



Supplemental Comments from the Center for Economic Justice

To the NAIC (EX) Committee on Race and Insurance

May 14, 2021

The Center for Economic Justice (CEJ) submits the following comments to the NAIC Committee on Race and Insurance regarding proposed 2021 charges to supplement our initial comments of April 10, 2021.

CEJ continues to urge the Committee to develop a more systematic approach to examining issues of race and insurance. What are your goals? What are your strategies? How do you measure the problem and how do you measure success?

To illustrate, let's look at the Diversity, Equity and Inclusion goals and strategy. We can both define and measure the problem – a lack of presence of members of communities of color among insurers, producers and regulatory agencies. The starting point should be to measure the problem – how many people from communities of color are there on insurer boards? In insurer senior management? Among licensed producers? Among senior regulatory staff? Among NAIC management and staff? Among presenters and panelists at NAIC events? These initial measurements are the baseline against which to judge progress over 6 month intervals. Measurement is essential to determine progress and the effectiveness of strategies.

While the Committee has structured itself as five workstreams, there are really two principal efforts – one directed at Diversity, Equity and Inclusion and one directed at insurer practices and public policy that reflect and perpetuate systemic racism in insurance. The Committee has separated the first activity – DE&I – into insurer and regulator streams. As set out in our April 10, 2021 letter, there must be a third stream dedicated to improving consumer stakeholder engagement, generally, and community of color stakeholder engagement, particularly, in NAIC and state regulatory processes.

The effort to address systemic racism in insurance must be a NAIC-wide effort with every part of the NAIC and every committee, task force and working group explicitly considering issues of race for each activity. For NAIC meetings and events, it means doing a better job of including an equal number of consumer stakeholders as industry stakeholders and including many consumer stakeholders of color among the consumer stakeholders. For NAIC committees, task forces and working groups, it means asking each group to look at their specific topic area, learn about systemic racism and identify possible impacts of such systemic racism on the insurance activities related to the groups' area of responsibility. CEJ has experienced

firsthand several NAIC groups excusing any discussion of racial disparity in their subject matter area by claiming that the Committee on Race will be examining those “issues.” As set out in our April 10, 2021 comments, we urge the NAIC to assign every NAIC committee, task force and working group a charge to identify insurer or producer or regulatory practices that may reflect and perpetuate systemic racism.

We cannot stress the importance of examining all aspects of insurers’ operations and regulatory practices for racial bias. While regulators and a number of state legislators have taken up the issue of racial bias in pricing, there has been no attention to examining the impacts of systemic racism on marketing, claim settlement and antifraud. Yet, each of these aspects of industry operations presents far greater risk of racial bias than pricing. While data and algorithms used in pricing have been subject to some regulatory review and activity by the NAIC, there has been no similar effort for the other three areas. Yet, insurers’ use of big data and ability to micro-target marketing efforts means that underwriting is now happening at the marketing phase of the insurance life cycle.

Similarly, no attention has been given to potential racial bias in claims settlement and anti-fraud, despite the fact that these parts of the insurance operation utilize big data and AI as much or more than used for pricing. Consider the following from the May 17 issue of *Auto Insurance Report*:

A pair of European companies – **Friss** from the Netherlands, and **Shift Technologies** from France, are gaining traction in the United States with insurance fraud software tools driven by artificial intelligence. Though [similar tools](#) have been in the market for some time, insurers’ willingness to take a chance on newcomers with little U.S. experience speaks to the rapid changes in artificial-intelligence (AI) modeling that has enabled a wider range of competitors the ability to offer different tools to address fraud and expand their models to include underwriting.

By looking at an insurer’s claims data, the companies apply AI-based solutions to identify possible fraudulent activity.

Friss says it processes 103 million claims a year. After downloading an insurer’s claims data, it tests the model against known claim outcomes – be it paid, denied, fraudulent, settled or otherwise resolved. The model then links those findings with external data sources, ranging from the insurer’s historical claims data set, the **National Insurance Crime Bureau**, weather data, **Carfax** data, data found by scraping the web and social media, as well as the claimant’s credit score and previous bankruptcies. Thus armed, Friss builds a fraud score for each claim.

Friss is now expanding into underwriting with its acquisition last month of **Ohio-based Terrene Labs**, which provides data – such as business demographics, risk scores and information scraped from the Web – for pre-filing commercial lines applications and other forms. The idea is to provide similar insights found in the claim process up front during the underwriting process.

[Friss] Using historical claims data from the insurer as well as third-party information, such as that available through **TransUnion's** TLOxp system, Shift assesses the fraud risk. Shift's software analyzes the text of documents and searches for discrepancies like the use of different fonts, evidence of the use of Photoshop, and repeated uses of a photo. Shift's AI checks that the reported damage is actually covered by the policy and looks to make sure the accident and repairs relate.

What could go wrong with AI systems using data sources known to be biased against communities of color? Of course, these are just new entrants – there are several other vendors who have been providing antifraud data sources and algorithms for many years.

Which brings us to the strategy for identifying and addressing systemic racism in insurer practices – the institutional structures that reflect and perpetuate historic discrimination. We start again with measurement. Here, the measurement responsibility starts with insurers to examine proxy discrimination and disparate impact of their practices. As set out in prior comments and included in the attached presentation, proxy discrimination refers to practices which involve predictive variables – whether for marketing, pricing, claims settlement or antifraud – which are predicting race and not the outcome variable. With proxy discrimination, the correlation between the predictive variable and the outcome is, at least in part, spurious – because it is predicting race and not the actual outcome. Regulators have authority now to address proxy discrimination because proxy discrimination clearly fits into current regulatory definitions of unfair discrimination.

Disparate impact refers to racial bias in outcome because the outcomes themselves reflect historic discrimination. For example, recent studies have shown that historically-redlined communities are at greater risk of flooding, impacts of climate change and environmentally-linked illnesses. Addressing disparate impact requires a policy decision – in the same way that public policy has prohibited the use of race for distinguishing consumers in pricing or claims settlement.

Whether proxy discriminating or disparate impact, the starting point is measurement of the problem. There is a common methodology to examine and identify both proxy discrimination and disparate impact, as shown in the attached presentation. While such testing is the core of the effort to address systemic racism in insurance, there are supporting pieces needed, again, as set out in our April 10, 2021 comments.

One of the most important messages we offer to the Committee is that utilizing this common methodology to identify and eliminate proxy discrimination and identify and minimize disparate impact moves the debate about race in insurance beyond arguments about banning or permitting certain types of data. You are familiar with the arguments we seen over the past 25 years – consumer stakeholders argue that certain data sources are biased against communities of color and produce either proxy discrimination or disparate impact. Industry argues that they don't use race and that the data sources are predictive of claims. Putting aside the fact that insurers use many of the questionable data sources to predict profitability, not claims, one of the benefits of utilizing a standard methodology to test for proxy discrimination and disparate impact

is that it by-passes these debates. If a data source is simply a proxy for race, the methodology will eliminate its value. If a data source is partly a proxy for race and partly predictive of outcome, then the methodology will endorse using that data source, but shorn of its correlation with race. It is impossible to overstate the value of moving beyond these historical arguments to meaningfully address systemic racism in insurance.

First, there must be clarity on the legal and policy framework about the definition of unfair discrimination. The recent NCOIL action to define proxy discrimination as only intentional use of a proxy designed to discriminate on the basis of race or other protected class factors must be rejected. The NAIC must develop definitions of proxy discrimination and disparate impact that both reflect current regulatory practice to stop proxy discrimination and establish a clear framework for considering practices that have significant disparate impact.

Second, there must be a more robust regulatory data collection framework to evaluate actual consumer outcomes, including the outcomes of communities of color. Auditing an algorithm is simply not sufficient for at least two reasons. First, an algorithm may not produce the intended results. Second, regulators are seriously over-matched by insurers when it comes to the technical expertise involved in designing and auditing big data / AI models.

Third, regulatory capabilities and resources must be upgraded in the areas of data collection, database management, data scientists and data analytics. This is not a criticism of regulators, but simply a recognition that the auditing approach to insurance regulation must give way to a more data-driven analytical approach.

Fourth, the subject matter committees, task forces and working groups must be tasked with learning about systemic racism and examining their subject areas for regulatory and public policies that may reflect and perpetuate historic discrimination. While the Committee has workstreams for major lines of insurance – life/annuity, health, property /casualty – there are no workstreams targeted at marketing, claims settlement and antifraud. Similarly, there is no workstream targeted at examining insurer investments that promote, for example, environmental racism or predatory lending targeting communities of color.

We suggest that the Market Regulation (D) Committee should have one of, if not the most prominent, role in examining systemic racism in insurance – whether that is examining marketing or claims settlement or antifraud practice or developing resources, tools and guidelines for analyzing racial bias in insurer practice and consumer outcomes.

We also suggest that, at least for life/annuity and property casualty lines of business, the approaches are similar – define the key legal and policy concepts, measure current outcomes, identify proxy discrimination and disparate impact, recommend updated statutory or regulatory guidance. We urge the Committee to consider the recommendations of our consumer representative colleagues regarding health insurance and health-related issues.

We offer comments on specific charges. Charge F (1) for life insurance and annuities states, “The impact of traditional life insurance underwriting on minority populations, considering the relationship between mortality risk and disparate impact.” CEJ’s analytic framework provides a more systematic approach to this endeavor, as set out in these and our April 10, 2021 comments.

Regarding Charge (F) 2, the property casualty stream lists six items, but provide no systemic approach to examining the issues. Again, we suggest the framework set out our comments. We also suggest dropping the issue of correlation vs. causation. While we understand regulators’ desire to identify spurious correlations between predictive and outcome variables, that effort is best addressed by applying a methodology to identify proxy discrimination and disparate impact. Doing so will address regulators’ concerns while avoiding the rabbit hole of endless discussions about causation vs. correlation. Moreover, at the end of the day, whether the standard is correlation or causation doesn’t affect whether the data source or practice is having racially-biased outcome.

Regarding Charge G, we clearly support improved data collection for consumer market outcomes. However, we suggest that the most efficient and effective data collection regime is with transaction reporting of sales and claims – the type of reporting currently done for workers’ compensation and for large parts of the homeowners, personal auto and commercial lines markets and is underway for life insurance. We suggest that the D committee be assigned this charge given their current responsibilities for market regulation data collection.

Regarding Charge H (1) for life insurance, we urge the Committee to avoid wandering into “financial literacy” issues for a couple of reasons. First, systemic racism is about structure and policies that reflect and perpetuate historic discrimination. Considering financial literacy as a cause of racial disparity is essentially blaming the victim. We urge to the Committee to focus on the structural issues for which insurance regulators have authority and capability. We suggest a better focus is on whether insurers’ products are designed to serve communities of color. The fact is that the percentage of the population that purchases individual life insurance has massively declined over the past 30 years while the average coverage amount has increased dramatically – evidence that the life insurance industry decided to focus on more affluent consumers at the expense of communities of color. Second, there are many other groups working on consumer financial education and the value-added by the NAIC is likely quite low.

Regarding Charge H(2) for life insurance, we support examining disparities in the number of cancellations/rescissions among minority policyholders, but suggest that this is just one part of a broader examination of outcomes for communities of color. Further, with a well-developed data collection program, a variety of questions can be answered with the same data and better analytics can be applied than requesting data for a single issue.

Regarding Charge H(6) for property casualty, it is unclear what is intended by “mitigating the impact of residual markets, premium financing and nonstandard markets on disadvantaged groups.” We suggest that a first step is to measure the incidence of residual markets, premium finance and non-standard markets generally, and then on communities of color, specifically. Again, this can be done as part of a robust market outcome data collection program. Further, we suggest that the issue of residual markets might be examined with a view towards improving residual market products as a mechanism for market discipline for voluntary insurers.

We conclude as we started with a request for the Committee to revise its charges to provide a more systematic approach to examining issues of race and insurance –

- Measuring of the current state of racial inequities;
- Adding improved consumer stakeholder participation to NAIC and regulatory processes to the DE&I workstreams;
- Defining key unfair discrimination concepts;
- Requiring insurers to test for and eliminate proxy discrimination and test for and minimize disparate impact;
- Developing regulatory guidance, resources and tools to facilitate the testing requirement
- Developing a robust market regulation data collection regime to support the measurement of systemic racism in insurance; and
- Tasking each committee, task force and working group with identifying industry and regulatory practices that may reflect and perpetuate historic racial discrimination.

Our last request to the Committee is to not let the insurance trade associations – particularly the property / casualty trades – derail your efforts. As set out the attached presentation, these trades have consistently opposed efforts at the NAIC and in the states to identify and address systemic racism in insurance. These trades have demonstrated their intent to oppose any accountability for insurers regarding race and insurance – whether that was opposing the consideration of race in the principles for AI, their support for the NCOIL definition of proxy discrimination, their hired “experts” to claim “unintended consequences, their false claims about destroying risk-based pricing or their consistent opposition to reporting the data necessary to meaningfully test for unintended and unnecessary racial bias. We greatly appreciate the NAIC’s members for standing up to these trades to date in your efforts on race and ask you stand firm in the face of unwarranted defenses of the status quo.



Addressing Systemic Racism in Insurance

Presentation to Casualty Actuarial Society Spring Meeting

May 27, 2021

Birny Birnbaum
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 in 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 are generally found in two parts of insurance statutes: rating and unfair trade practices.

We find 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.

Why Do State and Federal Laws Prohibit 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.

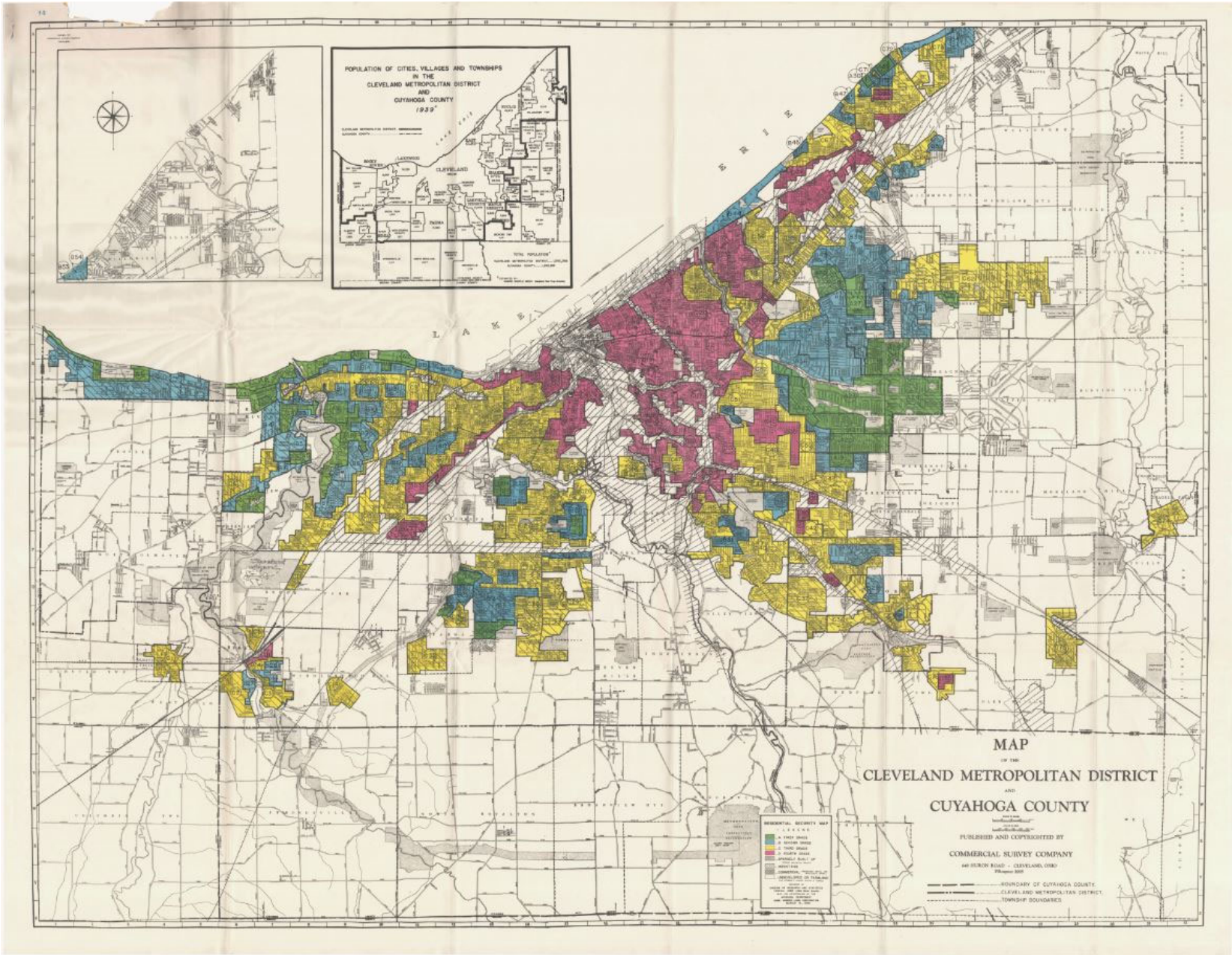
Why Are Race and Other Protected Class Characteristics Carved Out of Fair Actuarial Discrimination?

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.

What Information Does This Map of Cleveland Present?

- a. Concentration of Minority Population
- b. Eviction Rates
- c. COVID Infections and Deaths Rates
- d. Flood Risk
- e. Environment-related Illnesses
- f. Federal Home Loan Eligibility 1930's to 1960's



Systemic Racism¹

Structural racism is the policies and practices that normalize and legalize racism in a way that creates differential access to goods, services, and opportunities based on race.

Systemic racism refers to policies, practices, or directives that result in advantages or disadvantages to individuals or communities based on race, including harm caused by infrastructures that determine access and quality of resources and services.

¹ <https://new.finalcall.com/2021/03/09/death-by-zip-code-housing-discrimination-neighborhood-contamination-and-black-life/>

How Can Systemic Racism Manifest Itself in Insurance – Whether for Marketing, Pricing or Claims Settlement?

1. Intentional Use of Race – Disparate Intent
2. Disproportionate Outcomes Tied to Historic Discrimination and Embedded in Insurance Outcomes – Disparate Impact
3. Disproportionate Outcomes Tied to Use of Proxies for Race, Not to Outcomes – Proxy Discrimination

The Evolution of Insurers' Analytics: Univariate to Multivariate Analysis

In the past 30 years, insurers have moved away from univariate analysis to multivariate analysis – from analyzing the effects of one risk characteristic at a time to simultaneous analysis of many risk characteristics.

What the problem with univariate analysis?

If I analyze the relationship of age, gender and credit score – each individually – to the likelihood of a claim, the individual results for each risk characteristic are likely capturing some of the effects of the other risk characteristics – ***because age, gender and credit score (or other risk classifications) may be correlated to each other*** as well as to the outcome variable.

How does multi-variate analysis address this problem?

Testing for Disparate Impact and Proxy Discrimination:

A Natural Extension of Typical Insurer Practices

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, gender and credit score and we are trying to predict y – the likelihood of an auto insurance claim

Let's assume that all three X s 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 pricing model would might want to control for different state effects like different age distributions, different occupation mixes or differences in jurisprudence. An insurer would add one or more control variables.

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4C_1 + e = y$$

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.

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:

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4R_1 + e = y$$

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

How Do We Interpret the Disparate Impact Analysis?

$$b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4R_1 + e = y$$

Result: No Proxy Discrimination or Disparate Impact

Outcome	Interpretation	Indicated Action
R is not statistically significant and there is little change to b1, b2 and b3.	There is little correlation between X1, X2 and X3 and race, little or no disparate impact or proxy discrimination	None, utilize the model.

How Do We Interpret the Disparate Impact Analysis?

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

Result: Proxy Discrimination

Outcome	Interpretation	Indicated Action
R is statistically significant and b1 has lost its statistical significance	X1 was largely a proxy for race and the original predictive value of X1 was spurious. This is an example of proxy discrimination	Remove X1 from the marketing, pricing, claims settlement or anti-fraud model.

How Do We Interpret the Disparate Impact Analysis?

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

Result: Disparate Impact

Outcome	Interpretation	Indicated Action
R is statistically significant and has a large impact on the outcome, but b1, b2 and b3 remain largely unchanged and statistically significant	This is an example of disparate impact.	Are X1, X2 or X3 essential for the insurer's business purposes? Are there less discriminatory approaches available? Would eliminating a predictive variable significantly reduce the disparate impact but not materially affect the efficiency or productiveness of the model?

How Do We Interpret the Disparate Impact Analysis?

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

Result: Some Proxy Discrimination, Some Disparate Impact

Outcome	Interpretation	Indicated Action
R is statistically significant, but b1, b2 and b3 remain statistically significant with different values from the original.	X1, X2 and X3 are correlated to race, but also predictive of the outcome, even after removing the variables' correlation to race. This is an example of some proxy discrimination and some disparate impact.	Depending on the significance of the racial impact, utilize the model with the revised predictive variable coefficients, consider prohibiting a variable on the basis of equity or both.

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 X_1 , X_2 and X_3 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 b_1 , b_2 and b_3 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.

Algorithms Learn the Bias Reflected in Data and Modelers

*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.**²*

The fact that an insurer doesn't use race in an algorithm does not logically or factually result in no discrimination on the basis of race.

In fact, the only way to identify and eliminate the impacts of structural racism in insurance is to measure that impact by explicit consideration of race and other protected class factors.

² Barocas and Selbst

Why Test for Disparate Impact and Proxy Discrimination in All Aspects of Insurers' Operations?

Among the various parts of the insurance life-cycle – marketing, underwriting, pricing, claims settlement, antifraud – new data sources and complex algorithms for pricing currently get the most attention from regulators because in most states most insurers file personal lines rates. Data and algorithms used for marketing, in contrast, get little or no attention. ***Yet, it is the marketing function – and the new data sources and algorithms used in micro-targeting consumers – that has become the true gatekeeper for access to insurance.***

Consider the following quotes from 2005 to present. In 2005, in a meeting with investment analysts, the CEO of a major publicly-traded insurer was effusive about the benefits of the then relatively new use of consumer credit information— referred to as tiered pricing.

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.

This year, we've expanded from 7 basic price levels to 384 potential price levels in our auto business.

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.*

Now fast forward to 2017, when the new CEO of that insurer told investment analysts:

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"

And just recently, the telematics subsidiary of this insurer pitched its ability to identify the most valuable customers in real time:

Attract the most profitable drivers with telematics-based targeting

Traditionally, insurance marketing has relied on demographic and behavioral data to target potential customers. While useful at a high level, these proxies fall short when it comes to considering customer value and retention. Now, you can reach the most profitable customers from the outset using the nation's first telematics-based marketing platform.

Company intelligently layers driving score onto insurer campaign targeting criteria to purchase the ideal audience based on quartiles of driving risk. [The] Scored user receives a targeted offer via awareness and performance channels

Not to be outdone, another telematics data vendor announced a partnership with an auto manufacturer

Insurers can harness the power of connected Hyundai vehicles as a new marketing channel to support the profitable growth of their behavior- or mileage-based programs. Discount Alert allows insurers to deploy personalized marketing offers directly to drivers through Hyundai's online owner portal and contains robust tools to anonymously segment ideal risk targets—ensuring your offers are only sent to qualified leads.

All of this begs the questions, what about consumers and businesses who don't have the wealth to provide the value sought by insurers? How do these strategies line up with public policies against discrimination on the basis of race and promoting widespread availability of insurance?

A Comprehensive Regulatory Approach to Addressing Systemic Racism in Insurance

1. Affirm the Legal and Policy Framework for Unfair Discrimination

This is the foundational activity of defining disparate impact and proxy discrimination and affirming such outcomes as unfair discrimination in insurance.

a. Define Disparate Impact and Proxy Discrimination for insurance.

b. Require insurers to test for and eliminate proxy discrimination and minimize disparate impact.

c. Establish equity standards for minimizing disparate impact.

1. Seek approaches that reduce disparate impact without compromising efficiency of the algorithm; and

2. Establish an equity/efficiency trade off of 20 to 1: For example, reduce algorithmic efficiency by 2% if disparate impact can be reduced by 40% or more.

Definitions

Disparate Impact: Use of a non-prohibited factor that causes disproportionate outcomes on the basis of prohibited class membership and that such disproportionate outcomes cannot be eliminated or reduced without compromising the risk-based framework of insurance.

Proxy Discrimination: Use of a non-prohibited factor that, due in whole or in part to a significant correlation with a prohibited class characteristic, causes unnecessary, disproportionate outcomes on the basis of prohibited class membership.

Or

Proxy Discrimination: Use of an external consumer data and information source, algorithm, or predictive model whose predictive capability is derived in substantial part from its correlation with membership in one or more of such protected classes.

Regulatory Guidance to Implement the Policy Framework

- a. Guidance for insurers to test for disparate impact and proxy discrimination;
- b. Guidance for insurers to report test results and actions taken in response to test results;
- c. Guidance for safe harbors for insurers who follow regulatory guidance; and
- d. Guidance to implement principles for Artificial Intelligence.

The Murder of George Floyd Raised Awareness of Systemic Racism How Did Insurer CEOs React?

“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.

How Have the Insurer Trades – Particularly NAMIC and APCIA – Responded to the Insurer CEOs’ Calls?

- Opposed the inclusion of “Consistent with the risk-based foundation of insurance, AI actors should proactively . . . avoid proxy discrimination against protected classes” in the NAIC Principles for Artificial Intelligence.
- Have opposed the application of disparate impact liability under the federal Fair Housing Act to home insurance.
- Supported the gutting of the U.S. Housing and Urban Development’s disparate impact rule – despite pleas from several insurers to leave the rule alone in the aftermath of the murder of Black Americans at the hands of police.
- Pushed NCOIL to adopt a resolution opposing the CASTF White Paper because it suggested that regulators could ask insurers to show a rational relationship between new data sources and insurance outcomes.

How Have the Insurer Trades – Particularly NAMIC and APCA – Responded to the Insurer CEOs’ Calls? (con’t)

- Opposed state bills to limit the impacts of credit-based insurance scores during a pandemic, citing insurers’ need for “risk-based pricing,” while supporting efforts to permit such deviations when insurers find it convenient – price optimization, consumer lifetime value.
- Sued regulators in NV and WA who sought temporary limits on the use of credit-based insurance scores disrupted by the pandemic and the CARES Act.
- Pushed NCOIL to adopt a definition of proxy discrimination that would block any efforts to identify and address disparate impact and proxy discrimination and shield insurers from any accountability for their practices.

NCOIL's "Definition" of Proxy Discrimination Must Be Rejected

At the urging of the P/C Trades, NCOIL recently adopted the following:

For purposes of this Act, as well as for the purpose of any regulatory material adopted by this State, or incorporated by reference into the laws or regulations of this State, or regulatory guidance documents used by any official in or of this State, "Proxy Discrimination" means the **intentional** substitution of a neutral factor for a factor based on race, color, creed, national origin, or sexual orientation **for the purpose of discriminating** against a consumer **to prevent that consumer from obtaining insurance or obtaining a preferred or more advantageous rate due to that consumer's race, color, creed, national origin, or sexual orientation.**

At best, this action represents a profound misunderstanding of how systemic racism affects insurance. At worst, it is a conscious act of stopping insurance regulators and states from even attempting to address racial justice. The language memorializes insurer practices that indirectly discriminate on the basis of race, discourages insurers from examining such racial impact and restricts current regulatory efforts.

Consider Criminal History Scores

“TransUnion recently evaluated the predictive power of court record violation data (including criminal and traffic violations)

“Also, as court records are created when the initial citation is issued, they provide insight into violations beyond those that ultimately end up on the MVR—such as violation dismissals, violation downgrades, and pre-adjudicated or open tickets.”

What is the likelihood that TU Criminal History Scores have a disparate impact against African-Americans? Consider policing records in Ferguson, Missouri.

US DOJ Investigation of the Ferguson Police Department

Ferguson's approach to law enforcement both reflects and reinforces racial bias, including stereotyping. ***The harms of Ferguson's police and court practices are borne disproportionately by African Americans, and there is evidence that this is due in part to intentional discrimination on the basis of race.***

Ferguson's law enforcement practices overwhelmingly impact African Americans. Data collected by the Ferguson Police Department from 2012 to 2014 shows that African Americans account for 85% of vehicle stops, 90% of citations, and 93% of arrests made by FPD officers, despite comprising only 67% of Ferguson's population.

US DOJ Investigation of the Ferguson Police Department (2)

FPD appears to bring certain offenses almost exclusively against African Americans. For example, from 2011 to 2013, African Americans accounted for 95% of Manner of Walking in Roadway charges, and 94% of all Failure to Comply charges.

Our investigation indicates that this disproportionate burden on African Americans cannot be explained by any difference in the rate at which people of different races violate the law. Rather, our investigation has revealed that these disparities occur, at least in part, because of unlawful bias against and stereotypes about African Americans.

Practices That Raise Concerns About Disparate Impact and 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.

Why Do Efforts to Address Discrimination on the Basis of Race Require Explicit Consideration of Race?

New York Times, August 10, 2015: Algorithms and Bias: Q. and A. With Cynthia Dwork

Q: Some people have argued that algorithms eliminate discrimination because they make decisions based on data, free of human bias. Others say algorithms reflect and perpetuate human biases. What do you think?

A: Algorithms do not automatically eliminate bias. . . .Historical biases in the . . .data will be learned by the algorithm, and past discrimination will lead to future discrimination.

Fairness means that similar people are treated similarly. ***A true understanding of who should be considered similar for a particular classification task requires knowledge of sensitive attributes, and removing those attributes from consideration can introduce unfairness and harm utility.***

Steve Bellovin, “Yes, ‘algorithms’ can be biased. Here’s why. A computer scientist weighs in on the downsides of AI.”³

This is what's important: machine-learning systems—“algorithms”—produce outputs that reflect the training data over time. If the inputs are biased (in the *mathematical* sense of the word), the outputs will be, too. Often, this will reflect what I will call “sociological biases” around things like race, gender, and class.

One thing is to exercise far more care in the selection of training data. Failure to do that was the likely root cause of Google Images labeling two African-Americans as gorillas. Sometimes, fixing the training data can help.

Of course, this assumes that developers are even aware of the bias problem. Thus, another thing to do is to test for biased outputs—and some sensitive areas, such as the criminal justice system, simply do not use these kinds of tools.

³ <https://arstechnica.com/tech-policy/2019/01/yes-algorithms-can-be-biased-heres-why/>

There are several reasons to be wary of the "algorithmic" approach. One reason is that people put too much trust in computer output. Every beginning programmer is taught the acronym "GIGO:" garbage in, garbage out. To end users, though, it's often "garbage in, gospel out"—if the computer said it, it must be so. (This tendency is exacerbated by bad user interfaces that make overriding the computer's recommendation difficult or impossible.) We should thus demand less bias from computerized systems precisely to compensate for their perceived greater veracity.

The second reason for caution is that computers are capable of doing things—even bad things—at scale. There is at least the perceived risk that, say, computerized facial recognition will be used for mass surveillance. Imagine the consequences if a biased but automated system differentially misidentified African-Americans as wanted criminals. Humans are biased, too, but they can't make nearly as many errors per second.

Our test, then, should be one called disparate impact. "Algorithmic" systems should be evaluated for bias, and their deployment should be guided appropriately. Furthermore, the more serious the consequences, the higher the standard should be before use.

“The Real Reason Tech Struggles with Algorithmic Bias”⁴

These are mistakes made while trying to do the right thing. But they demonstrate why tasking untrained engineers and data scientists with correcting bias is, at the broader level, naïve, and at a leadership level insincere.

No matter how trained or skilled you may be, it is 100 percent human to rely on cognitive bias to make decisions. Daniel Kahneman’s work challenging the assumptions of human rationality, among other theories of behavioral economics and heuristics, drives home the point that human beings cannot overcome all forms of bias. But slowing down and learning what those traps are—as well as how to recognize and challenge them—is critical. As humans continue to train models on everything from stopping hate speech online to labeling political advertising to more fair and equitable hiring and promotion practices, such work is crucial.

⁴ Yael Eisenstat at <https://www.wired.com/story/the-real-reason-tech-struggles-with-algorithmic-bias/>

Insurers Don't Collect Applicant's Race – How Can an Actuary Get Data on Race to Perform a Disparate Impact Analysis?

1. Assign a racial characteristic to an individual based on racial characteristic of a small geographic area – Census data at the census block level.
2. Utilize the Bayesian Improved Surname Geocoding Method, based on census geography and surname data.⁵
3. Reach out to data brokers and vendors for a new data service.

⁵ See Consumer Financial Protection Bureau, "Using publicly available information to proxy for unidentified race and ethnicity."
<https://www.consumerfinance.gov/data-research/research-reports/using-publicly-available-information-to-proxy-for-unidentified-race-and-ethnicity/>
and Yin Zhang, "Assessing Fair Lending risks Using Race/Ethnicity Proxies."

Ethical Algorithms -- Sources

Pauline T. Kim, "Auditing Algorithms for Discrimination"

<https://www.pennlawreview.com/online/166-U-Pa-L-Rev-Online-189.pdf>

Claire Whitaker, "Ethical Algorithms"

<https://www.kdnuggets.com/2019/03/designing-ethical-algorithms.html>

Erin Russel, "The Ethical Algorithm"

<https://www.cognitivetimes.com/2019/01/the-ethical-algorithm/>

Barocas and Selbst

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2477899

Kroll, et al, "Accountable Algorithms:

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2765268

Virginia Eubanks, *Automating Inequality: How High Tech Tools Profile, Police and Punish the Poor*

Selbst and Barocas, "The Intuitive Appeal of Explainable Machines

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3126971

Levy and Barocas, "Designing Against Discrimination in Online Markets

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3084502

New York Times, "Algorithms and Bias, Q and A with Cynthia Dwork," 10 August 2015

<https://www.nytimes.com/2015/08/11/upshot/algorithms-and-bias-q-and-a-with-cynthia-dwork.html>

Martin, Kirsten E. M., What Is an Ethical Algorithm (And Who Is Responsible for It?) (October 21, 2017). Available at SSRN:

<https://ssrn.com/abstract=3056692> or <http://dx.doi.org/10.2139/ssrn.3056692>

Kirsten Martin, "Ethical Implications and Accountability of Algorithms"

<http://kirstenmartin.net/wp-content/uploads/2013/11/Martin-JBE-Ethics-and-Accountability-of-Algorithms.pdf>

Kirsten Martin, DATA AGGREGATORS, BIG DATA, & RESPONSIBILITY ONLINE

<http://kirstenmartin.net/wp-content/uploads/2013/11/AAPOR-Martin-Info-Value-Chain-v2.pdf>

AIandBigData: A blueprint for human rights, social and ethical impact assessment Alessandro Mantelero

<https://reader.elsevier.com/reader/sd/pii/S0267364918302012?token=3836947F0CAD3C145A1F273E3CBE6C38F67E777DD7E4D590548F481916130DAACA8D57BED4667BD1FE1F4D8FC80E7C56>