for whom we have a post-1981 SSA race/ethnicity response, or who responded "Black" pre-1981. Individuals for whom we had only a pre-1981 response which was either "White" or "Other," have separate records for each race or ethnicity that had a positive estimated probability, with a weight equal to the estimated probability. Race or ethnicity was included in models only where indicated.

Tract-Level Income

The median tract income relative to the Metropolitan Statistical Area median income. This variable takes the values of less than 80% of the MSA median ("low income"), 80% and greater but less than 120% of the MSA median ("middle income"), and 120% of the MSA median and greater ("high income"). Income was only used where indicated.

Age / Gender / Marital Status

The effects of age, gender, and marital status are all inter-dependent. The effect of age on risk varies with gender and marital status, the effect of gender on risk varies with age and marital status, etc. Fully interacting the three variables, however, leads to literally hundreds of possible combinations. To reduce the set of controls used in the models, we created groupings of age/gender/marital status that were of similar risk. We first created a set of seven age ranges. The age ranges were determined by estimated frequency risk models with varying age bands, which in turn were based in part on the public rate filings of several firms. The chosen categories were interacted with gender and marital status. Because gender could take three values (male, female, unknown) and marital status could take four values (single, married, divorced or widowed, unknown), this produced a total of 7x3x4=84 cells. We then ran risk models for each of the four major coverages using all 84 cells. The results showed that the effects on risk of the age/gender/marital status categories were fairly similar across the accident-related coverages (the liability coverages and collision), but somewhat different for comprehensive coverage. We therefore created two sets of age/gender/marital status categories. After examining the estimated risk effects of the 84 cells, we created nine risk categories for the accident-related coverages and six categories for comprehensive. This was done based on the predicted risk for the 84 cells, with attention paid to creating "reasonable" categories made up of cells that were "close" to each other on a grid of age/gender/marital status.

Territorial Risk

The territorial risk variable was calculated by EPIC using three-year average property damage liability claims for the five companies, by ZIP-code. This is described in more detail in Appendix C. Territorial risk entered the model as quintiles, five groups that each contain 20% of the vehicles in the sample, weighted by property damage liability coverage earned car years. As described in Appendix F, using deciles instead of quintiles did not affect the risk models.

CLUE Data

The CLUE data contains information on the number and size of claims for the full range of coverages. Several variables were used to capture that information for inclusion in the risk models.[177]

CLUE Data – Prior Uninsured Motorist / Underinsured Motorist Claims

The number of claims that involved an uninsured or underinsured motorist claim with a positive dollar value in the prior three years. It takes the values of "0" and "1 or more."

CLUE Data – Prior Bodily Injury / Property Damage Claims

The number of claims that involved a bodily injury or property damage claim with a positive dollar value and did not involve uninsured or underinsured motorist claims, in the prior three years. This variable takes the values "0," "1," "2," and "3 or more."

CLUE Data – Prior Collision / Medical Payments / Personal Injury Claims

The number of claims that had a collision, medical payments or personal injury claim with a positive dollar value, and did not have uninsured or underinsured motorist, bodily injury, or property damage claims, in the prior three years. This variable takes the values "0," "1," and "2 or more."

CLUE Data – Prior Comprehensive-Only Claims

Number of claims involving only comprehensive coverage with a positive dollar value, in the three prior years. This variable takes the values "0," "1," "2," and "3 or more."

CLUE Data – Prior Towing and Labor-Only Claims

Number of claims involving only towing and labor with a positive dollar value, in

[177] Because we received prior-claims data only for people who had the same address in the company data and in the CLUE data, the prior claims data used in the FTC's analysis may be more limited than that used by companies when they underwrite and rate policies. Companies can ask applicants for prior addresses, and submit those addresses to be matched, as well.

the prior three years. This variable takes the values "0," "1," "2," and "3 or more."

CLUE Data – Prior Rental Reimbursement Claims

Number of claims involving rental reimbursement, in the prior three years. This variable takes the values "0," "1," and "2 or more."

Number of Accidents

Number of accidents indicates the number of "chargeable" accidents that occurred prior to the beginning of the policy period. [178] This variable came from the companies, and may only reflect claims made policies at that company. The variable is missing for a large portion of the sample. The definition of "chargeable accident" may vary by company and by state, but is usually based on a dollar threshold and often on whether the driver was found to be at fault. For an accident to be considered chargeable, it must typically have occurred in the previous three years. This variable takes the values of "zero," "one or more," and "unknown."

Number of Violations

The number of violations indicates the sum of major and minor moving violations for the driver assigned to a car that occurred prior to the beginning of the policy period. The definition of major violation may vary by company and by state. Typically, this variable only includes major and minor violations in the past three years. This variable takes the values "zero," "one or more," and "unknown."

Tenure

Tenure is the number of years the customer had been with the company. Each year of tenure is a separate category for years 1 through 14, and then years of tenure are

[178] This variable may in many or all cases exclude accidents that occurred while the consumer was a customer of a different firm, which is one reason the CLUE data provides important additional information.

combined into categories for “15 or 16 years,” “17, 18, or 19 years,” and a final category for tenures of 20 years or more.

Property Damage Liability Limits

This is the maximum amount customers would be reimbursed for a property damage liability claim. It was used only in liability regressions. Property Damage liability limits takes the values “$5,000 - $10,000,” “$15,000 - $20,000,” “$25,000 - $45,000,” “$50,000 - $80,000,” “$100,000 - $200,000,” “$250,000 - $325,000,” “$500,000 - $2,000,000,” and “missing or zero.” (Note that when these ranges are non-contiguous there were no policies in the database with values between the ranges.)

Bodily Injury Liability Limits

Bodily injury limit is the maximum amount customers would be reimbursed for bodily injury claims. There are two limits on bodily injury liability, the per-person limit and the total cost limit per occurrence. The two limits are highly correlated, so we based our bodily injury liability limit variable on the per-person limit. It was used only in liability regressions. It takes the values “$10,000,” “$12,500 - $15,000,” “$20,000,” “$25,000 - $40,000,” “$50,000 - $75,000,” “$100,000 - $150,000,” “$200,000 - $250,000,” “$300,000 - $400,000,” “$500,000 - $2,000,000,” and “missing or zero.” (Note that when these ranges are non-contiguous there were no policies in the database with values between the ranges.)

State Minimums

State minimums indicated whether the policy had only the minimum liability coverage required by law. It takes the values of “yes” and “no”. The FTC created this variable by comparing the liability limit variables with data on state legal minimum liability requirements. Information on state minimums, as of 2000, came from the NAIC 2001/2002 Auto Insurance Database Report.[179]

Collision Deductible

This is the deductible for collision claims. It takes the values "$0 - $50," "$100 - $150," "$200," "$250 - $400," "$500," "$1,000 - $1,500," and "missing." This variable was used only in collision regressions. (Note that when these ranges are non-contiguous there were no policies in the database with values between the ranges.)

Comprehensive Deductible

This is the deductible for comprehensive claims. It takes the values "$0 - $25," "$50," "$100 - $150," "$200," "$250 - $300," "$400 - $750," "$1,000 - $5,000," and "missing." This variable was used only in comprehensive coverage regressions. (Note that when these ranges are non-contiguous there were no policies in the database with values between the ranges.)

Annual Mileage

Estimated annual mileage as reported by the customer. It takes the values of "7,500 miles or less," "more than 7,500 miles," and "unknown."

Principal / Occasional Driver

Principal or occasional operator identifies whether the driver assigned to a vehicle was the primary user of the vehicle, or only used it occasionally. It is an indicator that is typically used only for young drivers. The variable had categories for "principal (driver)," "occasional (driver)," and "unknown".

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179 National Association of Insurance Commissioners, "Auto Insurance Database Report 2001/2002" (2004).

Use

Vehicle usage reflects whether the vehicle was used primarily for “pleasure,” “farm,” “business,” “travel to work,” “all other uses,” or whether the use was “unknown.”

Homeowner

Indicates whether the customer owned a home. It takes the values “yes” and “no.”

Multi-line Discount

Multi-line discount designates whether a customer had multiple types of insurance with their auto carrier. The discount is commonly applied when a customer purchases homeowners insurance from the same company. Multi-line discount takes the values of “yes,” “no,” and “unknown.”

Multi-Car

Multi-car indicates whether there were multiple cars in the household covered by the same insurer. It takes the values “yes,” “no,” and “unknown.”

State

State where the vehicle was principally garaged.

Model Year

Model year of the vehicle. Each model year is a separate category, except the following groups of years: “2001 – 2002,” “1981 – 1984,” and “1980 or older.”

Body Type

Data from Edmund’s on the vehicle type. Body type takes the values “convertible,” “coupe,” “extended or crew cab pickup,” “regular cab pickup,” “four-door SUV,” “two-door SUV,” “hatchback,” “passenger minivan,” “wagon,” “sedan,” and "unknown."

Restraint System

Data from Edmund's on airbags and seat belts. Restraint system takes the values "only passive seatbelts," "only active seatbelts," "seatbelts and driver's front airbag," "seatbelts and driver and passenger front airbags," "more than seatbelts and front airbags," and "unknown."

Displacement

Data from Edmund's on the size of the engine in the vehicle. Engine displacement is an indicator of the power of the engine. It takes the values "less than 2.7 liters," "2.7 – 4.3 liters," "More than 4.3 liters," and "unknown."

APPENDIX E

THE SCORE BUILDING PROCEDURES

APPENDIX E. Score Building Procedures

E. 1. Developing the FTC Base Model

The FTC credit-based insurance score-building methodology produces "pure premium" scoring models. That is, the models are developed to predict total dollars paid out on claims on a policy in a year.[180] To have a single scoring model that predicts losses for any of the four major coverages, we combined total claims across coverages into a single measure of losses.[181]

The steps for building a credit-based insurance scoring model are first described, and then the logic underlying the procedure is discussed.

- An ordinary least squares model ("OLS model") is run using total dollars of claims as the dependent variable, and the 180 credit history variables as the explanatory variables.[182] The results of the OLS model are used to generate a "proto-score."

- A Tweedie GLM model is run, using total dollars of claims as the dependent variable, and all the standard risk variables and the proto-score as the explanatory variables.[183] Predicted total dollars of claims are calculated for each record using the results of the Tweedie GLM model.[184] An "adjusted claims" variable is calculated by dividing actual total dollars of claims by predicted total dollars of claims.

- Each credit history variable is then divided into optimal "bins." This is done using an approach developed by staff of the FRB. The relationship between each credit history variable and adjusted claims is evaluated separately. First, the

[180] Because many of the records are for less than a full year, total dollars of claims are adjusted for the period of time each car was actually covered by one of the companies in the sample.
[181] Claims on first party medical coverages – MedPay and personal injury protection – are also included in the "total losses" variable.
[182] The credit history variables were first converted from continuous variables into discrete variables. This was done using a simple rule of thumb of dividing the values into "bins" that each contains at least roughly 10% of the sample. (So, if 50% of the sample had a value of zero for a given variable, there would be one category for "zero," and up to five additional bins.)
[183] Because we are combining claims from across coverages, we also include dummy variables indicating whether the policy included collision, comprehensive, MedPay, and/or personal injury protection coverage.
[184] The "proto-score" is used in the model estimation as a control, but is not used when the predicted pure premium is calculated. The use of a "proto-score" in this way follows a suggestion from several score builders at firms. It is done simply to minimize the effect of other variables that are correlated with score, such as age, picking up variation that would be attributed to score if score were included in the model.

credit history variable is divided into the two categories that create the biggest difference in mean adjusted claims between the two categories. These categories are then divided into additional categories, until the point where further divisions would not lead to statistically significant differences in mean adjusted claims across new categories.[185]

- A forward-selection OLS model is run, with adjusted claims as the dependent variable, and the binned credit history variables as the candidate explanatory variables. The process works by first choosing the variable that, on its own, is most predictive of risk, based on an F-test. The next variable chosen is the variable that adds the most predictive value when used in a model with the first variable chosen (again, based on an F-test). This process continues, with credit history variables being added, one by one, until a pre-determined threshold is reached.

- A Tweedie GLM model is run with actual total dollars of claims as the dependent variable, and the standard risk variables and the "winning" credit history variables as the explanatory variables.

- The coefficients on the credit history variables from the Tweedie GLM estimated in the previous step are used to generate a scorecard for the "FTC credit-based insurance scoring model."

The underlying logic of this procedure is that we are attempting to find the set of credit history variables that best predict total dollars of claims, after controlling for non-credit risk variables. The non-credit risk variables are initially included in the model by adjusting total dollars of claims by a measure of risk based on these variables. Steps one and two do this. The third step, the binning of the credit-history variables, is done for two reasons. (The alternative would be to keep the credit-history variables as continuous variables.) Dividing the values into bins is a simple way of allowing the effects of the variables to vary in complex non-linear ways over the range of values. Using bins also

[185] Two restrictions are placed on the binning process. The first is that no bin could be less than ½% of the total sample. This is done to avoid "over fitting" the data, and to avoid convergence problems when binned data are used in the Tweedie GLM stage. The binning procedure was also run using either a monotonicity requirement, meaning that average claims must either rise or fall across the range of bins, or a "single-turning" requirement, meaning that if average adjusted claims were not monotonic, they could first go up and then down, or vice-versa, but not go up-down-up or down-up-down, etc. Both restrictions led to the same set of optimal bins.

makes the scorecard – the tool for actually calculating a score – much simpler than would other ways of allowing non-linear effects.

The fourth and fifth steps are the core of the score-building process. First, the most predictive credit-history variables are determined by the forward-selection procedure. The forward-selection procedure runs a separate OLS model regression, with adjusted claims as the dependent variable, for every credit-history variable (*i.e.*, 180 separate regressions). It then determines which credit-history variable provides the most predictive power. It then runs through that same process, and chooses the variable that adds the most predictive power to a model that includes the "winning" variable from the first step. This process continues, adding variables one-by-one, until it hits some stopping rule.[186] We used two stopping rules. The first was that if the estimated effect on adjusted claims of the next potential variable was not statistically significantly different from zero ("no effect") at the 10% level, the procedure stopped. This approach tended to produce a model with a very small number of variables, fewer than ten. We also used an alternative where the procedure continued until it had selected the first fifteen "winning" variables. Fifteen was chosen arbitrarily, based on scorecards we reviewed and discussions with professional score builders and staff at the Federal Reserve Board.

The final step in the score building process is calculating the scorecard. This is done by estimating a Tweedie GLM with actual total claims, instead of adjusted total

[186] Ideally, the forward selection procedure would be run using a Tweedie GLM model, as that is the preferred way of modeling total dollars of insurance claims. Maximum likelihood procedures are apt to "crash," however, especially when run on data with many highly-correlated variables, like credit history data. (It is common in the industry to use some form of OLS-based variable selection procedure.) Our approach is a compromise. We use the OLS model for the forward-selection procedure, which determines the "winning" variables, but estimate the final scoring model using a Tweedie GLM model of the actual pure premiums with all of the non-credit variables.

claims, as the dependent variable. All of the non-credit risk variables are included in the model, along with the "winning" credit history variables. The scorecard is made up of the estimated coefficients on the credit history variables. The scorecards we report show the inverse of the exponentiated coefficients. A score is calculated by multiplying together the coefficients for each credit history variable, and this produces the inverse of the predicted relative risk. The coefficients must be exponentiated because the Tweedie GLM has a log-linear functional form. We use the inverse of the coefficients so that a higher score will be associated with a lower predicted risk.

E.2 Developing "Race Neutral" Models

The FTC used two approaches to controlling for race, ethnicity, and income in the score-building process. One approach was to include controls for race, ethnicity, and income in the forward-selection step, when the "winning" credit history variables were chosen.[187] This means that the variables were not chosen because of a correlation with race, ethnicity, or income. Race, ethnicity, and income controls were also included when the final Tweedie GLM was run to generate the scorecard. So, any relationship between risk and race, ethnicity, and income was controlled for, and would not be picked up by the weights on the credit history variables. (Note that while race, ethnicity, and income are included in the model that determines the scorecard, they are not themselves used to calculate a score.)

[187] An alternative approach we used was to include race, ethnicity, and income controls in the step of the model-building process when the "adjusted pure premium" is calculated. The adjusted pure premium was therefore adjusted for those variables. The binning of the credit history variables was therefore done in a way that was purged of any relationship between race, ethnicity, and income, and claims. In addition, the forward-selection process was done with the race adjusted pure premium as the dependent variable. So, the credit history variables were chosen for the model using a dependent variable that was adjusted for race, ethnicity, and income. This approach gave very similar results to results of the model discussed in the body of the report.

The other approach was to build the model using only non-Hispanic whites. This was done by limiting the development sample to people who answered "White, Non-Hispanic" to the post-1981 SSA questionnaire and the records that represent the "non-Hispanic white" imputed probabilities of people for whom we only have pre-1981 SSA data (which include the weight from the imputation process).

E.3 Discounting Variables for Differences across Racial and Ethnic Groups

To force the model-building procedure to produce models with smaller differences across racial and ethnic groups, we modified the forward selection step to take those differences into account. Normally, the forward selection step runs a series of OLS regression models, with adjusted total claims as the dependent variable and credit history variables as the explanatory variables. One regression is run for each credit history variable. The credit history variable with the largest impact on predicted risk at each step, as measured by an F-test, is added to the set of "winning" variables.

This step was modified by also running an OLS regression for each credit history variable with race and ethnicity as the dependent variable. Race and ethnicity was captured using indicator variable for whether the individual was non-Hispanic white or minority (*i.e.*, all minority groups were combined into one category, to simplify the modeling). The R^2 statistics were then calculated for the risk OLS model and the race/ethnicity OLS model, and used jointly to choose winning variables. The R^2 statistic from the risk equation is a measure of how much power the credit history variable has to predict risk. The R^2 statistic from the race and ethnicity model is a measure of how much the credit history variable differs by race and ethnicity. We used these two measures to choose variables for the model in a variety of ways. The approach described in the body of the report was to first normalize the R^2 statistics within each set of regressions – the risk regressions or the race and ethnicity regressions – by dividing the R^2 for the regression for each variable by the largest R^2 in that set of regressions. That is, the R^2 statistics from the risk regressions for each credit history variable were divided by the largest R^2 from all of the risk regressions, and similarly for the race and ethnicity regressions. We then compared the normalized R^2 statistics to select the variables to include in the model.[188]

[188] The model described in the body of the report was determined by subtracting twice the normalized R^2 of the race and ethnicity regression for each variable from the normalized R^2 of the risk regression for that variable. At each step, we chose the variable with the largest difference as the winning variable. Taking the difference between the normalized R^2 statistics, without doubling the normalized R^2 from the race/ethnicity regression, resulted in a model with much larger differences across racial and ethnic groups. Using the ratio of the R^2 statistics from the two regressions resulted in a model that was very similar to that discussed in the body of the report.

APPENDIX F

ROBUSTNESS CHECKS AND LIMITATIONS OF THE ANALYSIS

APPENDIX F. Robustness Checks and Limitations of the Analysis

The FTC conducted numerous additional analyses to confirm the results presented in the body of the report, and to test whether those results are robust to the credit score used, the database used, the use of a sub-sample, and a variety of modeling decisions. There remain several limitations of the database and the analysis that could not be fully addressed through these robustness checks.

F.1 Limitations of the Data and the Analysis

No Information on People who did not Obtain Insurance

The FTC did not have information on insurance applicants who were denied coverage by the firms that provided data. We could therefore not directly evaluate the impacts of credit-based insurance scores on consumers' ability to obtain insurance from a given firm. However, the analysis of state residual markets data in NAIC reports shows that scores do not appear to have adversely affected consumers' ability to obtain insurance through the normal, voluntary market for automobile insurance.

Single National Model

Underwriting and rating plans are determined by firms below the national level, and often at the state level. The FTC's analysis includes controls for state, but does not separately model risk by state. The results of our national model may differ from the results of separate state-level models, especially if the effects of particular risk variables differ across states.

Pooled Company Data

The FTC risk models were estimated using pooled data from multiple firms.

Individual firms estimate the risk posed by their customers, and the results of models estimated using data from a single company may differ from those of a model estimated using pooled data.

Sub-Sample of Industry

The FTC database includes data from five firms that together represented over ¼ of the entire automobile insurance market as of 2000. Despite having data from a fairly large share of the market, we know that this sample likely under-represents the highest-risk segment of the market. (An analysis that focuses on a sub-sample of the riskiest policies in our database is presented in section F.2, below.) In addition, there may be other ways in which these firms differ from the market, as a whole.

Territorial Risk Variable

The territorial risk variable in the FTC database is based on ZIP-code average property damage liability claims. It is a powerful predictor of risk for property damage liability, bodily injury liability, and collision coverages, but it may differ from the territorial risk measures used by individual firms. More importantly, this territorial risk variable is not a powerful predictor of risk for comprehensive coverage. As discussed in the text, this is likely to lead to over-estimates of the relationship of both score and demographic characteristics like race, ethnicity, and neighborhood income to comprehensive coverage risk.

F.2 <u>Robustness Checks</u>

FICO Score

The credit-based insurance score results reported in the body of the report are for the ChoicePoint Attract Standard Auto score. All of the analyses were also run using the

FICO "Standard Auto, Greater than Minimum Limits" credit-based insurance score. The results were similar, both qualitatively and quantitatively, to the results for the ChoicePoint score.

No Nationally Representative Weights

The level of racial, ethnic, and income diversity of the sample could affect the results of the "proxy" analysis. The analysis in the body of the report was done using a sample weighted to match the racial, ethnic, and neighborhood income distribution of the national population of car owners. While this seems a reasonable approach, that population may have a different racial, ethnic, or income mix than the national population of car insurance customers, or the mix of the pool of customers of any individual firm. We also did the analysis without using the tract and race weights that make the sample nationally representative. The results were qualitatively very similar to the results from using the weights. The impact of scores on the estimated risk of African Americans and Hispanics was slightly larger, with the impact on African Americans being an average increase of 11.6% (versus 10.0% with weights) and for Hispanics 5.8% (versus 4.2% with weights). The estimated proxy effect was very similar.

Outliers

We suspected that policies with more than six claims on a coverage may have reflected data errors, so those policies were dropped from the analysis reported in the body of the report. Leaving those policies in did not affect the results of the analysis.

The use of nationally representative weights resulted in several claims becoming outliers, despite the capping of those weights at the 99.95th percentile. There were four people with large claims and small earned car years who lived on Census tracts that were highly under-represented in the database whose claims became outliers when the Census tract weights were applied. Two of these had no impact on any results. These were a collision claim paid to a Hispanic consumer in the lowest score decile, and a comprehensive claim paid to an African American consumer in the 3rd-lowest score decile. There were two outliers that did have a small impact on the results described in the body of the report. There was one bodily injury liability claim, filed by a non-Hispanic white consumer in the second score decile (the second from the bottom) that became an outlier. Capping the weighted value of the claim at the size of the next-largest weighted claim reduced the estimated risk effect of the second decile in the bodily injury liability model by several percentage points. This did not affect any other results of the analysis. There was one comprehensive claim, filed by an African American consumer in the 9th score decile (second from the top) that became an outlier when the nationally representative weight was applied. This did not affect the estimated risk effect for the 9th decile in the overall comprehensive claims model, and therefore does not affect any of the overall results of the analysis. It did have a large effect on the estimated risk effect of the 9th decile for African Americans when race and ethnicity were interacted with score deciles (this is shown in Figure 14). Capping this claim brought that estimated risk effect down somewhat, but only when the observation was dropped did the estimate fall in line with the surrounding deciles. In any case, the estimated risk for the 9th decile for African Americans was not statistically significantly different from that of the overall sample, even when the outlier was not capped.

Full-Sample Models

With the exception of the analysis of the CLUE claims data, the results in the body of the report are based on a sub-sample of records. Much of the analysis required the SSA race ethnicity data, and therefore could be done only with the sub-sample for which we obtained those data. We also estimated the basic risk models, without race/ethnicity/income controls, on the complete sample. The results were very similar to the results from the sub-sample that are described in the body of the report.

Census-Only Race and Ethnicity Data

In the body of the report, we combined data on race and ethnicity from three sources: Social Security Administration records, a Hispanic Surname match, and Census data. We also estimated models using only Census race and ethnicity data, measured at the Census block level. This resulted in a weaker relationship between race/ethnicity and claims risk, which, in turn, resulted in a smaller estimated "proxy effect." These results are what would be expected when race and ethnicity are measured less precisely.

Absolute Income Measure

The results presented in the body of the report that relate to income are based on assigning people to one of three income categories based on the median income of the Census tract where the person lived relative to the median income in their MSA. To determine whether using relative income instead of absolute income affects the results of our analysis, we re-ran the analysis using three categories based on tract median income, not relative to the MSA median. This did not affect the results of the analysis.

Race and Ethnicity Imputation Cut-Offs

As discussed in Appendix C, when multiple data sources were used to impute the race and ethnicity of people for whom we only had a pre-1981 SSA race/ethnicity answer, we imposed a minimum cut-off on the predicted likelihood that someone was of a given race or ethnicity. When the estimated likelihood of being of a particular race or ethnicity was very low, we set the probability to zero. To test whether this decision affected the results, we re-ran the analysis without using the cut-off. This did not affect the results.

High-Risk Sub-Group

Because of the way the sample was drawn by the companies, the FTC database probably under-represents the highest-risk portion of the automobile insurance market. In an attempt to determine whether our analysis would extend to that portion of the market, we estimated risk models limited to the riskiest people in our database, as determined by non-credit factors. To do this, we first ran a risk model without credit score, on the full model sample, that combined claims from the four major coverages. We then predicted each individual's expected total claims (their risk), and created a sub-sample consisting of the 20% of the sample with the highest predicted total dollars of claims. We then ran risk models for each of the four major coverages that included credit scores on the "risky" sub-sample. The estimated relationships between risk and score for the sub-sample were similar to the relationships in the overall sample.

Estimating Total Losses by Modeling Frequency and Severity Separately

Most of the results in the report are from Tweedie GLMs of total dollars of claims. In addition, we modeled total dollars of claims by separately modeling frequency of claims, using Poisson regressions, and severity of claims, using Gamma GLMs, and then combined the estimates from the two models. The estimated relationships between score and risk from combining the results from these two models were essentially identical to the results from the single-step model.

Single Combined-Coverage Model

In the body of the report, we present results from analyzing each type of automobile coverage separately. In addition to the separate models by coverage, we estimated a combined-risk model for the four major coverages. This was done by summing claims on the four major coverages into a single claims variable. Indicator variables were included to control for differences in the set of coverages purchased by consumers. Scores were predictive of risk in this combined-coverage model, and the effects of scores on the predicted risk of different racial and ethnic groups from the combined-risk model were very similar to the results from combining the results from the separate coverage models. The overall "proxy" results for scores were also similar to the results from combining the results from the separate coverage models.

"Tiering"

The risk models used in the body of the report are single-equation models, where all risk factors enter into the single equation. Some firms use credit-based insurance scores to determine the risk category in which a customer is placed. This may allow the effects of non-credit risk variables to vary depending on a person's score (essentially interacting score with other risk variables). To determine whether this would affect the results of our analysis, we divided the sample into three groups based on score. We then ran separate risk models for the three groups, with and without score, and measured the impact on predicted risk for different racial and ethnic groups. The results were very similar to the single-model approach used in the body of the report.

Number of Score Categories

We use score deciles throughout the report. To test whether the choice of deciles was important to the results, we re-ran the analysis using 20 categories of scores ("ventiles"). The results for predicted risk, predicted impacts on minorities, and the results relating to "proxy effects" from using ventiles was very similar to the results from using deciles.

Number of Geographic Risk Categories

In the results reported in the body of the report, we use controls for geographic risk that assign people to five categories ("quintiles"). To test whether the choice of quintiles was important to the results, we re-ran the analysis using ten categories of geographic risk (deciles). Using deciles of geographic risk, instead of quintiles, did not affect the results.

APPENDICES
TABLES

TABLE A1.
Development of Nationally Representative Weights: Share of Vehicles by Race, Ethnicity and Neighborhood Income

	Census	FTC Database		
	(a)	Unweighted (b)	With Tract Weights (c)	With Tract and Race Weights (d)
Race				
African Americans	8.4%	4.3%	6.0%	8.4%
Hispanics	7.8%	2.8%	3.7%	7.8%
Asians	3.1%	3.1%	2.9%	3.1%
Non-Hispanic Whites	80.8%	89.8%	87.5%	80.8%
Income				
Low	18.2%	12.3%	17.6%	19.2%
Medium	50.6%	44.0%	51.0%	50.3%
High	31.3%	43.7%	31.4%	30.5%

Notes:

1) Percentages are relative to the group of consumers included in these calculations.

2) The tract weights were calculated using the ratio of the share of vehicles in the 2000 Census in each tract divided by the share of vehicles in the FTC database in each tract. The subsequent race weights are simply the ratio of the share of each race group in the Census data over the share of each race group in the FTC database, after applying the tract weights. See Appendix C for details on the development of the weights.

3) The final proportions differ slightly from those reported in the table on the sub-sample used for model estimation and analysis because that sample has several additional minor restrictions that were not applied to the sample used to develop the weights.

TABLE A2.
Summary Statistics for the Full FTC Database and the Sub-Sample Used for Model Estimation and Analysis

	Full Sample (a)	Model Sub-Sample (b)	Model Sub-Sample With Nationally Represenative Weights (c)
	(Median or Percent)	(Median or Percent)	(Median or Percent)
Gender			
Male	29.8%	29.2%	25.8%
Female	31.4%	32.1%	28.9%
Unknown	38.8%	38.7%	45.3%
Marital Status			
Single	12.3%	13.1%	12.3%
Married	31.6%	33.1%	27.4%
Divorced / Widowed	2.4%	2.6%	2.9%
Unknown	53.7%	51.1%	57.5%
Accidents			
Zero	56.8%	59.7%	60.7%
One or More	4.5%	4.9%	4.7%
Unknown	38.6%	35.4%	34.6%
Miles Driven			
<7500	22.1%	22.0%	22.5%
>7500	50.4%	50.6%	55.0%
Unknown	27.6%	27.5%	22.5%
Multi-Line Discount			
Yes	34.5%	34.1%	36.6%
No	35.3%	34.8%	40.4%
Unknown	30.3%	31.1%	23.1%
Principal Operator			
Yes	28.2%	27.8%	27.0%
No	6.0%	5.7%	5.9%
Unknown	65.8%	66.5%	67.1%
Use			
Business	0.7%	0.6%	0.6%
Farm	0.8%	0.6%	1.0%
Pleasure	42.3%	43.1%	44.0%
Work	15.7%	16.9%	18.5%
All Other	12.8%	9.6%	11.2%
Unknown	27.8%	29.2%	24.8%
Homeowner			
Yes	55.6%	56.3%	52.5%
No	44.4%	43.7%	47.5%
Multiple Cars			
Yes	61.8%	60.1%	53.0%
No	14.5%	14.8%	14.9%
Unknown	23.7%	25.1%	32.0%

(continued. . .)

TABLE A2.
Summary Statistics for the Full FTC Database and the Sub-Sample Used for Model Estimation and Analysis (Continued)

	Full Sample (a)	Model Sub-Sample (b)	Model Sub-Sample With Nationally Represenative Weights (c)
	(Median or Percent)	(Median or Percent)	(Median or Percent)
Major Violations			
Positive	0.3%	0.3%	0.4%
Zero	64.6%	64.9%	59.5%
Unknown	35.1%	34.8%	40.1%
Minor Violations			
Positive	5.1%	5.5%	5.1%
Zero	54.3%	53.9%	47.2%
Unknown	40.6%	40.6%	47.8%
Vehicle Body Type			
Convertible	1.6%	1.6%	1.2%
Coupe	5.5%	5.8%	6.2%
Ext/Crew cab pickup	4.4%	4.4%	4.8%
Four-door SUV	9.7%	9.8%	8.5%
Hatchback	3.7%	3.8%	3.7%
Passenger MiniVan	5.5%	5.7%	5.5%
Regular Cab Pickup	3.6%	3.5%	4.5%
Two-door SUV	1.8%	1.8%	1.8%
Wagon	2.9%	3.0%	2.1%
Sedan	31.0%	31.5%	30.2%
Unknown	30.4%	29.0%	31.5%
Restraint System			
Driver's front airbags	10.7%	10.9%	10.8%
Driver/Psgr front airbags	36.3%	37.4%	35.5%
Just active belts	12.1%	12.0%	12.5%
Just passive belts	5.6%	5.7%	6.1%
More than front airbags	5.0%	5.0%	3.5%
Unknown	30.4%	29.0%	31.5%
Prior Claim†			
Under & Uninsured Motorist	1.6%	1.7%	2.0%
BI & PD	14.4%	15.1%	14.4%
Coll., Med, & PIP	12.9%	13.9%	13.5%
Comprehensive	19.3%	20.6%	19.8%
Towing and Labor	6.7%	7.2%	8.1%
Rental Reimbursement	7.3%	8.1%	8.4%
None of the above	60.9%	58.3%	58.9%
Age	47	46	46
Share Unknown	*12.6%*	*12.3%*	*11.7%*
Tenure	10	10	8
Share Unknown	*11.7%*	*11.3%*	*12.8%*

(continued. . .)

TABLE A2.
Summary Statistics for the Full FTC Database and the Sub-Sample Used for Model Estimation and Analysis (Continued)

	Full Sample (a)	Model Sub-Sample (b)	Model Sub-Sample With Nationally Represenative Weights (c)
	(Median or Percent)	(Median or Percent)	(Median or Percent)
Property Damage Liability Limit	$50,000	$50,000	$50,000
Share Unknown	*3.2%*	*3.1%*	*2.0%*
Bodily Injury Liability Limit	$100,000	$100,000	$100,000
Share Unknown	*3.6%*	*3.4%*	*2.3%*
Collision Deductible	$500	$500	$300
Share Unknown	*0.0%*	*0.0%*	*0.0%*
Comprehensive Deductible	$200	$200	$100
Share Unknown	*0.0%*	*0.0%*	*0.0%*
Model Year	1994	1994	1994
Share Unknown	*0.8%*	*0.4%*	*0.3%*
Coverage Combinations			
All Four Main Coverages	77.3%	82.6%	80.6%
Liability and Comprehensive	13.3%	13.3%	15.4%
Liability Only	4.1%	4.1%	4.1%
Other Coverage Combinations	5.4%	0.0%	0.0%
Race/Ethnicity			
African American	NA	4.3%	8.4%
Hispanic	NA	2.8%	7.7%
Asian	NA	3.1%	3.1%
Non-Hispanic White	NA	89.9%	80.8%
Number of Policies	1,434,041	275,509	275,509
Number of Vehicles	2,284,330	458,940	458,940
Total Car Years	1,808,584	399,100	399,100

†: Some Prior Claims categories are not mutually exclusive, therefore the shares can add up to more than 100%

Note: See Appendix C for details on the data sources and the construction of the database. See Appendix D for a discussion of how the sub-sample used for model estimation and analysis was chosen.

ATTACHMENT 15

FTC Commissioner Statements
including
Dissenting Statement
Of Commissioner Pamela Jones Harbour

Federal Trade Commission Report to Congress
Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance
July, 2007

Concurring Statement of
Commissioner Jon Leibowitz

Study of Insurance Scores Pursuant to Section 215 of the Fair and Accurate Transactions Act of 2003 ("FACTA")

FTC Project No. P044804

I voted to release this Report because staff's analysis of the data – albeit data primarily provided by a subset of insurers that elected to submit their data for the study – makes a substantial contribution to public discussion in this area. While the analysis demonstrates that credit-based insurance scores are correlated with risk, countering the hypothesis that scores are used principally as a proxy for race or ethnicity, the results in today's Report are of course no cause for celebration. The differences in credit-based insurance scores across racial and ethnic groups are a disturbing reminder that our society is – still – not race blind, and that vestiges of our history of discrimination remain ever-present.

We can, and must, do more.

Statement of Chairman Deborah Platt Majoras, Commissioner William E. Kovacic, and Commissioner J. Thomas Rosch

Study of Insurance Scores Pursuant to Section 215 of the Fair and Accurate Transactions Act of 2003 ("FACTA")

FTC Project No. P044804

In response to a Congressional directive in Section 215 of the Fair and Accurate Transactions Act of 2003 ("FACTA"),[1] the Commission today issued a comprehensive report[2] describing its study of the effects of credit-based insurance scores on the availability and affordability of automobile insurance. As directed by Congress, the report also contains an extended discussion of the FTC's empirical analysis of the impact of these scores on racial and ethnic minority groups.

Section 215 of FACTA sets forth a series of specific requirements for studying the effects of credit-based insurance scores in the context of automobile insurance. It directs the FTC to: describe how credit-based insurance scores are created and used; assess the impact of scores on the availability and affordability of automobile insurance products; undertake a statistical analysis of the relationship between credit-based insurance scores and membership in racial, ethnic, and other protected classes; evaluate whether these scores act as a proxy for membership in racial, ethnic, and other protected classes; and analyze whether it is possible to construct alternative scoring models that predict risk effectively and result in narrower differences in scores among racial, ethnic, and other protected classes. In conducting the study, Section 215 directs

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[1] 15 U.S.C. § 1681 note.

[2] Federal Trade Commission, *Credit-Based Insurance Scores: Impacts on Consumers of Automobile Insurance* (July 2007) ("the Report"), available at http://www.ftc.gov/os/2007/07/P044804FACTA_Repor_Credit-Based_Insurance_Scores.pdf

the Commission to seek input from federal and state officials, consumer, civil rights, and housing organizations, and the public concerning methodology and research design.

In directing the Commission to perform this study, Congress entrusted the FTC with a difficult task that raises important and sensitive policy issues. As explained in more detail below, a talented and dedicated team of career Ph.D. economists produced a study in the manner that Congress instructed. The research team consulted with numerous stakeholders, examined voluminous public comments concerning methodology and survey design, developed a database, painstakingly evaluated the underlying data, and conducted multiple, rigorous evaluations of the data, including an analysis of data obtained from an independent source. We stand by the conclusions reached through this process.

Pursuant to the directive of Congress, the FTC published two Federal Register Notices[3] soliciting comments from the public concerning methodology and research design. The agency received nearly 200 public comments in response to these notices. Commission staff also met with community, civil rights, consumer, and housing groups, as well as with government agencies and private companies. Based on extensive contributions from all of these stakeholders, the FTC's expert economic researchers made well-informed decisions regarding the data to be collected and the methodology to be used in analyzing that data.

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[3] Public Comment on Data, Studies, or Other Evidence Related to the Effects of Credit Scores and Credit-Based Insurance Scores on the Availability and Affordability of Financial Products, 70 Fed. Reg. 9652 (Feb. 28, 2005); Public Comment on Methodology and Research Design for Conducting a Study of the Effects of Credit Scores and Credit-Based Insurance Scores on Availability and Affordability of Financial Products, 69 Fed. Reg. 34167 (June 18, 2004).

FTC staff economists developed a database to analyze the specific issues set forth in Section 215 of FACTA. As an initial matter, the agency obtained, through a third party,[4] automobile insurance policy data for five firms representing 27% of the United States automobile insurance market in 2000. The data, which included ChoicePoint credit-based insurance scores, covered a two-year period (2000-01). Because the automobile insurance companies do not have any data concerning the race and ethnicity of their customers, the FTC staff had to obtain this information from other sources. Commission staff obtained non-public race and ethnicity information about the insurance company's customers from the Social Security Administration and a non-public Hispanic surname match, and obtained similar public information from the Bureau of the Census. The agency staff also obtained and added to its database non-public credit history information from ChoicePoint and credit-based insurance score information from Fair Isaac Corporation. All of this information was combined to create the FTC database, which the agency's economists then used to evaluate the relationship between credit-based insurance scores and risk, as well as the effects of these scores on racial, ethnic, or other protected classes.

Commission staff also obtained data that ChoicePoint had collected from most major insurance companies in the ordinary course of its business concerning past claims that customers had filed.[5] The staff used this data to conduct tests of the relationship between credit-based insurance scores and risk. The tests using this data from Choicepoint independently assessed the

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[4] The third party that provided the data was EPIC Actuaries, LLC, an actuarial and financial risk management and consulting firm which specializes in property and casualty insurance.

[5] This ChoicePoint data and its use are discussed more fully in the Report at 28-29.

results of tests using the FTC database, and both sets of tests showed the same relationship between scores and risk.

Our colleague dissents from the issuance of the report. Commissioner Harbour criticizes the data used, disagrees with the methodology employed, and "doubt[s] the reliability of any conclusions the report might draw." Nearly all studies involving the collection and statistical analysis of large amounts of empirical data require the exercise of judgment in making many decisions about which reasonable minds might differ. While we respect the dissent's views as to the data and methodology used here, we have confidence in the quality of the process that the Commission staff used and soundness of the results obtained.

In her dissenting statement, Commissioner Harbour raises a number of concerns about the data the agency used. She emphasizes that the Commission did not issue Section 6(b) orders[6] to compel insurance companies to provide relevant data about their customers. In our view, the critical question is not the particular method the Commission selected to obtain relevant information; instead, it is whether the data obtained is reliable, regardless of the specific method used.

The FTC uses many techniques for gathering the information it uses in its research and policy development projects. Section 6(b) orders constitute one important technique, but there are other useful methods as well. The Commission has issued a number of significant reports

[6] Section 6(b) empowers the Commission to require the filing of "annual or special * * * reports or answers in writing to specific questions for the purpose of obtaining information about "the organization, business, conduct, practices, management, and relation to other corporations, partnerships, and individuals" of the entities to whom the inquiry is addressed. 15 U.S.C. § 46(b). As with FTC civil investigative demands, the recipient of a 6(b) order may file a petition to quash, and the Commission may seek a court order requiring compliance.

where we obtained industry-specific data without using the 6(b) process.[7] In addition, as noted above, insurance companies do not acquire or maintain race and ethnicity data about their customers. Obtaining information from insurance companies alone through any method, including 6(b) orders, therefore would not have allowed the FTC to conduct the analysis Congress requested. Moreover, because the information collection, retention, and storage practices and procedures of insurance companies vary, even if the Commission staff had obtained information directly from insurance companies through 6(b) orders, we would have had to reconcile the data so that necessary tests could be conducted.

Commissioner Harbour states that the underlying data used in the study is not reliable because it comes from only "two sources of information: data the insurance industry was willing to turn over voluntarily, and data that were publicly available." We respectfully disagree for three reasons. First, we do not assume that data is unreliable simply because it can be obtained

[7] *See, e.g.*, Federal Trade Commission Report, Marketing Violent Entertainment to Children (April 2007), available at http://www.ftc.gov/opa/2007/04/marketingviolence.shtm (industry voluntarily provided internal marketing documents to FTC staff as part of study of marketing of violent entertainment to children); Federal Trade Commission Report, Marketing Violent Entertainment to Children (April 2004), available at http://www.ftc.gov/os/2004/07/040708kidsviolencerpt.pdf (same); Federal Trade Commission Staff Report, The use of Slotting Allowances in the Retail Grocery Industry (Nov. 2003) (data for study of slotting allowance in grocery stores obtained through voluntary access letters to industry); Federal Trade Commission Report, Marketing Violent Entertainment to Children (Dec. 2001), available at http://www.ftc.gov/os/2001.12/violencereport1.pdf (Industry voluntarily provided internal marketing documents to FTC staff as part of study of marketing of violent entertainment to children); Federal Trade Commission Report, Marketing Violent Entertainment to Children (Sept. 2000), available at http://www.ftc.gov/reports/violence/vioreport.pdf (same); Robert P. Rogers, The Effect of State Entry on Retail Automobile Markets, Bureau of Economics Staff Report to the Federal Trade Commission 11 (Jan. 1986) (industry voluntarily provided pricing data to FTC staff as part of a study on state laws restricting the establishment of new automobile dealerships in the vicinity of present dealers selling cars of the same make).

from publicly available sources such as the Bureau of the Census.[8] Second, as described above and in more detail in Appendix C of the report, the Commission used proprietary data from insurance companies and credit score developers (ChoicePoint and Fair Isaac Corporation), non-public data from the Social Security Administration, and publicly available data from Bureau of the Census and a Hispanic surname match. Third, and most significantly, the FTC has a sound basis for believing that the information it received voluntarily from the insurance companies was reliable. The dissent states that the insurance participants "never provided the Commission with written verification of the accuracy, authenticity, or representativeness of the data." Yet the companies did provide written assurances of the data's reliability on March 30, 2007.[9] These assurances could be used to help establish criminal liability under 18 U.S.C. § 1001 if a company submitted false data. We believe that the potential of criminal liability has a deterrent effect.

In addition, nothing suggests that the data submitted were false. Because insurance companies do not acquire or maintain information about the race and ethnicity of their customers, they could not have manipulated the data with regard to race and ethnicity. The FTC staff later matched customer information it received from insurance companies with race and ethnicity data the agency obtained from the Social Security Administration, a Hispanic surname match, and the

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8 Researchers often use Census Bureau data, presumably because they believe it is reliable.

9 Although the Commission staff had not obtained such assurances at the time that the Commission discussed this issue in a letter to now-House Financial Services Committee Chairman Barney Frank on December 8, 2005, these assurances were provided subsequently to Commission staff. *See* Letter from Richard A. Smith, Towers Perrin Tillinghast, to Jesse Leary, Ph.D, Assistant Director, Division of Consumer Protection, Bureau of Economics, Federal Trade Commission (Mar. 30, 2007) (on file with the FTC). Consequently, although there was a time at which these assurances had not been provided to Commission staff, staff ultimately did obtain them.

Bureau of the Census. At the time of submission, insurance companies could not have known what data to manipulate to try to obtain a particular result.

Commissioner Harbour also writes that the FTC's data was inadequate because "it did not accurately reflect the racial and economic demographics of the country,"[10] and, therefore, the Commission staff had to "use statistical weighting to make the pool more racially and economically diverse." As we understand the sector, no insurance company is likely to have a base of customers who fully reflect the racial and economic demographics of the entire United States. Like other businesses, automobile insurance companies compete with one another based on price, location, coverage, service, and other factors. These variations make it unlikely that the customers of a single insurance company, or even a group of companies, will have the same racial or economics demographics of the entire country. Consequently, the use of a statistical technique to weight the sample would have been necessary to produce a representative sample of all customers for any subset of automobile insurance customers. In other words, the need for weighting the sample was not the product of the particular data that the Commission staff obtained and used.[11]

The dissent further observes that the FTC's data on race was problematic because it was

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[10] The Texas studies that our colleague suggests as a template, *see infra* n. 8, also did not assess whether the data it obtained from six insurance companies was representative of the racial and economics demographics of the United States or Texas.

[11] The dissent also notes that the FTC's data did not contain "critical elements" on individual consumers, such as street addresses and actual premiums. The Commission staff had access to street address information, which was used to separate out consumers based on a wide variety of geographic information. The FTC staff also received information on the actual premiums consumers paid, but, as described in the text of the report, *see* Report at 36-37, actual premium information was used only on a very limited basis, *see* Report at 66 n.199, because credit-based insurance scores often had not been used to calculate these premiums.

based on: (a) Social Security Administration data that did not include Hispanic and Asians categories before 1981, and (b) Census Bureau information concerning the block on which consumers live. She also notes that ethnicity was based on a Hispanic surname match.[12] We acknowledge that these methods are imprecise. But we are not aware of any available measures that are more precise.[13]

With regard to the reliability of the FTC's data, the dissent suggests that the agency could have used as a "template" the type of data that the Texas Department of Insurance ("TDI") used in its studies evaluating credit-based insurance scores and automobile insurance risk. Although the TDI used its regulatory authority to obtain data directly from individual companies, both the Texas and FTC studies reached similar conclusions. Both studies found that scores were negatively correlated with total dollars of claims; as the scores of customers increased, the total amount that insurance companies paid out in claims decreased.[14] Both the Texas and FTC studies also found that African Americans and Hispanics have lower credit-based insurance scores on average than non-Hispanic whites and Asians.[15] The results of these two studies

[12] A Hispanic surname match also was used in the Texas Department of Insurance studies that Commissioner Harbour suggests as a template for the FTC study. Texas Department of Insurance, "Use of Credit Information by Insurers in Texas: The Multivariate Analysis"(Jan. 31, 2005) (supplemental report); Texas Department of Insurance, "Use of Credit Information by Insurers in Texas" (Dec. 30, 2004) (collectively "the Texas studies").

[13] The Texas studies that the dissent suggests as a template for the FTC study matched information from insurance companies with race and ethnicity information from the Texas Department of Public Safety. We are not aware of any reason to believe that the race and ethnicity data that the Commission staff obtained from the Social Security Administration and Bureau of Census is less reliable than the data TDI acquired from the Texas Department of Public Safety.

[14] *See* Report at 22-23.

[15] *See* Report at 52.

therefore are consistent on the key issues studied, regardless of whether the TDI data or the FTC data are used.

Commissioner Harbour also faults the study for concluding that "we don't really know" whether a credit-based risk-scoring model could be created that would predict risk effectively while narrowing the differences between members of racial and ethnic minority groups. Our colleague "suspect[s] that, given a more robust data set, [the Commission] might have been able to answer this question more definitively."

We do not know whether her suspicion is correct. What we do know is that the FTC undertook a comprehensive empirical analysis of a reliable data set. We were not able to reach a conclusion about whether a model could be constructed with the desired effects. It is very difficult to prove that something could not exist, and so the conclusion that we do not really know whether such a model could be constructed is not particularly surprising. Indeed, inherent in an objective application of the scientific method to the available facts, especially when researchers are asked to prove a negative, is that sometimes the correct answer will be that "we really don't know."

In short, we have confidence in the quality of the process used and the results obtained in the study, and we anticipate that the information in the report will prove useful to policymakers in the on-going debate concerning the use of credit-based insurance scores.

Finally, we agree with Commissioner Harbour that it is important for the Commission to promote financial literacy in all communities, including, particularly, poor and racial and ethnic minority communities. This is part of the Commission's core mission as evidenced by our extensive and continuing educational activities.[16]

[16] The Commission engages in extensive consumer education and policy research activities to enhance financial literacy. For a more complete description of these activities, please see Prepared Statement of the Federal Trade Commission, "Consumer Protection in Financial Services," before the House Committee on Financial Services 15-20 (June 13, 2007), available at www.ftc.gov/os/2007/06/070613.pdf.

DISSENTING STATEMENT OF COMMISSIONER PAMELA JONES HARBOUR

Study of Insurance Scores Pursuant to Section 215 of the Fair and Accurate Credit Transactions Act of 2003 ("FACTA") Commission File No. P044804

Today's Commission report explores the impact that credit-based insurance scores may have on the availability and affordability of automobile insurance. This report responds to a Congressional directive. Section 215 of the Fair and Accurate Credit Transactions Act of 2003 ("FACTA") requires the Commission to conduct a study and issue a report to inform Congress on whether the use of credit-based insurance scores "could result in negative or differential treatment of protected classes under the Equal Credit Opportunity Act, and [whether such] underwriting systems . . . could achieve comparable results through the use of factors with less negative impact."[1]

I respectfully dissent from this report for several reasons:

- I disagree with the methodology used to generate the report. The data collection and analysis fell short of the Commission's gold standard for rigor and completeness, and did not reflect the agency's best practices. Better alternatives were available and should have been utilized.
- Because I distrust the integrity of the underlying data set upon which the study was based, I also doubt the reliability of any conclusions the report might draw.
- For these and other reasons, the report, with improved methodology, could have more aptly addressed Congress's questions.

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1 Pub. Law 108-159 § 215(a)(3), 111 Stat. 1952, 1985 (Dec. 4, 2003).

In no way do I question the good faith of Commission staff, or of my fellow Commissioners who have approved the submission of today's report. Since 2003, skilled professionals in the Commission's Bureau of Economics have done their best possible work, using the limited data made available to them. Unfortunately, however, I do not believe the efforts of staff were sufficient to overcome incomplete and unreliable data.

Methodological Problems

When Congress created the Federal Trade Commission in 1914, the Commission was equipped with a wide range of research and investigatory tools. In particular, Section 6(b) of the Federal Trade Commission Act broadly empowers the Commission to issue orders to compel, under oath, "reports or answers in writing to specific questions, furnishing to the Commission such information as it may require . . . ."[2]

A statistical study is only as sound as the underlying data. In recent years, the Commission repeatedly has relied on its Section 6(b) powers to acquire comprehensive and credible industry information. The Commission's May 2006 report on gasoline pricing in the aftermath of Hurricanes Katrina and Rita is one noteworthy example.[3] Section 6(b) orders were served on 99 companies in the oil industry, along with an additional 139 Civil Investigative Demands; sworn testimony also was received.[4] In September 2005, the Commission issued a report on pharmacy

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[2] 15 U.S.C. § 46(b).

[3] INVESTIGATION OF GASOLINE PRICE MANIPULATION AND POST-KATRINA GASOLINE PRICE INCREASES (May 22, 2006), *available at* http://www.ftc.gov/reports/060518PublicGasolinePricesInvestigationReportFinal.pdf.

[4] *Id.* at iv-v.

benefit managers' ownership of mail-order pharmacies;[5] to conduct the underlying study, the Commission had subpoenaed documents and information from nearly 20 industry participants.[6] The Commission's July 2002 study of generic drug entry prior to patent expiration is another example;[7] the Commission subpoenaed documents and information from 78 brand-name and generic drug manufacturers.[8]

In stark contrast, this report relies solely on two sources of information: data the insurance industry was willing to turn over voluntarily, and data that were publicly available. The data from the insurance industry came from a study of credit-based insurance scores that the industry sponsored. Not all of the firms that contributed to the study agreed to have their data forwarded to the Commission. Staff ultimately used a subset of the industry's data that came from five insurance

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5 PHARMACY BENEFIT MANAGERS: OWNERSHIP OF MAIL-ORDER PHARMACIES (Aug. 2005), *available at* http://www.ftc.gov/reports/pharmbenefit05/050906pharmbenefitrpt.pdf.

6 *See id.* at iii-iv.

7 GENERIC DRUG ENTRY PRIOR TO PATENT EXPIRATION: AN FTC STUDY (July 2002), *available at* http://www.ftc.gov/opa/2002/07/genericdrugstudy.shtm (includes link to full report).

8 *Id.* at 3. In addition, the Commission currently is in the early stages of a study on "authorized generic" drugs. The study will rely on data collected pursuant to Section 6(b). Two Federal Register notices have been published, and the study is pending approval by the Office of Management and Budget. *See* FTC News Release, FTC Proposes Study of Competitive Impacts of Authorized Generic Drugs (Mar. 29, 2006), *available at* http://www.ftc.gov/opa/2006/03/authgenerics.shtm; FTC For Your Information: Federal Register Notice Issued on Authorized Generic Drug Study (April 30, 2007), *available at* http://www.ftc.gov/opa/2007/04/fyi07238.shtm (both include links to Federal Register notices). "Based on a preliminary analysis, approximately 80 brand-name drug manufacturers, several authorized generic drug companies, and 100 generic companies will receive Special Orders." 72 Fed. Reg. 25306 (May 4, 2007).

companies.[9] As the Smith letter cited in footnote 9 of the majority's statement confirms, these industry participants never provided the Commission with written verification of the accuracy, authenticity, or representativeness of the data.[10] Moreover, records were stripped of identifying data, such that individual records could not be linked to specific companies. The data cannot be independently verified to determine whether any bias was introduced during the selection process.

The data did not contain critical elements on individual policyholders. For example, staff did not have access to all of the characteristics upon which the insurers based their underwriting tier placements. Nor did staff use street addresses, which would have enabled staff to make better assessments based on geography. Staff's analysis did not incorporate data on actual premiums charged to individual policyholders.

Commission staff then adjusted the insurance industry data, based on multiple layers of assumptions and publicly-available data sources, to create an "FTC database" that was not reflective of any actual insurance company's practices. Staff immediately recognized that the original data set did not accurately reflect the racial and economic demographics of this country. Minorities and poor people were under-represented in the sample provided by the insurance industry. Staff recognized

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9 Appendix C § C.2.

10 *Compare* Majority Statement at 5-6 ("Yet the companies did provide written assurances of the data's reliability.") *with* Commission letter to Congressman Barney Frank (Dec. 8, 2005) at 4 ("The agency will not be able to independently verify the accuracy of the data received on automobile policies (the "EPIC") data [sic], nor the data expected on homeowners policies. Staff had expected to receive and rely upon written representations from the firms that contributed the data, stating that the data had been selected randomly following a methodology that staff agreed was appropriate. However, because of the reluctance of the firms to identify themselves to the agency and risk being identified publicly, the agency has not been able to receive such written assurances.").

this shortcoming and used "statistical weighting" to make the pool more racially and economically diverse. It would have been vastly preferable to use data reflecting actual insurance policies purchased by a representative sample of U.S. residents.

Appendix C to the report describes how the FTC database was created. Staff needed to make many assumptions to address deficiencies in the original, incomplete data set. Just the first few pages of Appendix C provide the following examples:

- larger firms were under-represented relative to their market share;
- drivers in small states were over-represented;
- important risk variables were missing from the data, including prior claims and territory;
- credit-based insurance scores had never been calculated for many of the policies in the database;
- among policies that had been scored, different companies used different models, which may have varied by state;
- a score was calculated only for the first-named insured on each policy, which may have skewed the results for multi-driver and multi-car households; and
- high-risk drivers likely were under-represented.[11]

Appendix D to the report explains that the data on race were compiled using imperfect data from the Social Security Administration. Race was sometimes recorded using a predicted probability based on the race of persons on a Census block. The Hispanic surname match is also imprecise;

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[11] Appendix C, § C.1.

many people who have an Hispanic surname do not report themselves as Hispanic, and vice-versa. There were so few Native Americans in the sample that they were not included in the analysis.[12]

By serving insurance companies with 6(b) orders, Commission staff could have obtained a more accurate and complete data set, which would have provided a strong foundation for staff's complex econometric analyses.

Notably, the University of Texas conducted a study in 2003, which triggered follow-up studies in 2004-05 by the Texas Department of Insurance, addressing the exact issue of using credit-based insurance scores for automobile insurance purposes. The Texas studies were based on a far more detailed data set, including hundreds of characteristics of individual policyholders, as well as actual underwriting decisions by insurance companies. The scope of the Texas data collection – especially its heavy reliance on raw, unbiased data – might have provided a template for the Commission's own data collection efforts.

Substantive Conclusions Drawn By The Study

In light of these significant methodological problems, I cannot endorse the report's favorable view of using credit-based insurance scores to inform decisions related to automobile insurance. I recognize that credit-based insurance scores may be effective predictors of risk under automobile policies. But as the report acknowledges, it is impossible to know *why* this correlation exists, based on the Commission's study alone.

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[12] Appendix D, § D.1.1.

Even using the "best" data the industry had to offer, the study still found that credit-based insurance scores have a small effect as a "proxy" for membership in racial and ethnic groups. Given the incompleteness of the data, it is unclear whether the actual proxy effect might be greater.[13]

Responsiveness of Study to Congressional Inquiry

Congress asked the Commission to conduct a study based on real-world facts. Congress specifically called upon the Commission to study "the extent to which, if any, the use of underwriting systems relying on [credit-based] models could achieve comparable results through the use of factors with less negative impact." Reading between the lines of the report, the answer I take away is, "we don't really know." Rather than answering the question of what insurers actually are doing, today's report discusses at great length whether a theoretical insurer with a nationally-representative, hypothetical book of automobile insurance business might have been able to engage in some form of credit-based insurance scoring in a manner that was not unduly "negative or differential" in its treatment of protected classes.

The report devotes only a few pages to a discussion of alternative scoring models. Commission staff endeavored to create a model that did not "derive predictive power from a relationship with race, ethnicity, and income."[14] Staff tried several different approaches and was

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[13] The report notes that several states (California, Massachusetts, Georgia, Hawaii, Illinois, Maryland, Oregon, and Utah) restrict the use of consumer credit history or credit-based insurance scores in insurance. Report at 19.

[14] Report at 76.

unable, using the available data, to build a model that predicted risk but narrowed the differences in scores among racial and ethnic minority groups.[15]

The report concedes, however, that the FTC's "inability" to build such a model is "by no means definitive. Perhaps someone could develop a model that meets both of these objectives."[16] I suspect that, given a more robust data set, staff might have been able to answer this question more definitively. I also would have preferred to see a more balanced discussion of the benefits and detriments of using credit scores and credit-based insurance scores.

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Congress is faced with difficult policy questions regarding possible racial bias in the insurance industry. Congress asked the Commission to apply its substantial expertise to study one potential problem – the possible use of credit-based insurance scores to disadvantage protected classes – and to report on how consumers actually are being treated in the insurance marketplace.

Had this report been based on the real insurance marketplace – using actual, verifiable data on individual policyholders, from a broad cross-section of insurance companies – reliable answers might have emerged. Staff made their best, good-faith efforts to work with the data they were given. But in the end, I cannot endorse this report due to my grave methodological concerns. This study fell short of the rigorous research and data-collection standards to which the Commission usually adheres.

Section 215 of FACTA requires the Commission to conduct a similar analysis with respect to homeowners' insurance. The Commission should use all available investigative powers, including

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15 Report at 72.

16 Report at 80.

6(b) orders, to assemble a more reliable data set – just as it has done in other superbly executed studies involving other critical industries. The study should include a more thorough and balanced discussion of alternative predictors of risk, and their relative costs and benefits.

Finally, this report reminds me how important it is for the Commission to promote financial literacy in poor and ethnic minority communities. Credit scores clearly are affecting decisions outside of the credit context. The Commission should help all consumers to understand the extremely negative impact of paying bills late, making inquiries about credit, using payday lenders, and taking other actions that may reduce their credit scores. More than ever, protecting one's credit score is a critical step toward achieving financial stability and owning a piece of the American dream.