February 25, 2021

Oregon House of Representatives
Committee on Business and Labor
900 Court St. NE, Salem, Oregon 97301

Re: HB2043

Dear Chair Holvey, Vice Chairs Bonham and Grayber, and Members of the Committee,

I appreciate the opportunity to share insights with you about my research on automobile insurance rating. As a brief description of my background, I have a PhD in Risk Management and Insurance and I have been researching and teaching insurance topics for more than 20 years. Since 2015, I have served as Director and Senior Research Professional for the Center for Insurance Information and Research at the University of Alabama. Before that I was the Whitbeck-Beyer Professor of Insurance at the University of Arkansas, Little Rock.

I recently published a peer-reviewed article on the topic of this hearing in the National Association of Insurance Commissioners' (NAIC) *Journal of Insurance Regulation* (Powell, 2020). The paper, titled "Risk-Based Pricing of Property and Liability Insurance," is included with my testimony by reference.[1]

If enacted, HB2043 will restrict the variables that insurance companies may use to set rates for automobile insurance. During the hearing on February 24, 2021, several people testified in favor of the bill. The arguments offered by these individuals were largely incorrect or incomplete. In the remainder of this document, I demonstrate the following facts:

1) The variables used to set insurance prices, including credit-based insurance scores (CBIS), education, occupation, marital status, gender, and housing status, are accurate predictors of losses that match insurance premiums to risk.
2) Accurate premiums are objectively fair because they match premiums to losses.
3) Research shows that inaccurate premiums, and resulting cross subsidies, lead to more losses and higher premiums.
4) Proponents of HB2043 use an incorrect definition of a "safe driver," which invalidates nearly all of the statements they make about the accuracy of rating variables.
5) Drivers in California pay more in premium per dollar of loss than drivers in Oregon.

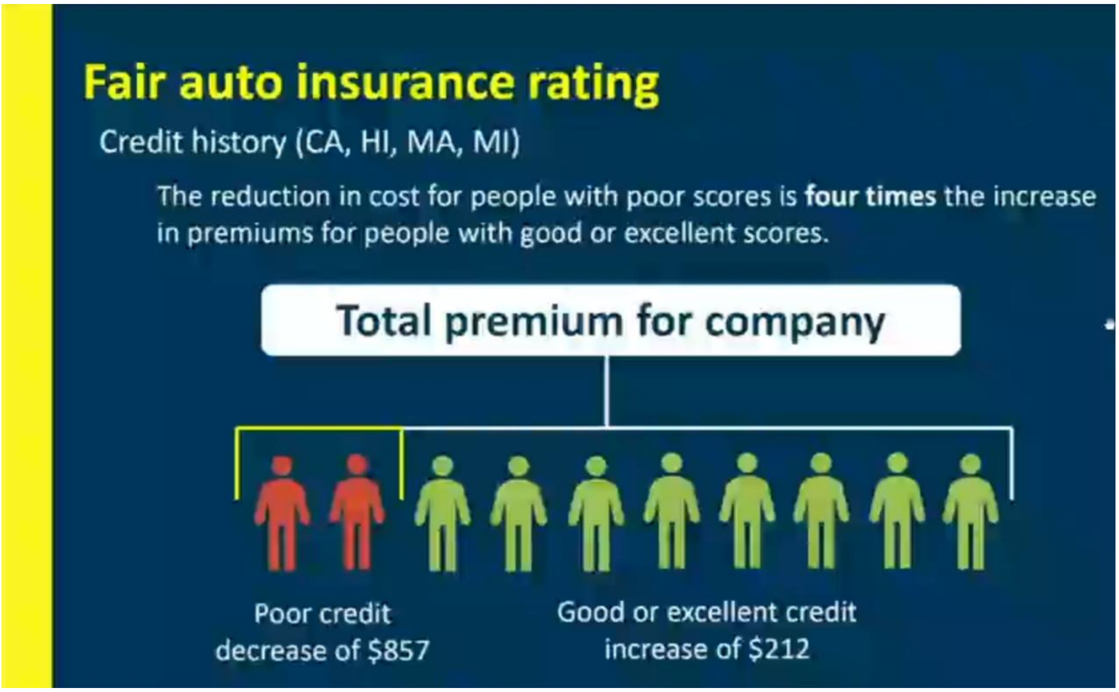
First, insurance rates are set by applying statistical methods to data describing drivers and losses. All of the variables used to set insurance rates demonstrate strong correlation with losses. These correlations are observed and approved by each state's insurance regulator. Every variable used to set insurance rates improves rate accuracy, meaning they match insurance premiums with expected losses. Accurate premiums are objectively fair because the people who are less likely to crash pay lower premiums.

The rating factors that HB2043 would exclude, such as CBIS, education, occupation, gender, marital status, and housing status are especially useful in the pricing process because they are inexpensive to collect and they can be observed accurately when a policy is first underwritten (Werner and Modlin, 2016). In addition, these factors align with underlying factors that are otherwise difficult to observe. CBIS,

[1] The article is available on the NAIC website at https://content.naic.org/sites/default/files/inline-files/JIR-ZA-39-04-EL.pdf.

occupation, and education all represent choice made by individuals that reveal risk tolerance (see Brockett and Golden, 2007; Hersch and Viscusi, 1990; Moore and Viscusi, 1988, 1990; and Viscusi, 2004). Gender and marital status correlate with miles driven, and time of day and locations when and where people drive.

When insurance rates are less accurate, good drivers must pay more so that bad drivers can pay less. In fact, the eleventh slide presented by Commissioner Stolfi and Ms. Soucy (copied below) demonstrates this outcome.



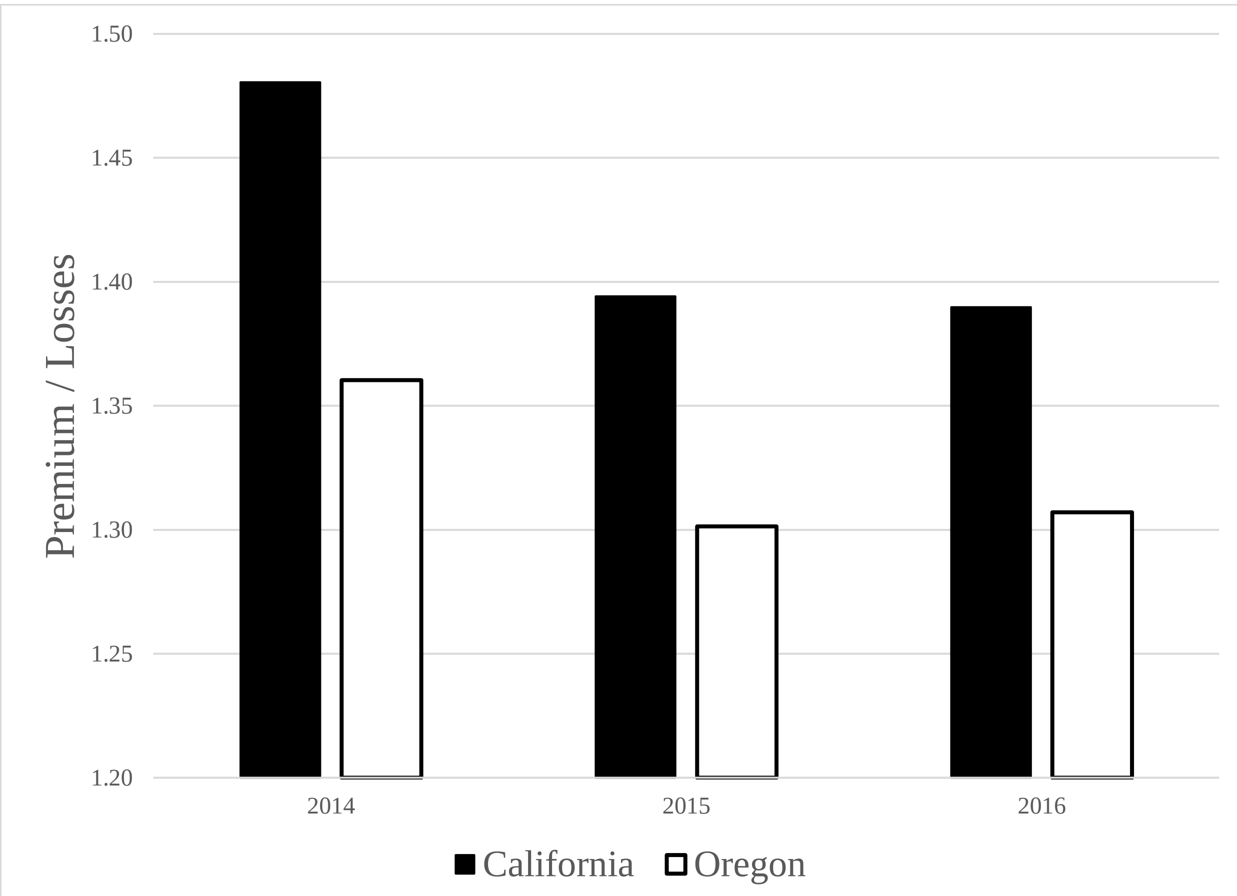
The cross-subsidy created by restricting rating variables is objectively unfair, but more importantly, it also creates incentives for bad drivers to drive more and for good drivers to drive less. Peer-reviewed academic research demonstrates that these incentives increase overall losses (Derrig and Tennyson, 2008; Weiss, et al., 2010). In other words, when insurance rates are less accurate, more people crash their cars. As a result, more property is damaged, and more people are injured and killed. This proven result from peer-reviewed research stands in stark contrast to Commissioner Stolfi's statement (on his final summary slide) that total premiums and losses do not change when the rating system changes.

Second, one overarching fallacy in the testimony supporting HB2043 is the definition of a "safe driver." For example, Commissioner Stolfi testified at 1:07:30 in the hearing that CBIS are related to insurance claims, but not to being a safe driver. This statement begs the question of how one defines a "safe driver." Commissioner Stolfi, Ms. Soucy, and Mr. Heller all define a safe driver as one who does not have a loss or traffic citation on her driving record. Five years is the typical period of time during which an insurance company considers one's driving record. Because the probability of crashing a car in any given year is quite low, it is common for relatively unsafe drivers to go several years without crashing. The average driver has about a 4% chance of crashing in a given year. A driver who is twice as likely to crash (i.e. has an 8% annual probability of crashing) is clearly less safe and should pay a higher insurance premium than the average driver. However, if we only observe loss events in a 5-year window, and make allowance for 5% of drivers to receive a traffic citation each year, 50% of these drivers will appear to be "safe drivers" by the proponents' definition, because they have not had a loss or a ticket *yet*.[2]

Third, Commissioner Stolfi, Ms. Soucy, and Mr. Heller each referenced California as a state that restricts the use of several accurate rating variables yet maintains a competitive insurance market. Although many insurance companies are active in California, Oregon should not aspire to emulate California's insurance market.

Figure 1 shows the difference the price of insurance between Oregon and California in the most recent years for which data are available.[3] The measure of price is premium divided by losses, which provides an "apples-to-apples" comparison. For each $1 of losses paid, insurers in California charged an average of $1.42 in premium, whereas insurers in Oregon charged $1.32 per $1 of loss.

Figure 1: Price of Insurance in California and Oregon



*Note: Data are from the 2020 NAIC Auto Insurance Database Report.

Figure 2 shows the average premium per insured vehicle in California and Oregon. The striped bars in the chart indicate the premium that would have been charged in Oregon if it had the same price ratio as

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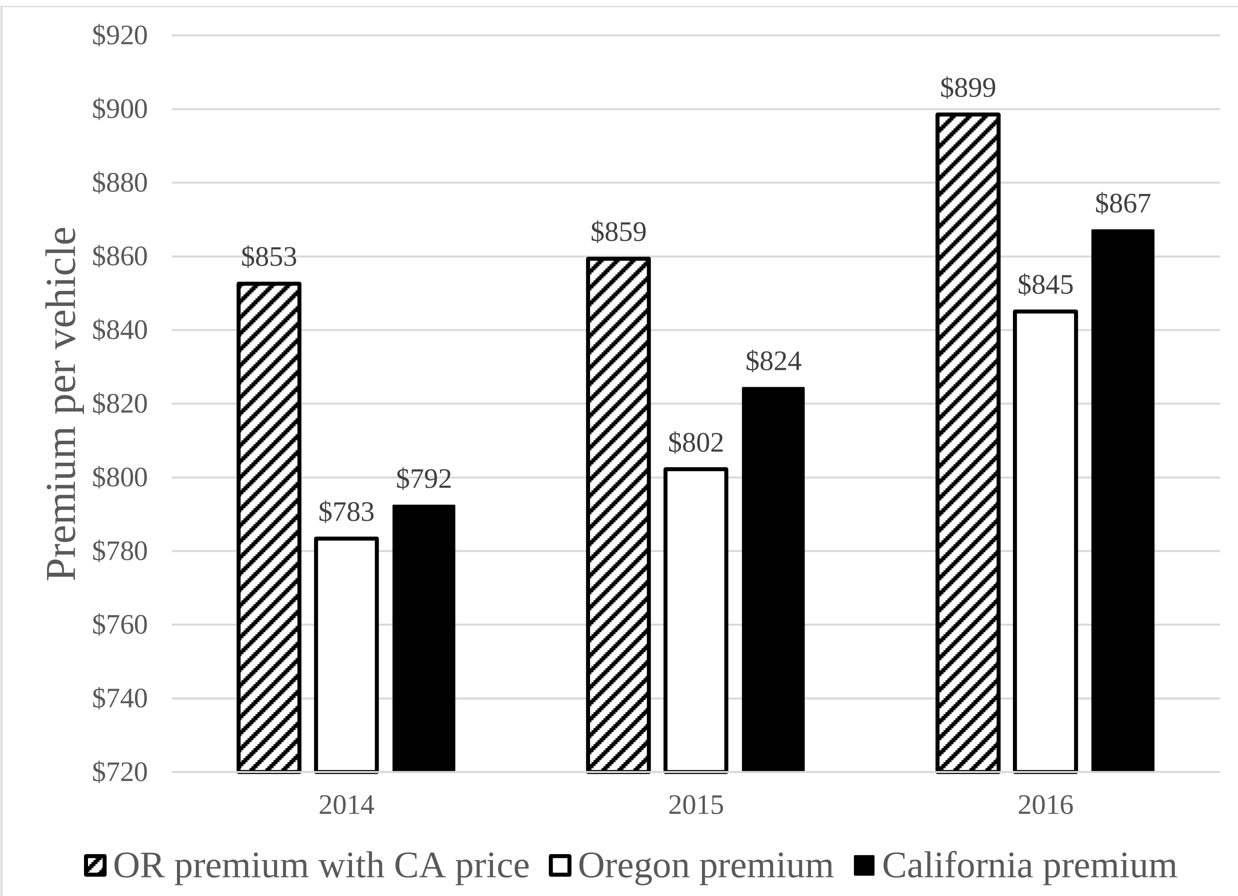
[2] The calculation is $(1-0.08)^5 = 0.6591$.

[3] These data are from the 2020 Edition of the NAIC Auto Insurance Database Report.

California. For example, in 2014 Oregon experienced $576 of losses per vehicle. Multiplying $576 times the price ratio in California (1.48) yields $853. This is $69 more than the $783 per vehicle Oregonians paid for auto insurance in that year. The average increase over the three years is $60 per vehicle, a 7.4% increase in premium. Imposing this surcharge on Oregon's 2,735,000 auto insurance policies creates an annual increase of more than $164 million to insure the same level of losses.

In summary, I have explained and demonstrated with data or numerical examples that the insurance rating factors that would be restricted by HB2043 will make insurance prices less accurate. The resulting cross subsidies created in insurance markets will be objectively unfair to insured drivers. The cross subsidies also create incentives for less-safe drivers to spend more time behind the wheel. Peer-reviewed academic studies find that this leads to more crashes and higher premiums. Finally, I show that Oregonians should not aspire to emulate California's insurance market. Based on observed loss and premium data, if Oregonians purchased insurance for their own losses from California's insurance market, there premiums would increase by 7.4%, or $164 million per year.

Figure 2: Premium per Vehicle in California and Oregon



*Note: Data are from the 2020 NAIC Auto Insurance Database Report.

For all of these reasons, I encourage you to vote against HB2043.

Sincerely

Lawrence Powell, PhD
University of Alabama, Center for Insurance Information and Research
Enclosures

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Risk-Based Pricing of Property and Liability Insurance

Lars Powell, Ph.D.

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Risk-Based Pricing of Property and Liability Insurance

Lars Powell, Ph.D.*

Abstract

Policymakers currently show renewed interest in restricting the use of certain accurate ratemaking variables in personal lines (automobile and homeowners) insurance. Policymakers are considering, and in some states enacting, laws that would exclude gender, education, occupation and credit-based insurance scoring (CBIS) as insurance rating variables. I argue that excluding accurate rating variables from the insurance pricing process has negative consequences. The accuracy of insurance prices decreases, creating cross-subsidies where lower-risk insureds pay higher premiums and higher-risk insureds pay lower premiums. In addition to being objectively unfair, cross-subsidies increase the overall cost of insurance and distort policyholder incentives to take appropriate precautions. The end result is higher prices, more property damage, more injuries and more fatalities. I also address arguments put forth by opponents of these rating variables and demonstrate the high level of competition in insurance markets.

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Introduction

Insurance pricing is inherently difficult, because insurers have to set prices before they know the ultimate costs of insurance coverage. They approach this task using statistical methods to predict future losses and expenses from historical data and observable characteristics.

The shared goal of ratemaking and underwriting is to charge accurate prices for insurance. Accurate prices support insurance company performance, but they also serve the greater good of society by imposing the cost of risk on those creating exposure. When drivers or homeowners bear the cost of their own risk, they should behave in ways that maximize benefits to society.

Despite the positive effects of risk-based pricing on insurance companies, insurance consumers and society, political advocates and some lawmakers frequently argue for restrictions on underwriting and ratemaking criteria, as well as limitations on rate differentials between classifications. Such arguments are generally premised on normative concerns of fairness or affordability (see, for example, Cooney et al., 2019; MCRC, 2017; WNYLC, 2015). However, both terms are hard to define in the context of insurance, and insurance regulation is poorly suited to address affordability (Grace et al., 2019).

When policymakers restrict the use of an accurate rating variable, two things happen. First, the average cost of insurance decreases for higher-risk policyholders. Second, the average cost of insurance increases for lower-risk policyholders. These results can objectively be categorized as unfair; however, such laws and regulations are often passed for the stated purpose of fairness.

This study explains the need for, and benefits of, risk-based pricing in a public policy setting. First, I describe how insurance prices are set. Second, I review the actuarial and economic criteria for insurance rating variables. Third, I address certain variables that are consistently controversial in some states. Fourth, I describe the negative effects of restricting the use of accurate rating variables. Finally, I demonstrate that insurance markets are highly competitive and discuss how competitive markets lead to optimal outcomes for consumers. While the context of this work is auto and homeowners insurance, many of the principles discussed also apply to other lines of insurance.

How Insurance Prices Are Set

Insurance companies set prices by estimating correlations between past loss experience and observed characteristics of an insured risk. For auto insurance, observed characteristics include location, miles driven, age, gender, type of vehicle, driving record, claims history, credit history, education and employment. For homeowners insurance, insurers consider similar characteristics, but they apply to homeowners claims rather than auto claims. These include location, age of home, construction type, credit history and claims history.

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Correlations between losses and rating variables are estimated using multivariate statistical models. This is important because it makes the factors used in rating orthogonal. In other words, if age, type of vehicle and driving record are correlated with each other, only the additional information provided by each variable is considered in the model.

Market competition leads insurers to search for potential policyholders whom they can charge a lower rate than the incumbent insurer and still make a fair profit. Given this process, each company uses slightly different data and techniques, resulting in different prices across companies for the same driver or homeowner.

Choosing Rating and Underwriting Variables

Rating variables are used to assign drivers and homeowners to classifications based on expected losses. Rates charged to policyholders vary by classification. Insurers use several criteria to choose rating and underwriting variables.[1] Ideal variables should meet a set of statistical, operational and legal criteria.

The statistical criteria are accuracy, homogeneity and credibility. An accurate rating variable has a statistically significant correlation to losses. A distinct level of the variable indicates a distinct level of expected losses. For example, driver age is used to rate automobile insurance. Age is broken down into ranges, with each range correlated to a level of insured losses. The youngest drivers incur the most losses. As age increases, expected losses decrease until drivers reach a certain advanced age. After drivers reach this next threshold, losses increase with age. Finally, an accurate variable is ultimately fair because it distributes the cost of risk according to the riskiness of drivers.

Next, rating variables should create classifications in which the members have similar expected losses in both levels and variation. Such homogeneity within a classification promotes rate accuracy and equity. If policyholders in a given classification have sufficiently different expected losses and loss variability, additional rating variables or levels of existing variables should be added to achieve adequate homogeneity.

The last statistical criterion is credibility. A credible variable has a sufficiently large number of observations in each classification that the actuary can have statistical confidence in determining accuracy and homogeneity. Thus, actuaries must balance homogeneity and credibility to some degree in classification ratemaking. In practice, this constraint is rarely binding. More than 80 million homes and 200 million vehicles are insured in the U.S. each year, leaving ample observations for many classification variables.

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1. This section loosely follows information presented in American Academy of Actuaries (1980); *Actuarial Standard of Practice (ASOP) No. 12, Risk Classification (for All Practice Areas)*; Finger (2001); Harrington and Niehaus (2002); and Werner and Modlin (2016).

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Insurers must also consider operational characteristics of rating variables. Even if a variable meets the statistical criteria described above, it could be impractical due to operational concerns. Operational criteria include objectivity, verifiability and expense. First, the levels of an objective rating variable can be defined without judgment. An insurer might like to classify drivers or homeowners by their level of responsibility; however, responsibility is not directly observed. Instead, policyholders can be classified by objective variables related to responsibility, such as number of claims, late payments and number of speeding tickets.

The second operational characteristic is verifiability. A verifiable rating variable is one that can easily be verified by the insurer and cannot be easily manipulated by the applicant or insured. Age, gender, credit information, loss history, address and type of vehicle are easy to verify. Werner and Modlin (2016) suggest miles driven as a variable that is difficult to verify, although technology is on the brink of solving this problem.

The third operational characteristic is expense. If a variable is too expensive (relative to the insurance premium) to collect or verify, it is not useful, regardless of its predictive accuracy.[2] Specifically, if the cost of obtaining information is greater than the difference in premium from using that information in the rate calculation, all parties benefit from excluding such variables.

Insurance Rate Regulation

One set of constraints not mentioned above is that insurance rating variables must be legal. Insurance rating laws in every state indicate that insurance premiums must not be inadequate, excessive or unfairly discriminatory. An adequate rate prevents insurer insolvency and non-excessive rates prevent insurers from exploiting any potential market power.[3] In this context, fair rates are statistically related to losses. These criteria have been used by insurers since the mid-1800s, but they were first codified by the Kansas legislature in 1909 (Miller, 2009). Insurance is regulated at the state level and laws vary from state to state; however, laws in each state reference these criteria.

Many states define the term "unfairly discriminatory" in statute. There are two approaches to this definition. The Arkansas statute (Section 23-67-208(d)) provides a direct definition as follows:

> 1) A rate is not unfairly discriminatory in relation to another in the same class of business if it reflects equitably the differences in expected losses and expenses. Rates are not

2. Harrington and Niehaus (2002, Ch. 8) provide a comprehensive example of these characteristics in the context of competitive markets with adverse selection.

3. It is important to note that "excessive" rates are self-correcting in a competitive market. I discuss this further in the "Insurance Markets" section. Several state statutes specifically note that a rate in a competitive market is assumed not to be excessive.

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unfairly discriminatory because different premiums result for policyholders with like loss exposures but different expense factors, or with like expense factors but different loss exposures, if the rates reflect the differences with reasonable accuracy.

2) A rate shall be deemed unfairly discriminatory as to a risk or group of risks if the application of premium discounts, credits, or surcharges among the risks does not bear a reasonable relationship to the expected loss and expense experience among the various risks.

Another common approach to defining "unfairly discriminatory" is to describe appropriate classification procedures. For example, Maine Insurance Code Section 2303.1.G states:

G. Risks may be grouped by classifications for the establishment of rates and minimum premiums. Classification rates may be modified to produce rates for individual risks in accordance with rating plans that establish standards for measuring variations in hazards or expense provisions, or both. These standards may measure any differences among risks that may have a probable effect upon losses or expenses. No risk classification may be based upon race, creed, national origin or the religion of the insured.

Both types of definition establish that an unfairly discriminatory rate is one that is not statistically correlated with expected losses and expenses.

In addition to the three basic criteria, the states can pass laws limiting the use of rating variables for many reasons. Most variables that are not allowed by certain states are chosen based on subjective criteria such as "fairness" or "affordability." Proponents of excluding gender, age, education, employment and CBIS as rating variables do not offer evidence that these variables are inaccurate.

There are several potential rating variables that are consistently prohibited in all states.[4] These include race, ethnicity, national origin, religion and income. Importantly, it is not clear if these factors would increase the accuracy of insurance rates. However, society has deemed such factors sufficiently unpleasant that laws exclude them from practice.

4. Avraham et al. (2014) note that some states do not specifically ban these factors by name for all lines of business in statute. Nonetheless, insurers in each state realize that such rating factors are not allowed.

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Gender, Education, Employment and CBIS

Three rating factors—education, employment and CBIS—have received more public scrutiny in the past two decades than have other rating variables. In addition, seven states[5] restrict the use of gender in pricing auto insurance. The recent push to exclude gender may, in part, be responding to a recent finding that some insurers charge females more than males for the same coverage (Povich, 2019). Historically, males were charged more than females, which perhaps limited public policy interventions in the U.S. because males are not a protected class.[6] However, aggregate national data indicate that, although males drive more miles and crash more than females, females are involved in more crashes per mile driven than males.[7] As insurers continue to improve measurement of mileage (Hill, 2016), it follows logically that the effect of gender on the cost of auto insurance should change.

Recent public policy skirmishes over the remaining three variables have been much more intense, resulting in extensive study and public discussion of these factors. Since 1999, for example, the Federal Trade Commission (FTC), the U.S. House of Representatives' Financial Services Committee (FSC), the National Association of Insurance Commissioners (NAIC), the National Conference of Insurance Legislators (NCOIL), and nearly every state insurance regulator has issued a report, held hearings, or passed a bill related to CBIS.[8] In the 2019 state legislative sessions, legislators in at least six states filed bills aimed at ending the practice of CBIS.[9] Several of these hearings, studies and bills also applied to the use of education and occupation as rating factors. More recently, U.S. Rep Rashida Tlaib (D-MI) introduced H.R. 1756 in the 116th Congress, which would ban the use of CBIS in rating automobile insurance.[10] In addition, U.S. Rep. Bonnie Watson Coleman (D-NJ) and U.S. Rep. Tlaib are

5. These states are California, Hawaii, Massachusetts, Michigan, Montana, North Carolina and Pennsylvania.

6. In the early 1970s, however, Canadian men brought a successful campaign to eliminate gender rating. Dalhby (1982) finds that this change led to cross-subsidization and adverse selection in the market for auto insurance.

7. Sivak (2012) finds that females drove 41% of miles driven in 2010. National Automotive Sampling System / General Estimates System data from the same year (2010) show that females were involved in 43% of crashes. See *https://www.nhtsa.gov/research-data/national-automotive-sampling-system-nass*. Massie (1997) finds females were involved in 16% more crashes than males per mile driven in 1990.

8. NAIC (2013) provides a partial list of studies.

9. States include Illinois, Maryland, New York, South Carolina, Virginia and West Virginia.

10. See *https://www.congress.gov/bill/116th-congress/house-bill/1756/actions*.

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currently co-sponsoring H.R. 3963, which would outlaw the use of 12 rating factors including gender, education, occupation and CBIS.[11]

The accuracy of CBIS as predictors of loss is clear. The FTC (2007), Morris et al. (2017) and many other studies of CBIS find they are accurate predictors of loss.[12] Figure 1 is reproduced from Figure 1 in FTC (2007). It shows relative claims ratios by decile of CBIS for each type of coverage provided by automobile insurance policies. The important facts evident in Figure 1 are: 1) that drivers in the lowest credit decile incur the greatest amount of losses; 2) this negative relationship between claims and CBIS is consistent across all deciles; and 3) the relationship persists even after controlling for other common rating variables. Together, these characteristics indicate that CBIS are accurate predictors of loss.

In each section of Figure 1, the red (upper) line is the relative claims ratio, or the ratio of dollars paid out in claims for drivers in each CBIS decile to dollars paid out in claims for drivers in the highest CBIS decile. This line is consistently downward-sloping, indicating a negative relationship between CBIS and losses. For example, in property damage liability coverage, drivers in the lowest CBIS decile caused, on average, \$118.73 in losses per year. In the highest CBIS decile, drivers caused, on average, \$62.70 in losses per year. Thus, the relativity for the first decile is 118.73 ÷ 62.70 = 1.89. In other words, insurers pay out 1.89 times as much in claims for drivers in the lowest CBIS decile as they do for drivers in the tenth CBIS decile.

The blue (lower) line in each section is the expected relative claims ratio for each CBIS decile after controlling for other variables representing risk in automobile insurance rating models. Examples include driver age, driving record and loss history. Because the blue (lower) line is also downward sloping, we know that CBIS measures risk that other rating variables do not. Therefore, if insurers are not allowed to use CBIS, rates will be less accurate.

11. These factors include gender, level of education, occupation, employment status, homeownership status, ZIP code or adjacent ZIP codes, census tract, marital status, credit score or CBIS, consumer report, previous insurer or prior purchase of insurance by a consumer from that automobile insurer. The text of this bill is available at *https://www.congress.gov/116/bills/hr3693/BILLS-116hr3693ih.pdf*.

12. MIA (2004) reviews several CBIS studies. Others include Miller and Smith (2003), TDI (2004, 2005) and Golden et al. (2016).

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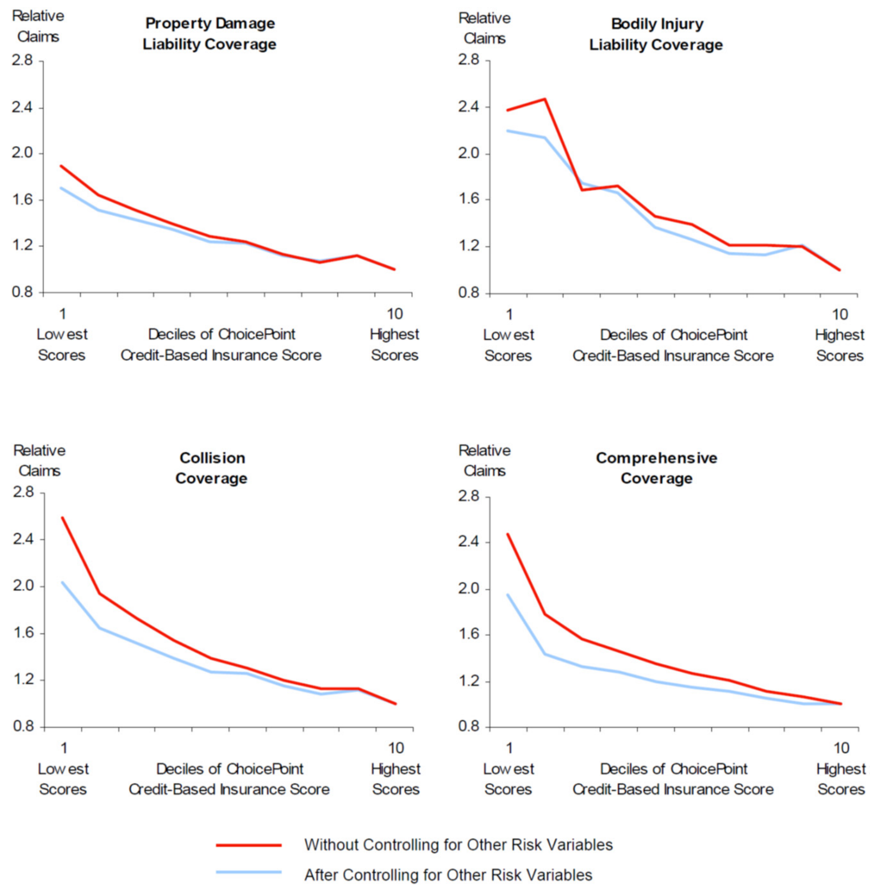
Figure 1
Estimated Average Amount Paid Out on Claims, Relative to Highest Score Decile



Notes [paraphrased from FTC (2007)]: 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. For example, the relativity for the lowest decile on the PD graph has a value of 1.89. This number is calculated by taking the average total paid on PD claims per year of coverage for the 1st decile ($118.73) and dividing it by the respective value for the 10th 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 a model that includes CBIS and other common rating variables (e.g., age, prior claims, use of vehicle). Modeling details and a description of the variables in the models are provided in Appendix D of FTC (2007).

Source: FTC (2007).

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Why are education, occupation and CBIS so controversial? Critics offer three arguments against using these factors.[13] Although each argument is incorrect, it is important to state them accurately and to understand why they are perennial targets of political action. First, critics claim education, occupation and credit are "non-driving" factors, meaning they have no causal relation to the frequency and severity of losses (Wu and Birnbaum, 2007; NJCA, 2008; Cooney et al., 2019; MCRC, 2018; Dorsey and White, 2017; Watson Coleman and Tlaib, 2019; and others). Second, opponents argue that these rating variables are inappropriate because they do not provide specific incentives for loss control (Birnbaum, 2002 and 2006). Third, some interest groups claim that these factors are proxies for prohibited factors, including race, ethnicity and income (McCarty, 2007; Dorsey and White, 2017; NYPIRG, 2014; WNYLC, 2015; Watson Coleman and Tlaib, 2019; and others). I address each claim in turn and explain why these factors are fair and accurate predictors of risk.

Identified causality is not a requirement for insurance rating variables. In fact, causality, as the term is used by critics of insurance rating variables, is a subjective rather than an objective metric. If insurance companies only used variables for which a direct causal relationship to insured losses is widely known by drivers, prices would be much less accurate. For example, critics of the current system uniformly support the use of claims and citation history to rate auto insurance. While these variables are correlated with losses, they are coarse (NJDOBI, 2008). In a given year, the average driver has a about a 3.5% probability of having a liability loss,[14] while the worst drivers have about a 20% probability of loss.[15] If insurers only use these factors as rating variables, they would misclassify 80% of the worst drivers, and they would have little information about average and good drivers for many years. In contrast, education, occupation and CBIS can be observed accurately every year. The consistency and relative granularity of these variables contribute to the accuracy of insurance rates.

NJDOBI (2008) offers the following persuasive discussion indicating causation is neither necessary nor appropriate as a criterion for insurance rating variables.

> "While [causation] 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

13. Opponents initially asserted that these measures are not related to insured losses (Wu and Birnbaum, 2007), but these claims have been proven false and are rarely repeated.

14. Insurance Services Office (ISO) Fast Track Database, 2019.

15. GEICO Teen Driving Statistics, *https://www.geico.com/information/safety/auto/teendriving/statistics*.

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> 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."

While causality is not a fundamental requirement of insurance-rating variables, peer-reviewed academic studies show that education, occupation and CBIS are linked to risk-taking, which is intuitively related to insured losses. For example, several studies use differences in probability of death or injury in an occupation or industry (controlling for education) to estimate the value of risk to individuals (Viscusi, 2004; Moore and Viscusi, 1988; Moore and Viscusi, 1990; and Hersch and Viscusi, 1990). These studies show that career and education choices are highly relevant to risk-taking behavior, and that many workers demand compensation for such risk differentials.

The link between credit and crashes has been recognized in the academic literature since Tillmann and Hobbs (1949) demonstrated a strong correlation. The authors find that a driver with poor credit history is six times more likely to crash than a driver with good credit history. The authors conclude that, "Truly a man drives as he lives. If his personal life is marked by caution, tolerance, foresight, and consideration for others then he will drive in the same manner." More recently, Brockett and Golden (2007) explain the correlation from biological and psychobehavioral perspectives. They show that the decision-making processes for behaviors that affect credit variables and crashes are governed by the same traits and brain chemistry. The sum of this evidence suggests that CBIS are causal variables for rating automobile insurance.

Observed consumer behavior provides the strongest evidence that consumers do not wish to be rated on causal variables. One striking example is the low take-up rate for telematics devices.[16] Such devices offer the ultimate causal and controllable method of rating automobile insurance, yet few drivers choose to participate in these programs. Though telematics is not sufficient to replace other rating variables, to the extent consumers are concerned about the causality of rating factors, telematics offers a ready solution.

The next criticism of these rating variables involves controllability and incentives for loss control. Birnbaum (2002, 2006) argues that education, occupation and CBIS are unfair rating variables because changing them does not make drivers less likely to crash their cars. While it is true that manipulating a policyholder's application information does not make him or her a better driver, increasing the cost of insurance for risky drivers creates a strong incentive for them to become safer drivers. If insureds demonstrating traits that are highly correlated with losses take more care in driving, these factors will no longer display correlation to losses.

16. Sams (2019) reports that an estimated 10 million to 11 million insured vehicles in the U.S. have been enrolled in a telematics program. This is approximately 5.5% of all insured automobiles in the U.S.

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The final criticism of education, occupation and CBIS is that these variables proxy for prohibited variables such as race, ethnicity or income. Because these arguments may seem intuitive and appear to be consistent with U.S. Census data (e.g., levels of income and minority status exhibit simple correlation with education, employment and credit in some instances), they have been evaluated many times by various states, academic researchers (Morris et al., 2017) and the FTC (2007). In each instance involving appropriate analysis, evidence refutes these claims.

NJDOBI (2008) presents a comprehensive evaluation of occupation and education as rating factors. They show that occupation and education are correlated with insured losses. They also find no evidence that insurers use occupation and education to proxy for prohibited rating variables.

The most extensive analyses of CBIS to date are Morris et al. (2017) and FTC (2007). Morris et al. (2017) study an insurer's underwriting and claims data. They conclude that CBIS do not proxy for income in automobile insurance rating models. Specifically, they find that CBIS are accurate predictors of risk within income groups, and that controlling for income in the rating model does not change the effect of CBIS. FTC (2007) performs similar tests using estimates of race and ethnicity. They find that CBIS are accurate predictors of losses within groups of Hispanics and African Americans.[17] They also find that CBIS are accurate predictors of losses even when a rating model specifically controls for race and ethnicity.[18]

Another benefit of CBIS is that it appears to increase the availability and decrease the cost of insurance. A survey conducted by the Arkansas Insurance Department since 2005 shows that of the 26,068,413 auto and 7,833,221 homeowners policies that have been rated using CBIS, only 14% of the auto policies and 13% of the home policies received rate increases from this practice. Powell (2013) shows that the use of CBIS coincides with depopulation of residual markets for automobile insurance. Powell and Zhuang (2019) use multivariate statistical methods to show that the price of insurance decreases as average credit risk increases. Their results suggest that the increased accuracy of rates from using CBIS during the "Great Recession" decreased the average price of automobile insurance.

Finally, the increased accuracy from using any accurate predictor of losses decreases the amount of capital needed to underwrite insurance, thereby decreasing the cost of insurance, improving the financial strength of insurers and decreasing the probability of insolvency.

17. The FTC included variables that estimate race, ethnicity and income, which they constructed for this analysis. Insurance companies do not collect data on these variables.

18. An error in the FTC (2007) analysis leads the authors to a conclusion that is not supported by empirical evidence. The FTC claims that CBIS act as "proxies" for race and ethnicity. See Miller (2009a) and Powell (2008) for a thorough explanation.

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Consequences of Tempering or Excluding Accurate Rating Variables

As mentioned in the introduction, there are serious consequences to restricting the use of accurate rating variables. Some states prohibit insurers from using certain rating variables, while other states temper the use of rating variables. Tempering the use of a rating variable is when regulators require that certain variables cannot have more than *X*-percent effect on rates, or when a binding limit is set on the difference in cost between higher-risk and lower-risk classifications.

When insurers are prohibited from using an accurate rating variable, or the use of a variable is tempered, the average price for higher-risk policyholders decreases, and that of lower-risk policyholders increases. The resulting difference in prices has a measurable effect on behavior. Lower-risk policyholders purchase less insurance and higher-risk policyholders purchase more insurance. This increases the average cost of insurance for all policyholders. For example, Weiss et al. (2010) find that cross-subsidies caused by rate regulation increase auto insurance loss frequency by 7% and loss severity by 14%. Similarly, Derrig and Tennyson (2011) show that cross-subsidies increased losses in Massachusetts by about 30%. It follows intuitively, and empirical evidence confirms, that more losses occur—and more property is damaged, and more people are killed or injured—when the price signal of risk is muted (Harrington and Danzon, 2000).

Disparate Impact

Disparate impact is a standard applied in employment law to prevent irrelevant factors from having a negative effect on members of protected classes. The difference between disparate treatment and disparate impact is that the former implies deliberate intent, but the latter does not. One can demonstrate disparate impact by simply showing that a standard or practice results in disproportionate negative outcomes for members of a protected class. The defense available to parties charged with disparate impact is to show that the practice in question serves a legitimate business purpose that could not be met by an alternative practice with less disparate impact.

The first application of disparate impact was in *Griggs v. Duke Power Co.* (1971) when the power company used literacy as a requirement for manual labor jobs that did not require reading.[19] Because the Caucasian workforce had a higher literacy rate than its complement, this requirement created a disparate impact on

19. See *Griggs v. Duke Power Co*., 401 U.S. 424 (1971). Congress codified the use of disparate impact analysis to prove employment discrimination claims in 1991 *(see* 42 U.S.C. § 1981a). HUD further codified disparate impact in housing practices in 2013, but litigation over this promulgated rule continues.

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non-Caucasian workers. Because literacy was not relevant to job performance, the legitimate business practice defense would not hold.

Some advocates argue that disparate impact should apply to insurance rating. Specifically, they assert that practices such as CBIS should be eliminated based on disparate impact concerns. However, there are three fundamental reasons why insurance rating does not fit the disparate impact paradigm. First, it is practically impossible for an insurance rating program to simultaneously avoid unfair discrimination and disparate impact. Second, avoiding disparate impact requires insurance companies to use illegal rating variables including race, ethnicity and religion when setting rates. Third, because insurers set rates to maximize accuracy, ratemaking rules serve legitimate business purposes, regardless of how outcomes are distributed across protected classes.

Though the names may appear similar, unfair discrimination and disparate impact are not the same. Unfair discrimination is based on expected cost, whereas disparate impact is based on minority status. Assume the underlying distribution of losses are the same across members of protected classes and other policyholders. Given the large number of rating classifications and the number of protected classes, random variation makes it statistically unlikely that the distribution of losses across each protected class within each rating classification will be identical. Therefore, in an accurate rating system, there are likely to be incidences of disparate impact.

The only way to avoid disparate impact is to set rates using protected class memberships as rating variables. Specifically, insurers would have to collect information such as race, ethnicity and religion and use these variables in ratemaking. The only time insurers would use these variables is when rates must be made less accurate to accommodate disparate impact concerns.

Finally, insurers have no incentive to discriminate by protected class and every incentive to set accurate rates.[20] It follows intuitively that insurers will only use rating factors that demonstrate significant correlations to expected costs in a multivariate analysis. Because such rating variables make insurance rates more accurate, they serve a legitimate business purpose. The legitimate business purpose nullifies claims of disparate impact. For example, in the case of CBIS, the FTC (2007) analyzed a large database of insurance policies and claims. They specifically tested for (and found) disparate impact. In addition, they tested the business purpose defense. The FTC analysts could not create a ratemaking model of equal accuracy with less disparate impact.

20. Some studies (Squires, 1997; Angwin et al., 2017) claim to find evidence of disparate treatment by insurance companies in the form of redlining. However, these studies do not control correctly for expected losses by territory (see Kabler, 2019). Other studies (Harrington and Niehaus, 1998; Block et al., 2008) test for disparate treatment and find that insurance companies discriminate based on expected losses, not by protected classes.

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Insurance Markets

The strongest form of consumer protection from unfair price discrimination is market competition. Competition drives prices from the highest market-clearing price to the lowest price at which insurers can offer coverage. In fact, the insurance rating statutes in some states indicate that prices are assumed not to be excessive in a competitive market.

Markets for personal lines insurance are highly competitive, indicating that rate regulation may be an inefficient practice (Harrington, 2000; Schwarcz, 2018). Indeed, many states have gone away from strict prior approval rate regulation to more lenient forms such as file-and-use, use-and-file and flex-rating systems that allow competition to protect consumers. Several studies show that such modernization of rate regulation benefits consumers with lower costs and more choices (D'Arcy, 2002; Grace et al., 2002; Harrington, 2000; Tennyson et al., 2002; Worrall, 2002; and others).

This section describes the high level of competition in markets for personal automobile and homeowners insurance. Competitive markets demonstrate four characteristics.[21] First, they include multiple independent sellers with low to moderate market shares. Second, there are multiple consumers with enough information to determine the value of the product. Third, the product is relatively homogeneous, allowing consumers to differentiate value across offered prices and expected levels of service.[22] Finally, barriers to entry and exit are low, allowing new suppliers to enter the market if prices rise above the fair-market price, or exit the market if they cannot produce the product at the fair-market price. Markets for automobile and homeowners insurance exhibit all of these traits.

Table 1 summarizes information from the NAIC's most recent annual *Competition Database Report*. There are five measures of competition representing the four characteristics of competitive markets at the state level. The first is concentration, a Herfindahl index[23] of premiums written by company. Possible values of the Herfindahl index range from 0 to 1, with 1 indicating a monopoly and 0 indicating an infinite number of insurers with equal market share. The average of concentration across states is 0.11 for auto insurance and 0.10 for homeowners insurance. Variation around the mean is modest, with a maximum of 0.20 for auto insurance and minimum of 0.04 for homeowners insurance. In comparison, the

21. Competition is defined as "workable competition" in the sense suggested by Clark (1940).

22. Schwarcz (2011) examines homeowners insurance policies from several companies in seven states. He notes several differences in policy language across companies and states. He does not present evidence of substantial differences is in claims payments; however, his analysis is consistent with some heterogeneity in insurance policies. It is likely that the vast majority of claims would be treated identically across policy forms.

23. The Herfindahl index for each state is calculated as follows: $\sum_{i=1}^{n}\left(\frac{C_i}{S}\right)^2$, where C_i equals premium written by company i, S equals total premium written in the state, and n equals the number of insurers writing automobile insurance in the state.

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U.S. market for new automobiles has a Herfindahl index of 0.115, and that of wireless communication services is 0.28.[24]

The next measure is the number of sellers. The average for auto insurance is 58.3 and that of homeowners insurance is 60.8. Alaska and Hawaii have the lowest numbers of sellers due to their small populations and remote locations. Alaska has 22 companies selling homeowners insurance and 25 companies selling auto insurance. Hawaii has 28 auto insurers and 30 insurers selling homeowners coverage. Otherwise, the number of sellers in each market loosely follows market size.

Potential sellers is the number of insurance groups or individual companies that do not currently write 1% of premium in a state, but are licensed to write the line of business in that state and write it in at least one other state. This measure demonstrates the low barriers to entry in each state for a large number of existing firms. For each measure (minimum, average and maximum) for both lines of business, the number of potential sellers exceeds the number of current sellers. Therefore, even if current market participants tried to collude or exercise market power, they would be subject to competition from many more firms with low barriers to entry.[25]

Table 1
State-Level Competition Measures (2017)

Line of Insurance		Concentration	Sellers	Potential Sellers	Entries	Exits	Return
Private Passenger Auto	Minimum	0.08	25	77	4	5	-0.03
	Average	0.11	58.3	106.6	12.3	17.6	0.06
	Maximum	0.2	97	148	30	33	0.15
Homeowners Multiple Peril	Minimum	0.04	22	73	6	7	-0.17
	Average	0.1	60.8	100.5	15.7	14.5	0.06
	Maximum	0.19	104	145	40	28	0.36

Notes: Concentration is a Herfindahl index where a monopolistic market equals 1. Sellers is the number of insurance groups and individual companies writing at least 1% of the market in each state. Potential Sellers is the number of insurance groups or individual companies that do not currently write 1% of premium in a state, but are licensed to write the line of business in that state and write it in at least one other state. Entries is the number of companies selling insurance in a state that were not selling there the previous year. Exits is the number of companies not selling insurance in the state that were selling there the previous year. Both Entries and Exits are summed over the previous five years. Return is the 10-year average return on equity.

Source: NAIC *Competition Database Report*, 2018, and NAIC InfoPro Database.

24. Automobile index is calculated using 2018 data from *https://www.statista.com/statistics/249375/us-market-share-of-selected-automobile-manufacturers*. The cellular index is calculated using data from the 2019 quarterly reports of AT&T, Verizon, Sprint, T-Mobile and U.S. Cellular.

25. I thank an anonymous referee for this suggestion.

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The number of firms entering and exiting each state in the past five years suggests that the barriers to entry and exit are low. For auto insurance, the lowest number of entries is 9% of the number of sellers and the lowest number of exits is 19% of sellers. The coinciding metrics for homeowners insurance are 13% entries and 15% exits. This indicates that, in addition to vigorous competition among current market participants, there is also constant pressure from potential new competitors entering each state.

The final competition metric is the 10-year average return on equity. The average return for auto and home insurance among all states is a modest 6%. Naturally, this measure fluctuates across states and time. The lowest return for each line of business is -3% for auto insurance in Michigan and -17% for homeowners insurance in Nebraska. Michigan's market for auto insurance combines strict rate regulation with a mandate to purchase unlimited lifetime health benefits. This has caused persistent rate suppression in the state with the highest losses per vehicle. Nebraska's negative returns are caused by extreme weather events such as hail and tornadoes. We observe the highest return on equity for both lines of business in Hawaii. The exposure to extreme natural hazards in Hawaii coupled with relatively mild recent loss experience suggest that the observed return on equity does not represent a market problem. Indeed, one year of catastrophic losses could make return on equity negative for the following decade.

The insurance industry also exhibits smaller returns than other industries. Figure 2 shows return on net worth for the property and casualty insurance industry and the Fortune Magazine All-Industry Index from 2008 through 2017. During the past decade, insurer returns averaged 5.2%, with a minimum of 2.2% and a maximum of 8%. Returns for the All-Industry Index were substantially higher, with an average return of 13.4%. The minimum return was 10.5% and the maximum return was 16.6%. Thus, the highest annual return for insurers was less than the lowest annual return for other industries. In fact, there were only two years in which insurance industry returns exceeded one-half that of other industries.

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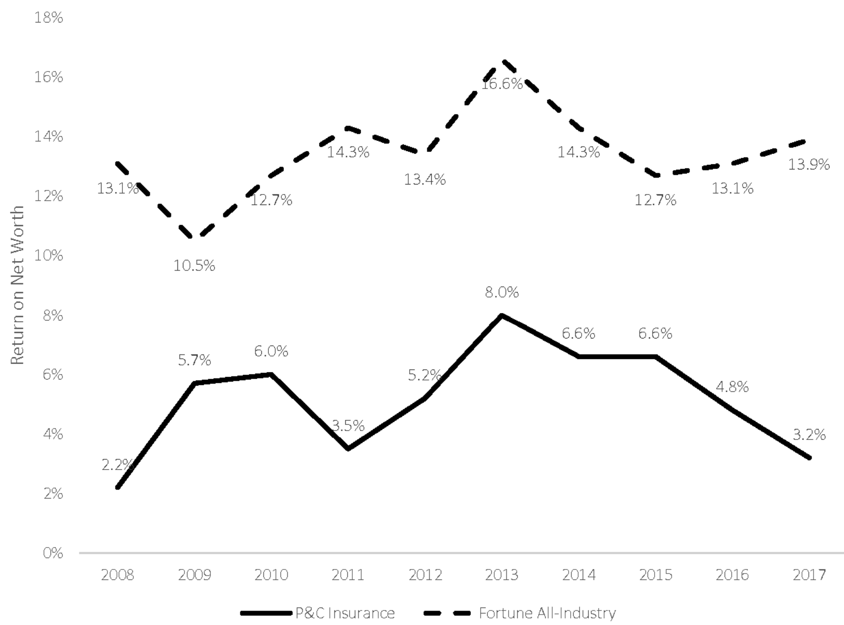
Figure 2
Comparison of Return on Net Worth



Source: *NAIC Report on Profitability by Line by State in 2017*.

Conclusions

Insurance companies use statistical models to estimate expected losses for groups of consumers. Insurers use these estimates to set the most accurate insurance prices possible for each group. Accurate insurance prices are optimal for policyholders, insurance companies and society, because accurate prices result in an efficient level of risk-taking. Accurate prices also distribute the cost of risk equitably, such that riskier insureds pay more than safer insureds.

Insurance companies choose rating factors based on a set of criteria that ensure rates will be accurate and meet legal requirements. State law requires that rates are not inadequate, excessive or unfairly discriminatory. Because the term "unfairly discriminatory" could fit a number of colloquial definitions, the insurance code in many states provides a definition. An unfairly discriminatory rate is one that is not statistically related to losses. In other words, **accurate rates are fair**.

A few common rating factors used by insurers are often criticized by some policymakers and consumer advocates. These include education, occupation and CBIS. I review the arguments offered by critics and explain why these arguments

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are not sufficient to exclude accurate rating variables. Specifically, I show that—although causality is not a requirement of rating variables—there are causal relationships between these variables and insured losses. Finally, I refer to studies demonstrating that these variables are not "proxies" for illegal variables such as race, ethnicity or income.

Because accurate rates are generally good for society, most states permit the use of these variables. However, when policymakers outlaw the use of accurate rating variables, the link between risk and price is distorted. When price does not reflect risk, higher-risk people buy more insurance and take more risk, while lower-risk people do the opposite. This results in higher prices, more losses, more property damage, and more injuries and fatalities.

Industry critics argue that the disparate impact standard should apply to personal lines insurance rating. I explain that unfair discrimination and disparate impact are intuitively incompatible. Due to the large number of rating classifications and protected classes, the probability of avoiding *prima facie* disparate impact is low—even if one assumes the underlying expected loss distribution is the same across protected classes and other policyholders. However, because insurers try to set accurate rates, the legitimate business practice defense should ultimately protect insurers from disparate impact claims. Nonetheless, accusations of disparate impact would be expensive to defend if the standard applied to insurance ratemaking.

Finally, I show that insurance markets are highly competitive. Because market competition provides strong consumer protection from inaccurate, unfair or excessive premiums, I argue that concerns over unfair pricing are misplaced and strict rate regulation does not serve the public interest in insurance markets.

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