CENTER for ECONOMIC JUSTICE | FAIR ACCESS FAIR TREATMENT

Addressing Systemic Racism in Insurance

Presentation to Buckeye Actuarial Continuing Education

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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.

What Information Does This Map of Cleveland Present?

a. Concentration of Minority Population

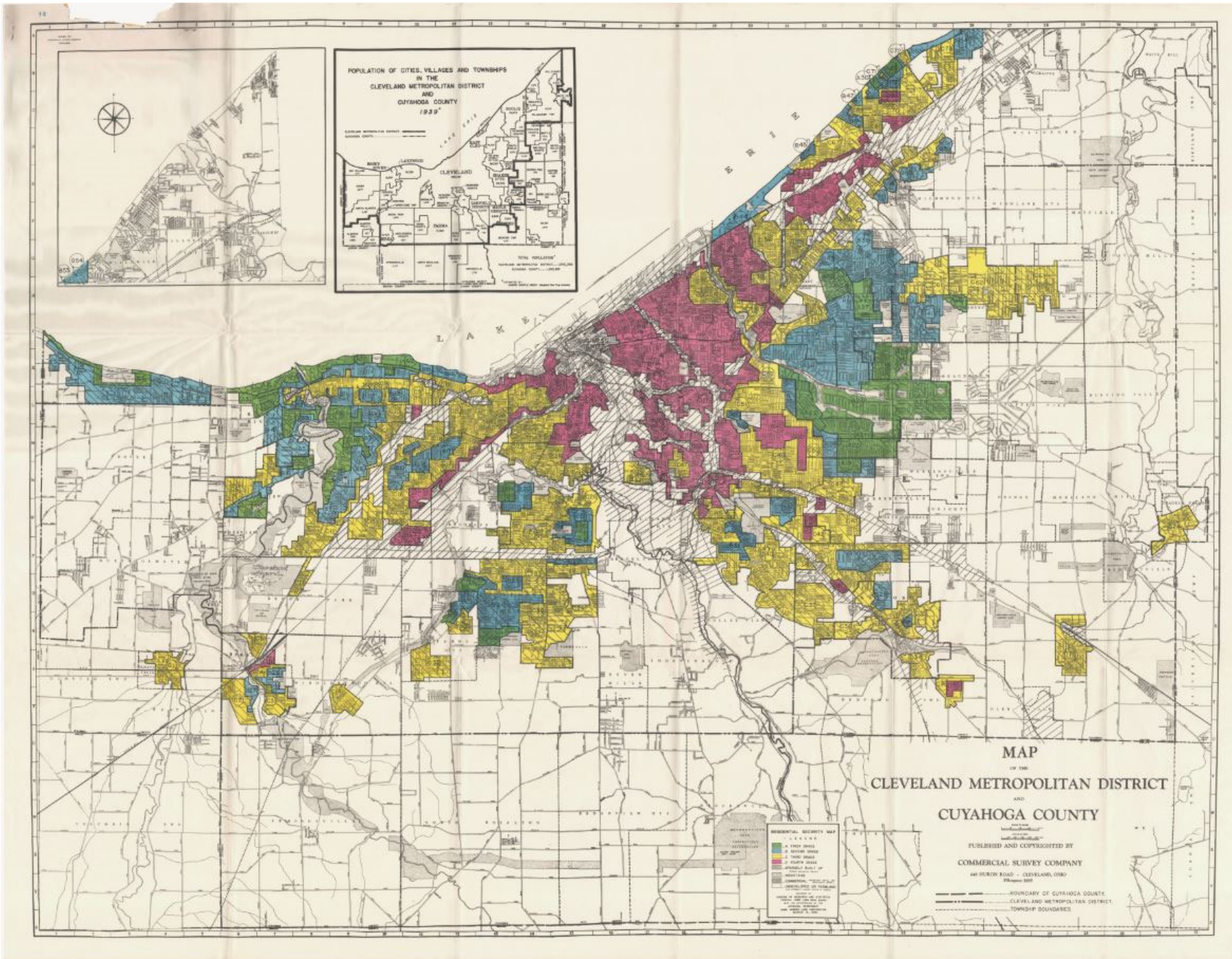
b. Eviction Rates

c. COVID Infections and Deaths Rates

d. Flood Risk

e. Environment-related Illnesses

f. Federal Home Loan Eligibility 1930’s to 1960’s


POPULATION OF CITIES, VILLAGES AND TOWNSHIPS
IN THE
CLEVELAND METROPOLITAN DISTRICT
AND
CUYAHOGA COUNTY
1939
LAKE ERIE
MAP
OF THE
CLEVELAND METROPOLITAN DISTRICT
AND
CUYAHOGA COUNTY
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Systemic Racism[1]

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

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.

Polling Question – Which best describes your experience?

a. My company has a policy to examine the development and impact of our algorithms for racial bias

b. My company has been receptive to suggestions to examine the development and impact of our algorithms for racial bias

c. My company has not been receptive to suggestions to examine the development and impact of our algorithms for racial bias

d. I would not suggest examining the development and impact of our algorithms for racial bias because of the reaction I think such a suggestion would create.

e. Since my company doesn't use, collect or consider racial characteristics, it is impossible to have racial bias in our practices.

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 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 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.

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

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.

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

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: 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 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.

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. <u>Affirm the Legal and Policy Framework for Unfair Discrimination</u>

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.

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 APCIA – 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.

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.

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 Khaneman’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.

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[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.

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