CENTER for ECONOMIC JUSTICE | FAIR ACCESS FAIR TREATMENT

Addressing Systemic Racism in Insurance

Presentation to the NCOIL Special Committee on Race

December 9, 2020

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Center for Economic Justice

The Center for Economic Justice

CEJ is a non-profit consumer advocacy organization dedicated to representing the interests of low-income and minority consumers as a class on economic justice issues. Most of our work is before administrative agencies on insurance, financial services and utility issues.

On the Web: www.cej-online.org

About Birny Birnbaum

Birny Birnbaum is the Director of the Center for Economic Justice, a non-profit organization whose mission is to advocate on behalf of low-income consumers on issues of availability, affordability, accessibility of basic goods and services, such as utilities, credit and insurance.

Birny, an economist and former insurance regulator, has worked on racial justice issues for 30 years. He performed the first insurance redlining studies in Texas in 1991 and since then has conducted numerous studies and analyses of racial bias in insurance for consumer and public organizations. He has served for many years as a designated Consumer Representative at the National Association of Insurance Commissioners and is a member of the U.S. Department of Treasury's Federal Advisory Committee on Insurance, where he co-chairs the subcommittee on insurance availability. Birny is also a member of the U.S. Federal Reserve Board's Insurance Policy Advisory Committee.

Birny served as Associate Commissioner for Policy and Research and the Chief Economist at the Texas Department of Insurance. At the Department, Birny developed and implemented a robust data collection program for market monitoring and surveillance.

Birny was educated at Bowdoin College and the Massachusetts Institute of Technology. He holds Master's Degrees from MIT in Management and in Urban Planning with concentrations is finance and applied economics. He holds the AMCM certification.

Why CEJ Works on Insurance Issues

Insurance Products Are Financial Security Tools Essential for Individual and Community Economic Development:

CEJ works to ensure ***fair access*** and ***fair treatment*** for insurance consumers, particularly for low- and moderate-income consumers.

Insurance is the Primary Institution to Promote Loss Prevention and Mitigation, Resiliency and Sustainability:

CEJ works to ensure insurance institutions maximize their role in efforts to reduce loss of life and property from catastrophic events and to ***promote resiliency and sustainability*** of individuals, businesses and communities.

Fair and Unfair Discrimination in Insurance

Provisions regarding unfair discrimination generally found in two places: statutes for rating and for unfair and deceptive practices.

Rating Statutes define two types of unfair discrimination:

- Actuarial – there must be an actuarial basis for distinction among groups of consumers; and
- Protected Classes – distinctions among groups defined by certain characteristics – race, religion, national origin – prohibited regardless of actuarial basis.

Unfair and Deceptive Trade Practices Statutes typically define unfair discrimination as distinction among groups based on a protected class characteristic.

NCOIL Model Act Language

<u>NCOIL P/C Insurance Modernization Act</u>

Section 6.A.3.a. For the purpose of this Act, "Unfairly discriminatory" refers to rates that cannot be actuarially justified. It does not refer to rates that produce differences in premiums for policyholders with like loss exposures, so long as the rate reflects such differences with reasonable accuracy.

Section 6.A.3.b. No rate in a competitive market shall be considered unfairly discriminatory unless it violates the provisions of section 6(B) in that it classifies risk, on the basis of race, color creed, or national origin. Risks may be classified in any way except that no risk may be classified on the basis of race, color, creed, or national origin.

NAIC Model Act Language

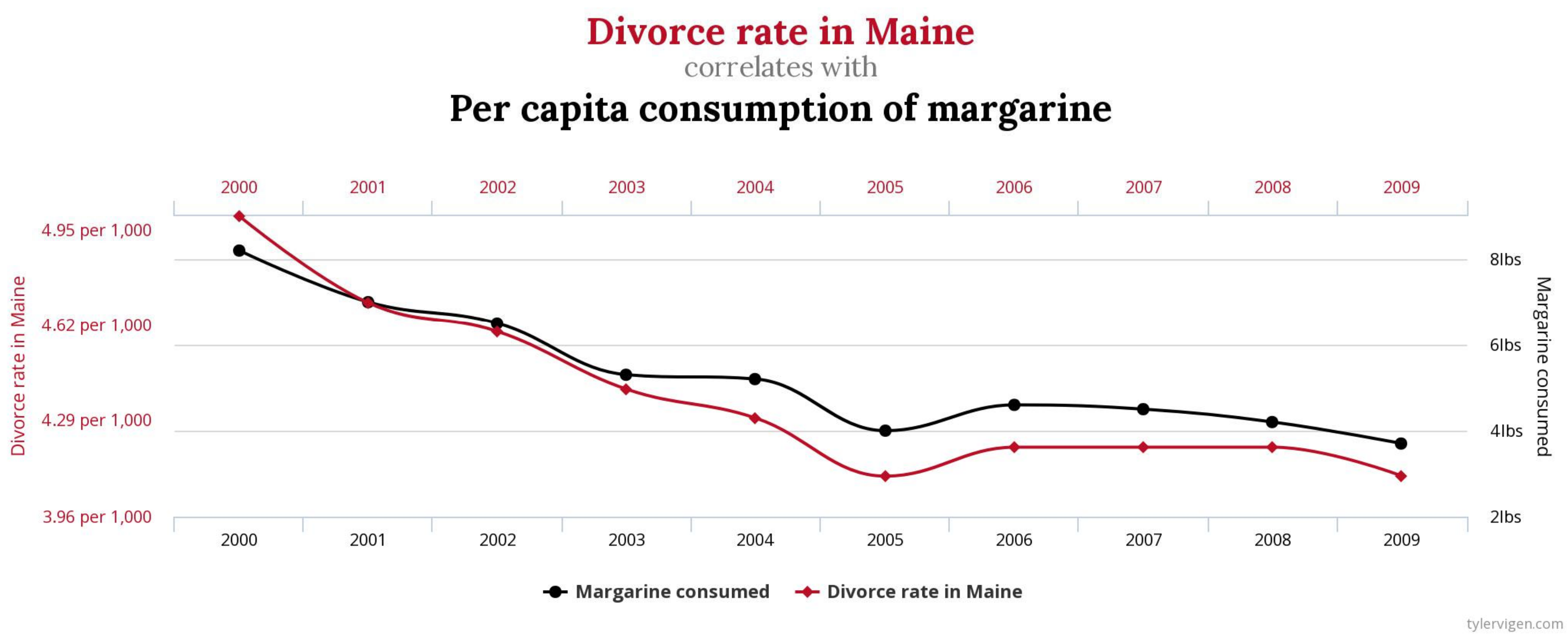
NAIC Property Casualty Model Rating Law, Model 1775

Section 5.A.3. Unfairly Discriminatory Rates. Unfair discrimination exists if, after allowing for practical limitations, price differentials fail to reflect equitably the differences in expected losses and expenses.

Section 5.A.4. Classification. 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 which establish standards for measuring variations in hazards or expense provisions, or both. Such standards may measure any differences among risks that can be demonstrated to have a probable effect upon losses or expenses. No risk classification, however, may be based upon race, creed, national origin or the religion of the insured.

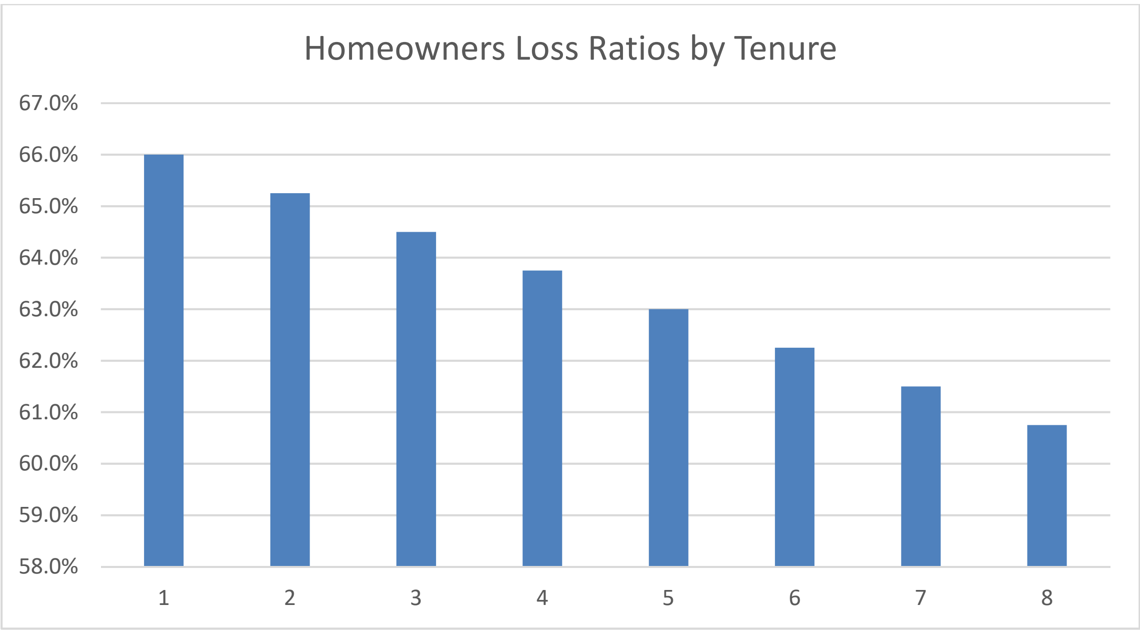
Correlation is Not the Standard for Fair Actuarial Discrimination

Statutes and actuarial standards don't refer to correlation, but demand a more robust relationship. Why? Here's an example of an almost perfect correlation – over 99%.



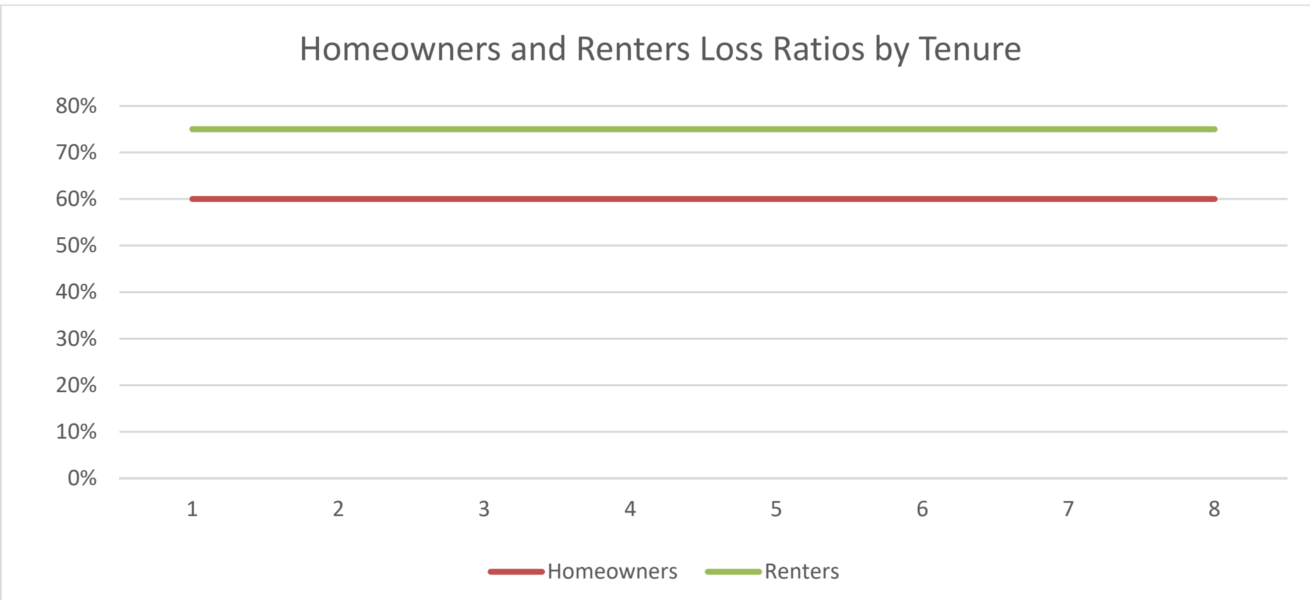
Spurious Correlation in Insurance

In the early 1990's, a company filed for a homeowners discount based on tenure with the company. The initial data presented show declining loss ratios with each additional year the consumer had a policy with the company. If a simple correlation was the only justification needed, this would have been the end of inquiry.



Spurious Correlation

But, we asked to see a break out of loss ratios by tenure for homeowners policies versus renters policies. Here's what we found – loss ratios did not change by tenure. The original chart was a spurious correlation that failed to reflect that with each year of tenure, the share of low-loss ratio homeowners policies increased, producing a lower overall loss ratio.



Why isn't a simple correlation relied upon or sufficient?

Because a predictive characteristic (or variable) may not be correlated in whole or in part to the outcome, but may also be correlated to other predictive variables.

Consider the difference between an outcome – say, claim frequency – and one predictive variable versus an outcome and multiple predictive variables.

There may be correlations between:

Driver Age and Auto Claim Frequency

Marital Status and Auto Claim Frequency

Vehicle Age and Auto Claim Frequency

Each of these represents a one-to-one – or univariate – relationship. But each predictive variable may be replicating part of another variable because of correlation between the predictive variables.

Eliminating Correlation among Predictive Variables: Multi-variate Analysis

Over the last 30 years, insurers and actuaries have developed new techniques to address the problems with univariate analysis. In our example, if we analyzed age vs. claims and marital status vs. claim separately and then used the results, we would likely be double-counting some effects because of the high correlation between age and marital status.

Insurers use a variety of techniques to eliminate correlations <u>among predictive variables</u> in order to isolate each individual predictive variable's unique contribution to explaining the outcome.

What Techniques Are Insurers Using?

Each month, the NAIC Casualty and Actuarial Task Force holds a “book club” with a presentation on new techniques insurers are using for pricing. Here are some recent techniques presented:

Families of Generalized Linear Models (Variations on Multiple Regression)

Gradient Boosting Models

Machine Learning

Hyperparameter Tuning

Neural Networks

Generative Adversarial Networks

Simple Correlation is to Today’s Insurance Big Data Algorithms as a Paper Plane is to a Boeing 787

How Does Multi-Variate Analysis Work?

Here's a simple illustration of a multivariate model. Let's create a simple model to predict the likelihood of an auto claim:

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + e = y$$

$X_{1,}$ X_2 + X_3 are the predictive variables trying to predict y.

Say that $X_{1,}$ X_2 + X_3 are age, marital status and credit score and we are trying to predict y – the frequency of an auto claim.

Let's assume that all three Xs are statistically significant predictors of the likelihood of a claim and the b values are how much each X contributes to the explanation of claim. The b values can be tested for statistical significance – how reliable are these estimates of the contribution of each X?

By analyzing these predictive variable simultaneously, the model removes the correlation among the predictive variables.

Use of Control Variables in Multivariate Insurance Models

Suppose an insurer want to control for certain factors that might distort the analysis? For example, an insurer developing a national auto insurance pricing model would want to control for different state effects like different age distributions, different minimum limits requirements and differences in jurisprudence. An insurer would add one or more control variables.

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \mathbf{b_4C_1} + e = y$$

C_1 is a control variable – let's say for State. By including State as a control variable, the correlation of the Xs to State is statistically removed and the new b values are now the contribution of the Xs, independent of their correlation to State, to explaining the likelihood of a claim. When the insurer deploys the model, it still only uses the X variables, but now with more accurate b values.

Legislators Are Familiar with Proxy Discrimination

Whether you call it proxy discrimination or not, you are familiar with the use of proxies to identify how people will vote. When state legislatures develop legislative districts – for state and federal legislators – the party in power seeks to maximize the number of districts whose voters will likely vote for members of their party. You know what voter characteristics are more likely to vote for one party or the other and you create districts based on these characteristics to either pack as many voters likely to vote for the opposing party in as few districts as possible or spread as many voters likely to vote for your party over as many districts as possible to gain a majority in as many districts as possible.

Proxy Discrimination Against a Protected Class in Insurance

The terms "proxy discrimination against a protected class" and "disparate impact" mean the same – discriminating on the basis of a protected class characteristic using a proxy for the protected class characteristic.

I hope we agree that denying coverage or otherwise discriminating against consumers because they are Black Americans or Evangelical Christians is unfair discrimination in insurance.

Suppose, now that we are in an era of Big Data where insurers have access to massive amounts of personal consumer information, that I found a perfect proxy for either of these protected class characteristics and the effect is identical to discriminating directly on the basis of the protected class characteristics. Should a regulator stop the use of these proxy variables on the basis of discriminating against a protected class?

The industry trades say no – the regulator has no such authority.

What is Systemic Racism and Inherent Bias?

"In the coming days, I encourage each of us to step outside of our comfort zones, seek to understand, engage in productive conversations and hold ourselves accountable for being part of the solution. We must forever stamp out racism and discrimination." Those are the words of Kirt Walker, Chief Executive Officer of Nationwide.

Floyd's death in Minneapolis is the latest example of "a broken society, fueled by a variety of factors but all connected by inherent bias and systemic racism. Society must take action on multiple levels and in new ways. It also requires people of privilege—white people—to stand up for and stand with our communities like we never have before," Those are the words of Jack Salzwedel, the CEO of American Family.

Why Do State and Federal Laws Prohibition Discrimination on the Basis of Race?

Justice Kennedy for the Majority in the U.S. Supreme Court's 2015 *Inclusive Communities* Opinion upholding disparate impact as unfair discrimination under the Fair Housing Act.

Recognition of disparate-impact claims is also consistent with the central purpose of the FHA, which, like Title VII and the ADEA, was enacted to eradicate discriminatory practices within a sector of the Nation's economy.

Recognition of disparate-impact liability under the FHA plays an important role in uncovering discriminatory intent: it permits plaintiffs to counteract unconscious prejudices and disguised animus that escape easy classification as disparate treatment.

Why Are Race and Other Protected Class Characteristics Carved Out of Fair Actuarial Discrimination?

The existence of historical, intentional discrimination based on these characteristics – discrimination that violates state and federal constitutions. But, also, the recognition that the historical discrimination has long-lasting effects that disadvantage those groups. Stated differently, you can't enslave a population for two hundred years and then expect the legacy of that enslavement will disappear overnight.

We continue to see those legacies of historical discrimination – systemic racism -- today both directly and indirectly in policing and criminal justice, housing, and the impacts of the Covid-19 pandemic.

Insurance Not Immune to Systemic Racism

There are numerous examples of insurer practices that have a disproportionate impact on the basis of race throughout the insurers' operations – marketing, pricing, claims settlement, anti-fraud.

Examples of practices that have disparate racial impact include:

- Credit-based insurance scores
- Consumer lifetime value scores
- Criminal history scores

The data used to develop these scores reflect historical discrimination in housing, credit and criminal justice. The scores reflect and perpetuate historic discrimination.

Disparate Impact as Both a Standard and a Methodology

Let's go back to multi-variate model, but now use Race as a control variable:

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \mathbf{b_4R_1} + e = y$$

R_1 is a control variable – by including race in the model development, the correlation of the Xs to race is statistically removed and the new b values are now the contribution of the Xs, independent of their correlation to race, to explaining the likelihood of a claim

What if X1 is a perfect proxy for Race?

Then once we add the control variable for Race, X1 no longer has any predictive value because all it was doing was predicting race, not the outcome y.

Disparate Impact Analysis Improves Cost-Based Pricing

There is a long history and many approaches to identifying and minimizing disparate impact in employment, credit and insurance. But, the general principle is to identify and remove the correlations between the protected class characteristic and the predictive variables.

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \mathbf{b_4R_1} + e = y$$

What if X1, X2 and X3 are not perfect proxies for Race, but still have high correlation? Then, the disparate impact analysis – and our simple model – removes that correlation and the remaining values for b1, b2 and b3 are the unique contributions of each predictive variable to explaining the outcome. The result is more – not less – accurate cost-based or risk-based analysis.

Why is it Reasonable and Necessary to Recognize Disparate Impact as Unfair Discrimination in Insurance?

1. It makes no sense to permit insurers to do indirectly what they are prohibited from doing directly. If we don't want insurers to discriminate on the basis of race, why would we ignore practices that have the same effect?
2. It improves risk-based and cost-based practices.
3. In an era of Big Data, systemic racism means that there are no "facially-neutral" factors. From Barocas and Selbst:

Advocates of algorithmic techniques like data mining argue that they eliminate human biases from the decision-making process. ***But an algorithm is only as good as the data it works with.*** *Data mining can inherit the prejudices of prior decision-makers or reflect the widespread biases that persist in society at large.* ***Often, the "patterns" it discovers are simply preexisting societal patterns of inequality and exclusion. Unthinking reliance on data mining can deny members of vulnerable groups full participation in society.***

Why is it Reasonable and Necessary to Require Insurers to Test for and Minimize Disparate Impact?

Insurer practices and algorithms do not necessarily use expected claims as the outcome variable. Sometimes the desired outcome is based on non-cost factors and these non-cost factors has disproportionate impact on communities of color.

In 2005, then CEO of Allstate, Ed Liddy told investment analysts about how credit scoring was helping Allstate avoid the wrong customers:[1]

> Tiered pricing helps us attract higher lifetime value customers who buy more products and stay with us for a longer period of time. That's Nirvana for an insurance company. That drives growth on both the top and bottom line.
>
> This year, we've expanded from 7 basic price levels to 384 potential price levels in our auto business.

[1] Transcript of Presentation to Edward M. Liddy, Chairman and CEO, The Allstate Corporation Twenty-First Annual Strategic Decisions Conference, Sanford C. Bernstein & Co., June 2, 2005.

Tiered pricing has several very good, very positive effects on our business. It enables us to attract really high quality customers to our book of business.

The key, of course, is if 23% or 20% of the American public shops, some will shop every six months in order to save a buck on a six-month auto policy. ***That's not exactly the kind of customer that we want.*** So, the key is to use our drawing mechanisms and our tiered pricing to find out of that 20% or 23%, to find those that are unhappy with their current carrier, are likely to stay with us longer, likely to buy multiple products and that's where tiered pricing and a good advertising campaign comes in.

These statements were made in the Stone Age of Big Data – 2005. Since then insurers' use of new, bigger and more granular personal consumer data has exploded.

Allstate CEO to Investment Analysts, May 2017[2]

The insurer's "universal consumer view" keeps track of information on 125 million households, or 300 million-plus people, Wilson said.

"When you call now they'll know you and know you in some ways that they will surprise you, and give them the ability to provide more value added, so we call it the trusted adviser initiative," said Wilson.

Progressives CEO to Investment Analysts, November, 2020[3]

[Analyst] Gary Ransom
Usually that just means your price is lowest on the comparative raters there. But is there more to it than that as well? Are they – are you seeing more coming into the agents? Is there -- are there agents' incentives or other things going on there?

[CEO Tricia Griffith]
But, yes, we have -- we do incentives and we have different commissions based on the type of customer that we get in namely preferred.

[2] "Allstate CEO: Agents Will Have Access to Data on 125 Million Households," Best's New Service, May 30, 2017
[3] https://seekingalpha.com/article/4385047-progressive-corporation-pgr-ceo-tricia-griffith-on-q3-2020-results-earnings-call-transcript

Practices That Raise Concerns About Proxy Discrimination on the Basis of Race

Price Optimization and Consumer Lifetime Value Scores

By definition, these algorithms used by insurers utilize non-cost factors to differentiate among consumers and the factors and data reflect bias against communities of color.

Credit-Based Insurance Scores

The consumer credit information factors used in CBIS are highly correlated with race. The Missouri Department of Insurance found that the single best predictor of the average CBIS in a ZIP Code was minority population.

Criminal History Scores

Here, the problem is not just the legacy of historical discrimination, but ongoing discrimination in policing and criminal justice.

What are the Benefits and Costs of Requiring Insurers to Test For and Minimize Disparate Impact?

If racial and economic justice are a priority, if cost-based insurer practices are a priority, if closing the protection gap and making insurance more affordable and available in traditionally underserved communities, then the benefits of requiring insurers to test for and minimize disparate impact far, far outweigh the costs.

While there are examples of disparate impact claims brought against insurers under the federal Fair Housing Act that have resulted in improved risk-based pricing and improved insurance availability in communities of color – e.g., challenges against underwriting based on age and value of the home – industry has not been able to cite a single example of a successful disparate impact claim that has harmed risk-based pricing.

Why is it Reasonable and Necessary to Test for and Minimize Disparate Impact in Every Aspect of Insurers' Operations?

Marketing – Today's Big Data algorithms and variety of marketing channels give insurers – like other businesses – the ability to micro-target consumers. This ability to micro-target gives insurers the ability to attract or discourage customers even before the pricing stage.

Claims Settlement and Anti-fraud – Just as insurers use non-cost factors for price optimization in rating, so do they use non-cost factors for claims optimization. Antifraud algorithms – including those use at underwriting for "propensity for fraud" – are most vulnerable to racial bias. Historical bias in what claims to examine for fraud results in bias in the claims identified as fraudulent. Biased antifraud algorithms become self-fulling – if there is racial bias in the claims you identify as potential fraudulent and investigate, there will be racial bias in the claims identified as fraudulent. You can't find fraud in a claim you don't investigate.