# Where Does Bias Hide?

## Defining Data Biases and Unfairly Discriminatory Considerations

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American Academy of Actuaries

# Agenda



- Sources of Algorithmic Bias
- NIST Iceberg Model of Bias
- Bias Identification in the Modeling Process
- A History of Bias in Medicine
- Current Trends in P&C Insurance Rate Modeling
- Modeler's Hippocratic Oath

**Bias in the Organization** – Is the business, industry or policies flawed at its core leading to bias without ML?

**Model Misuse & Incorrect Generalization** - Were the models extended for use cases or data sets that were not intended for during training?


**Bias in the Problem** – Is the problem defined to be solved in a way that will directly or indirectly discriminate and introduce or propagate biases?

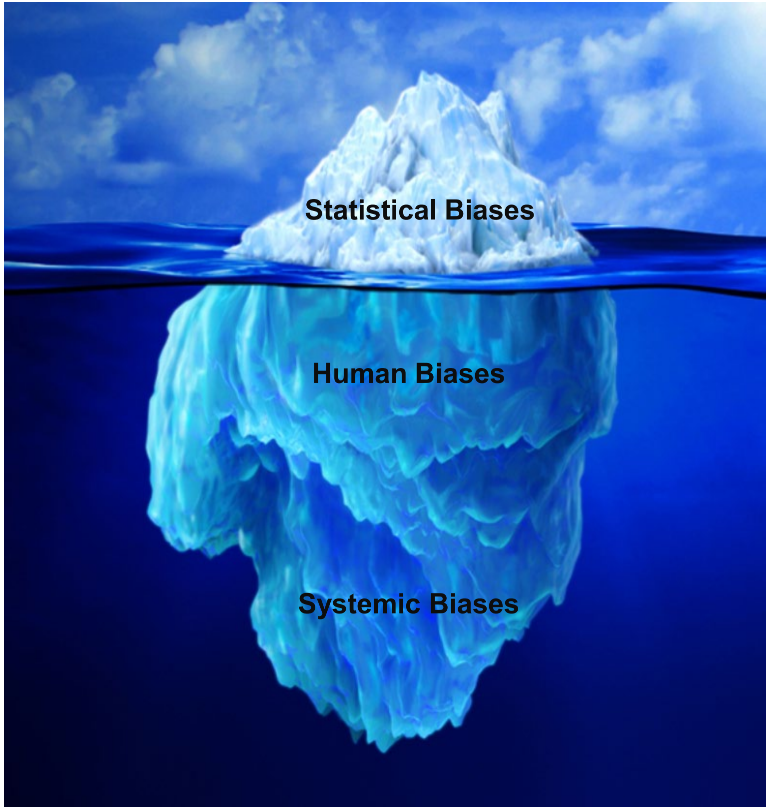
**Bias in the Model** - Is there learned biases found in the model's design or tuning, beyond ones inherited from the previous areas discussed above?

**Bias in the Data** – Does the data used for training or provided for inferences contain biased patterns or sampling issues that might be learned by a model?

# NIST Iceberg Model of Bias

- **Statistical Biases** – Lie above the waterline. The easiest to see and resolve.
- **Human Biases** – Lie just below the waterline. You can't change people; they have to change themselves!
- **Systemic Biases** – Lie at the deepest part of the iceberg. These are often the hardest to detect and change.

Diversity is key to detecting and mitigating these biases in modeling!



# Traditional versus Algorithmic Underwriting

## Current Transition in Insurance Underwriting

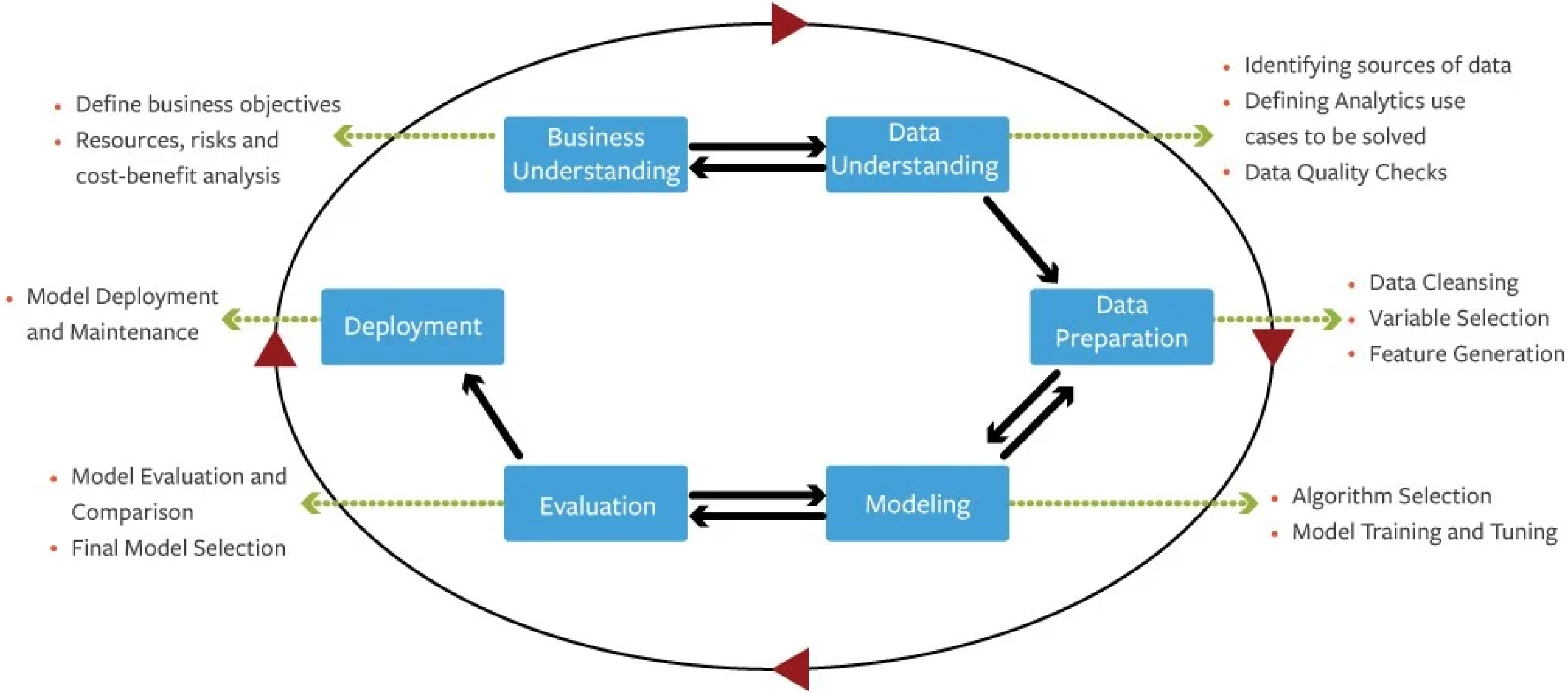
**Where we've been** **VS** **Where we're going**

- Indemnification product
- Rating/underwriting based on **who you are**
- Paper based
- Human underwriting
- Traditional sources of data
- Reliance on an agent
- Line of business focused
- Excel
- Assumption Bias

- Broader set of services along the complete value chain
- Rating/Underwriting based on **how you behave**
- Digital - Algorithms/Machine Learning
- Automated & Accelerated Underwriting – No Human
- New sources of data
- Sourced from a wide variety of channels
- Whole customer focused
- Perception: Fair, consistent, and unbiased

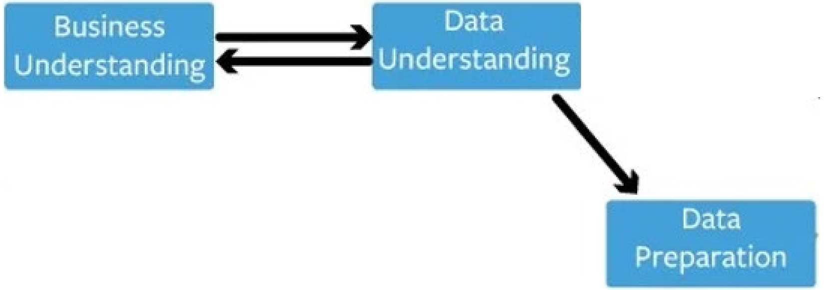
# Bias Identification in the Modeling Process

# The Modeling Process



# The Modeling Process

## Potential Biases




### Statistical Bias

When our expected prediction does not equal reality, we get a biased result. This follows the definition of the ISO.*

$$Bias = E\left[\hat{\theta}\right] - \theta$$

- Sampling Bias
- Selection Bias
- Measurement Bias
- Omitted Variable Bias

### Systemic Bias

Bias embedded in data elements due social policies and practices.

* International Organization for Standardization.

# The Modeling Process

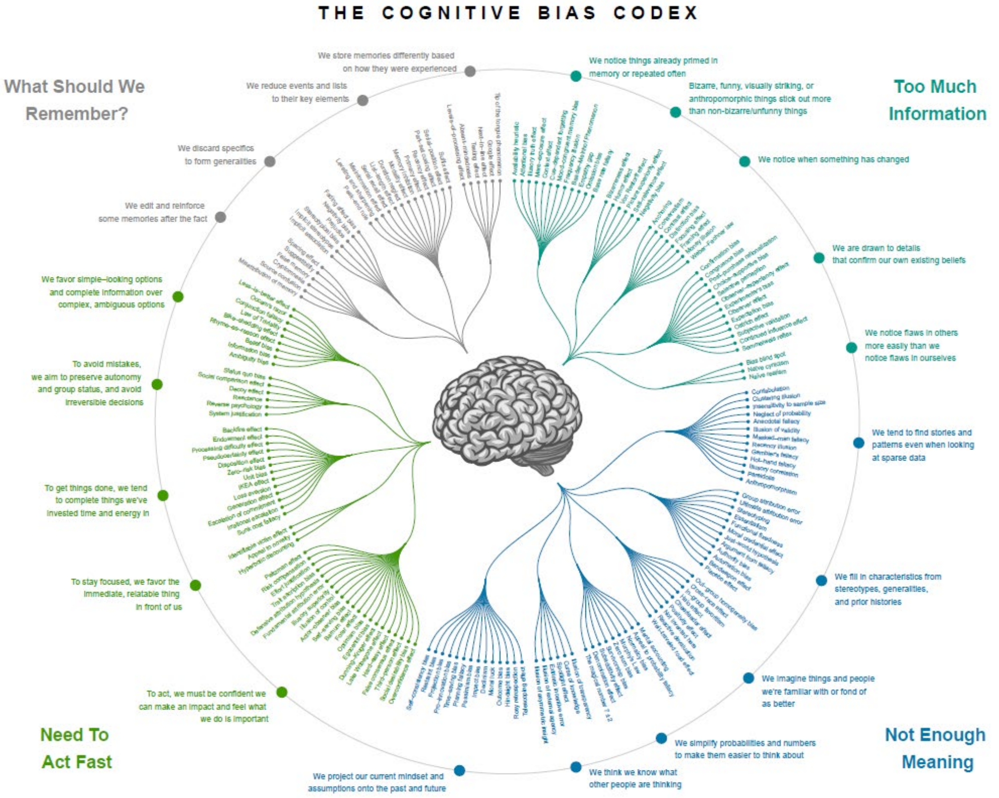
## Potential Biases

### Human Biases

There are over 180 cognitive biases than have been cataloged.

Some that are most relevant for machine learning are:

- ❑ Groupthink Bias
- ❑ Confirmation Bias
- ❑ Blind-spot Bias
- ❑ Ostrich Effect





Source: https://upload.wikimedia.org/wikipedia/commons/6/65/Cognitive_bias_codex_en.svg

# The Modeling Process

## Potential Biases


### Confirmation Bias

The tendency to search for, interpret and recall information in a way that supports what we already believe.

As a result, we're likely to dismiss credible information that calls our beliefs into question.

When modeling teams lack diversity of thought, confirmation bias can impact results.

**Diversity is the Key!**

# The Modeling Process

## Potential Biases

### Deployment Bias

Bias introduced by using a model inappropriately or misinterpreting its results. It is the interaction of society with the AI solution.

Human factors can introduce more damaging biases than the machine learning algorithm alone.

Governance structures are one means of mitigating this bias.


**Keys to Mitigate:**

- Strong Governance
- Strong Controls
- Constant Monitoring
- Training of Front-End
- Empower Overrides

# A History of Bias in Medicine

# Reflections on the History of Bias in Medicine

*Illustration of Dr. J. Marion Sims with Anarcha by Robert Thom.*

*Anarcha was subjected to 30 experimental surgeries.*

*Pearson Museum, Southern Illinois University School of Medicine*

# Statue of Dr. James Marion Sims removed from Central Park


Dr. Bernadith Russell hugs a friend as the statue of Dr. J. Marion Sims, is removed from New York's Central Park, Tuesday, April 17, 2018. Sims was known as the father of modern gynecology, but critics say his use of enslaved African-American women as experimental subjects was unethical. Russell, a gynecologist, said at the time she was in medical school, "He was held up as the father of gynecology with no acknowledgement of the enslaved women he experimented on."

MARK LENNIHAN, AP



American Academy of Actuaries

"Black people's nerve endings are less sensitive than white people's." "Black people's skin is thicker than white people's." "Black people's blood coagulates more quickly than white people's."

I find it shocking that 40% of first- and second-year medical students endorsed the belief that "black people's skin is thicker than white people's."

## ABSTRACT

Black Americans are systematically undertreated for pain relative to white Americans. We examine whether this racial bias is related to false beliefs about biological differences between blacks and whites (e.g., "black people's skin is thicker than white people's skin")....

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PNAS

Proc Natl Acad Sci U S A. 2016 Apr 19; 113(16): 4296–4301.
Published online 2016 Apr 4. doi: 10.1073/pnas.1516047113
PMCID: PMC4843483
PMID: 27044069

Racial bias in pain assessment and treatment recommendations, and false beliefs about biological differences between blacks and whites

Kelly M. Hoffman,[a,1] Sophie Trawalter,[a] Jordan R. Axt,[a] and M. Norman Oliver[b,c]

Proc Natl Acad

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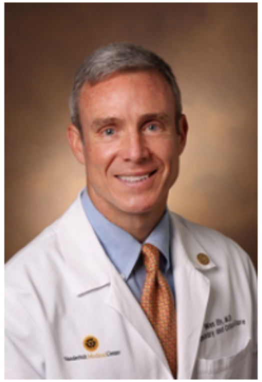
# E Wesley Ely, MD



Professor of Medicine

Grant W. Liddle Chair

## Professor of Medicine

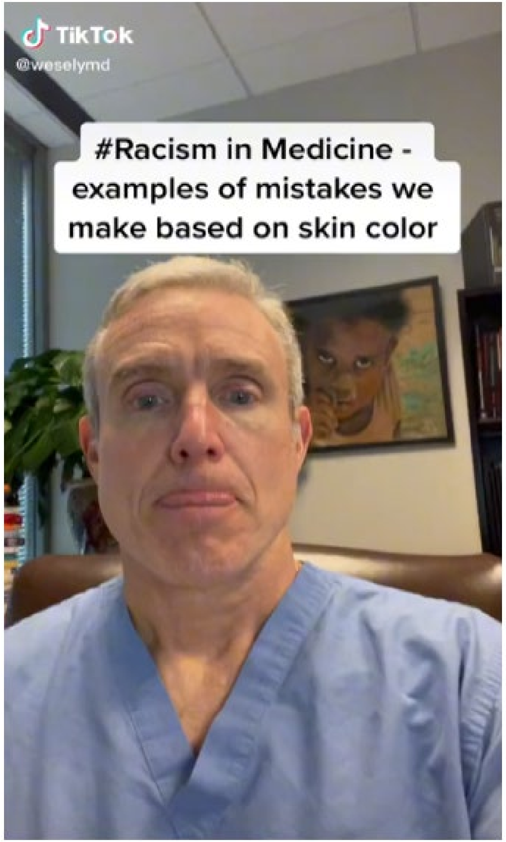
**Division:** Allergy, Pulmonary, and Critical Care Medicine

## Professional Bio

Twitter feed: https://twitter.com/WesElyMD?ref_src=twsrc%5Etfw

## Education

Master - Tulane Sch of Public Health-1989 - 1989
MPH - Tulane Univ - 1989
MD - Tulane University School of Medicine - 1989
Internship - Internal Medicine - Bowman Gray School of Medicine - 1990
Residency - Internal Medicine - Bowman Gray - 1992
Fellowship - Pulmonary & Critical Care - Bowman Gray - 1995

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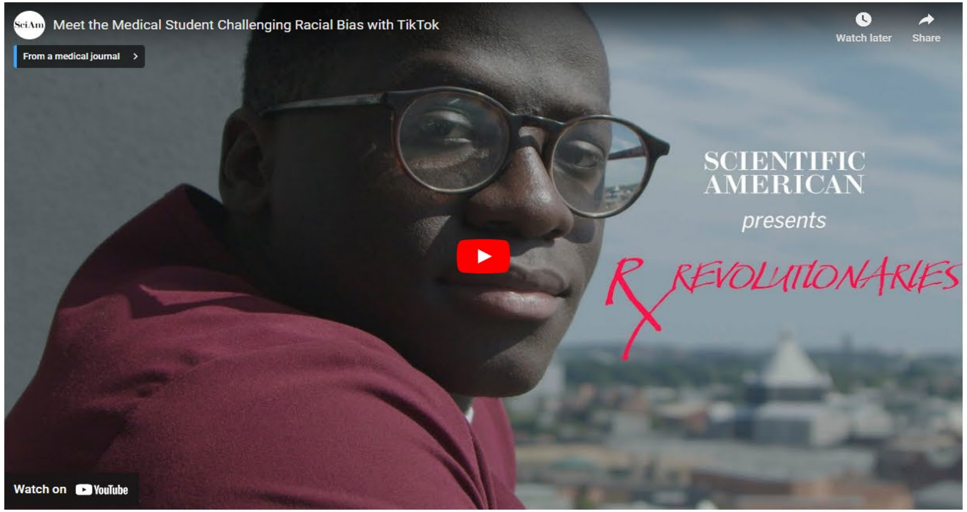
MEDICINE

# Meet the Medical Student Challenging Racial Bias with TikTok

By Tulika Bose on December 22, 2022



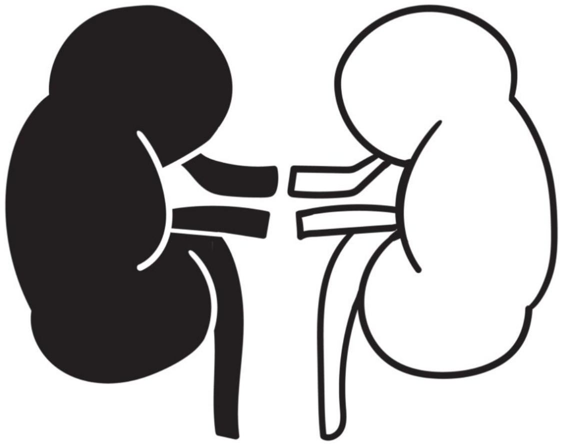

Joel Bervell
JoelBervell.com

# Bias in Kidney Testing

Three Popular Equations:

- The Cockcroft-Gault (CG) equation
- The Modified Diet Renal Disease (MDRD) Study equation
- The Chronic Kidney Disease Epidemiology (CKD-Epi) equation.

*These formulas are grounded in mathematics, but they give biased results.*

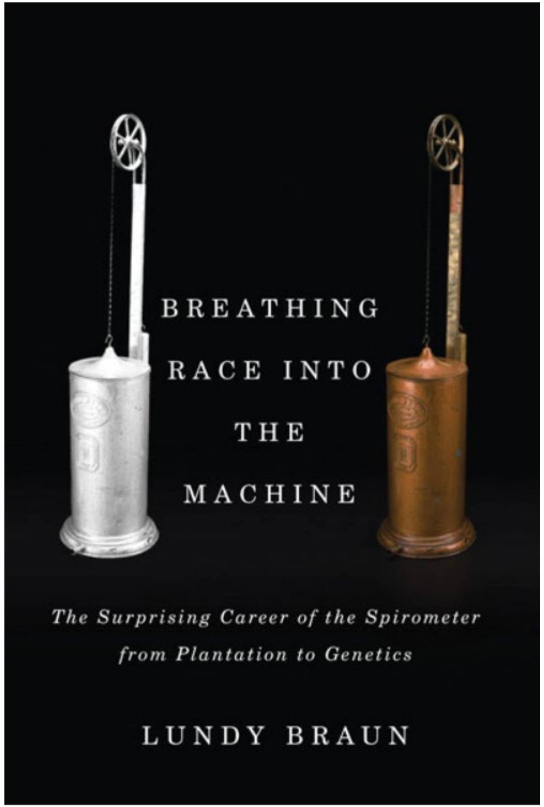


**Myth Masquerading as Medical Truth**
"Black people have higher average muscle mass compared to white people."

# Bias in Medical Machines

One outcome of global standardization projects is the common practice of 'race correction', also called 'ethnic adjustment.' Race correction is done by using a scaling factor for all people not considered to be 'white.'

Thomas Jefferson, former president and leading Enlightenment intellectual, featured lung differences between slaves and white colonists in his influential *Notes on the State of Virginia* .[1]




[1] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4631137/

## Faulty Target Variable

To compute who should qualify for this extra care, the algorithm's designers used previous patients' health care spending as a proxy for medical needs—a common benchmark.

## Problematic Definition

Blacks do not have the same access to healthcare as whites and do not have the same level of need and even when access is the same, blacks tend to use medical services less than whites.

SCIENTIFIC AMERICAN.

# Racial Bias Found in a Major Health Care Risk Algorithm

Black patients lose out on critical care when systems equate health needs with costs

By Starre Vartan on October 24, 2019

# Green Light Technology

Skin with more melanin blocks green light, making it harder to get an accurate reading. The darker your skin is, the harder it gets.

Journal of *Personalized Medicine*

MDPI

*Article*

**Accuracy in Wrist-Worn, Sensor-Based Measurements of Heart Rate and Energy Expenditure in a Diverse Cohort**

Anna Shcherbina [1,†], C. Mikael Mattsson [1,2,†], Daryl Waggott [1,3,†], Heidi Salisbury [3], Jeffrey W. Christle [1], Trevor Hastie [4,5], Matthew T. Wheeler [1,3] and Euan A. Ashley [1,3,5,*]

# DISB Hearing Example

## Michael DeLong

Research and Advocacy Associate

Michael DeLong of the **Consumer Federation of America**. In this role, he conducts research on auto insurance and advocates for better, fairer, and more affordable practices that will protect consumers. He is particularly focused on combating discrimination in insurance markets.

## Question:

Has the federation done any study, or do they have any data that shows the difference in premium or rating that impacts transgendered individuals differently?

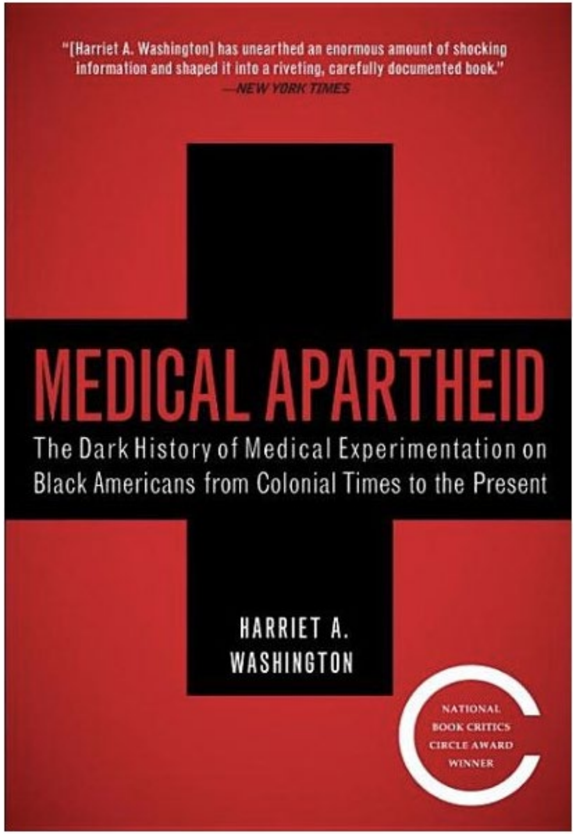
## Response:

We do not have a dataset, but we have a whole bunch of stories. There was one story of someone in Michigan, a transgender woman who underwent transition and her premium went up by a substantial amount. Everything else about her was exactly the same. We have been looking around for data. We don't have that right now.

# Medical Apartheid

Medical Apartheid is the first and only comprehensive history of medical experimentation on African Americans. Starting with the earliest encounters between black Americans and Western medical researchers and the racist pseudoscience that resulted, it details the ways both slaves and freedmen were used in hospitals for experiments conducted without their knowledge—a tradition that continues today within some black populations.

Harriet A. Washington
8 books · 383 followers



# Other Examples of Hidden Bias


GENDER- BIASED HIRING TOOL
amazon
NOW DISCARDED

JOURNAL ARTICLE ACCEPTED MANUSCRIPT

# Measuring racial and ethnic disparities in traffic enforcement with large-scale telematics data

William Cai, Johann Gaebler, Justin Kaashoek, Lisa Pinals, Samuel Madden, Sharad Goel

*PNAS Nexus*, pgac144, https://doi.org/10.1093/pnasnexus/pgac144

**Published:** 30 July 2022

**Abstract**

Past studies have found that racial and ethnic minorities are more likely than white drivers to be pulled over by the police for alleged traffic infractions, including a combination of speeding and equipment violations. It has been difficult, though, to measure the extent to which these disparities stem from discriminatory enforcement rather than from differences in offense rates. Here, in the context of speeding enforcement, we address this challenge by leveraging a novel source of *telematics* data, which include second-by-second driving speed for hundreds of thousands of individuals in 10 major cities across the United States. We find that time spent speeding is approximately uncorrelated with neighborhood demographics, yet, in several cities, officers focused speeding enforcement in small, demographically non-representative areas. In some cities, speeding enforcement was concentrated in predominantly non-white neighborhoods, while, in others, enforcement was concentrated in predominately white neighborhoods. Averaging across the 10 cities we examined, and adjusting for observed speeding behavior, we find that speeding enforcement was moderately more concentrated in non-white neighborhoods. Our results show that current enforcement practices can lead to inequities across race and ethnicity.

Discrimination, Disparate impact, Policing, Telematics

Source: https://doi.org/10.1093/pnasnexus/pgac144

PROPUBLICA

# Minority Neighborhoods Pay Higher Car Insurance Premiums Than White Areas With the Same Risk

Julia Angwin, Jeff Larson, Lauren Kirchner and Surya Mattu

April 5, 2017

Our analysis of premiums and payouts in California, Illinois, Texas and Missouri shows that some major insurers charge minority neighborhoods as much as 30 percent more than other areas with similar accident costs.

***"Insurance Premiums are Based on Risk of Loss"***

***– APCIA***

# PROPUBLICA

# How We Examined Racial Discrimination in Auto Insurance Prices

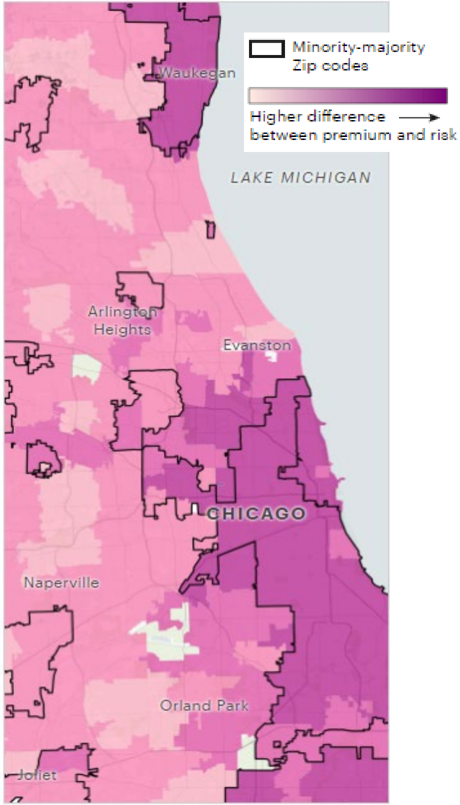
by Jeff Larson, Julia Angwin, Lauren Kirchner, Surya Mattu for ProPublica and
Dina Haner, Michael Saccucci, Keith Newsom-Stewart, Andrew Cohen, Martin Romm for Consumer Reports

April 5, 2017

**Approach:**

- Aggregate risk data by zip code collected by the insurance commissioners of California, Illinois, Missouri and Texas from insurers in their states.
- Compared that information with liability insurance premiums — the sum of bodily injury and property damage quotes — charged by the largest companies by market share in each of the four states.
- We found that some insurers were charging statistically significantly higher premiums in predominantly minority zip codes, on average, than in similarly risky non-minority zip codes.

$$\text{Average Loss} = \frac{\text{Dollars Paid Out for Liability Claims by Insurers}}{\text{Number of Cars Insured by Insurers}}$$




Source: https://www.propublica.org/article/minority-neighborhoods-higher-car-insurance-premiums-methodology

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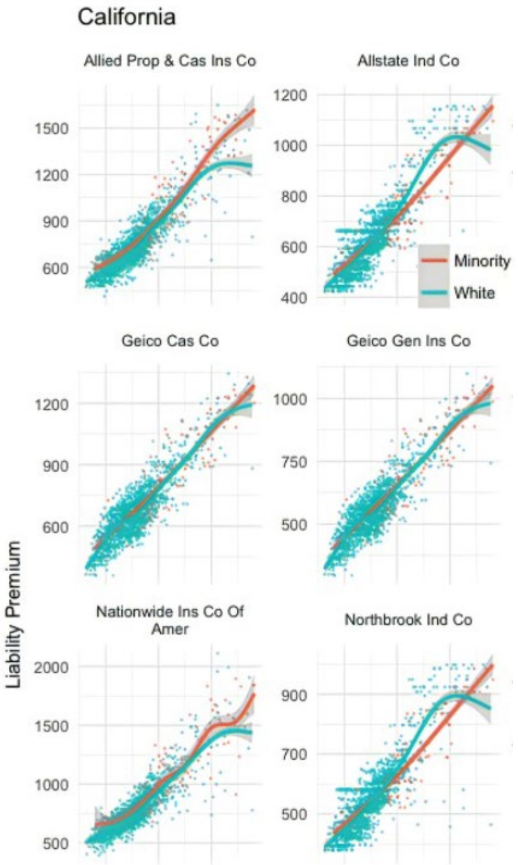
April 5, 2017

**The Data**

- We obtained data from two commercial data providers: Quadrant Information Services and S&P Global Inc. Quadrant provided us with 30 million premium quotes by zip code from the leading insurance companies across the nation. S&P provided us with rate filing manuals, which describe in detail how each insurer sets rates. Loss data was collected from insurance departments.

**Insured Profile Assumed**

- A 30-year-old female safe driver. Teacher with a bachelor's degree and excellent credit. No accidents or moving violations. Purchasing standard coverage with the company for the first time. She drives a 2016 Toyota Camry, and has a fifteen-mile commute, and drives around 13,000 miles a year. She is purchasing a policy for $100,000 of property damage coverage and $100,000 to cover medical bills per person up to $300,000 per accident.



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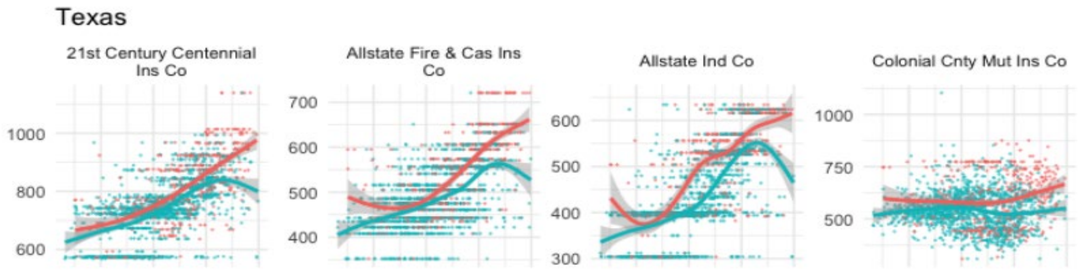
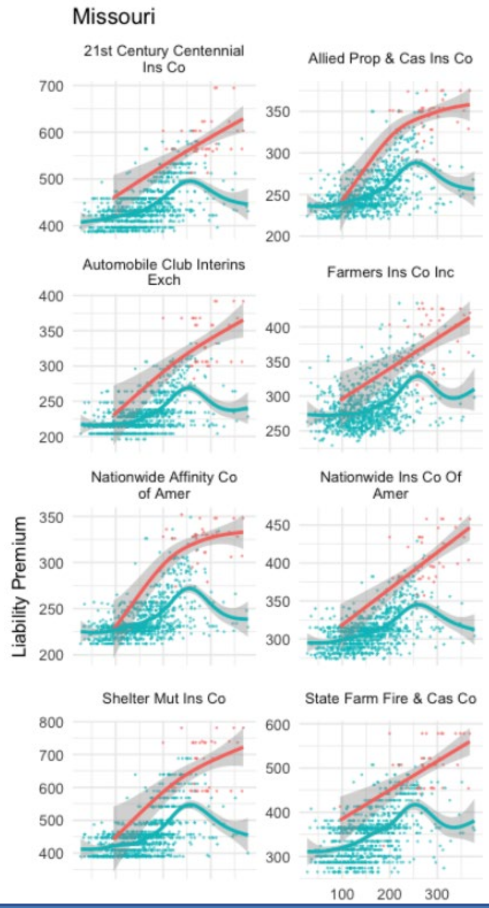
April 5, 2017

**Limitations and Conclusions:**

- Single variable model – Average Loss the only predictor
- Model results reflect low and negative R-Squared results
- Low $R^2$ values suggests that insurer premiums are weakly related to risk.
- Companies may have a different distribution of risk than the state’s aggregate risk numbers, but these differences are unlikely to result in a consistent pattern of higher prices for minority neighborhoods.

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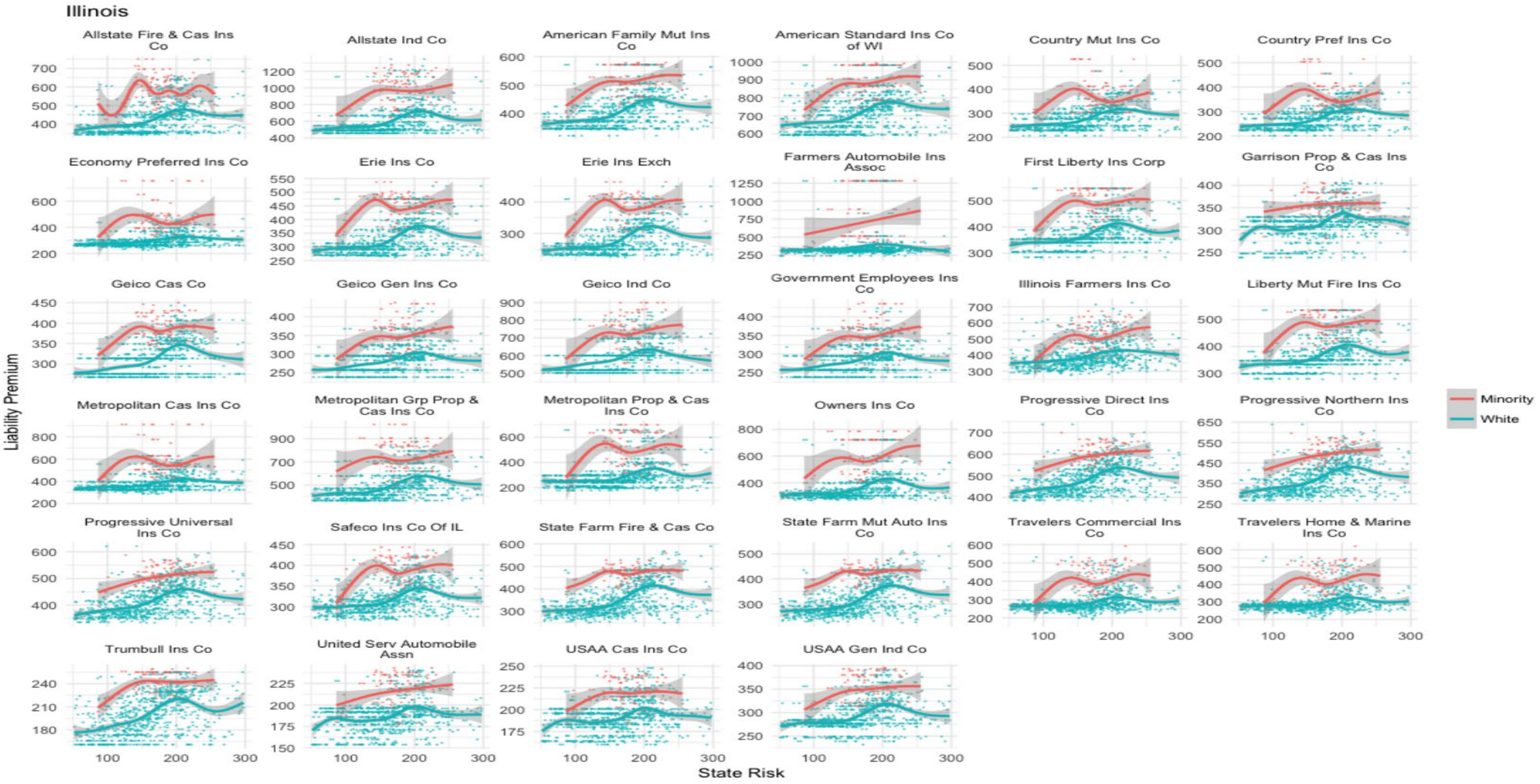

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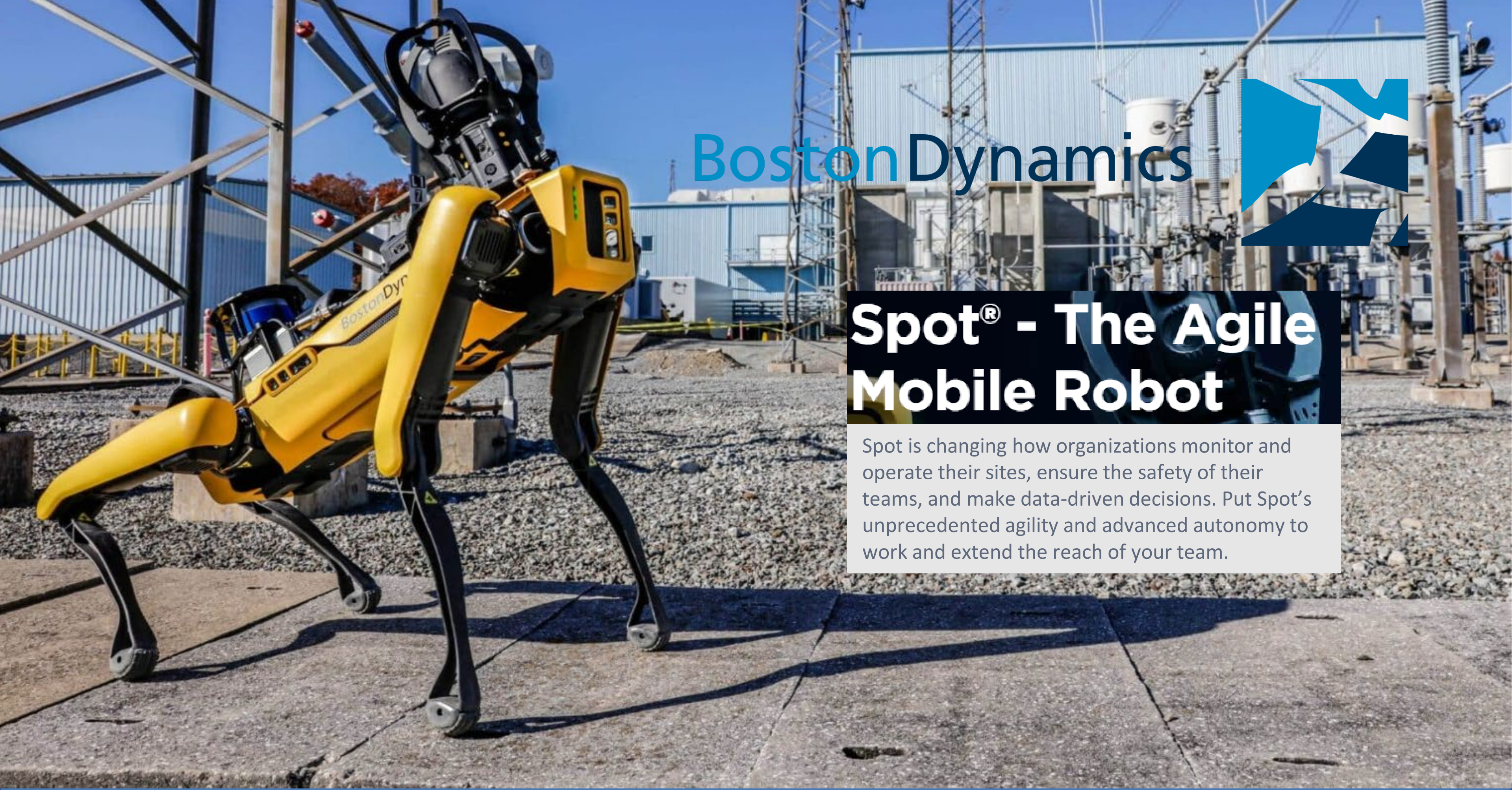
USAA Cas Ins Co
USAA Gen Ind Co
Liability Premium
State Risk
Minority
White



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Spot is changing how organizations monitor and operate their sites, ensure the safety of their teams, and make data-driven decisions. Put Spot's unprecedented agility and advanced autonomy to work and extend the reach of your team.

# Current Trends in P&C Insurance Rate Modeling

# Current Trend P&C Insurance Rate Modeling

# Modeler’s Hippocratic Oath

# The Modelers' Hippocratic Oath

*I will remember that I didn't make the world, and it doesn't satisfy my equations.*

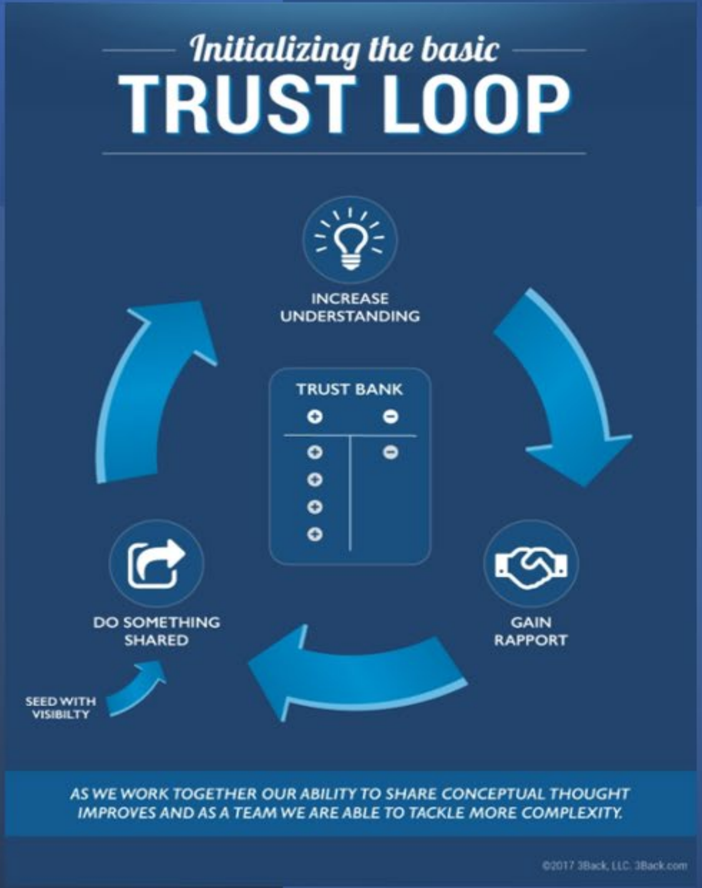
*Though I will use models boldly to estimate value, I will not be overly impressed by mathematics.*

*I will never sacrifice reality for elegance without explaining why I have done so.*

*Nor will I give the people who use my model false comfort about its accuracy. Instead, I will make explicit its assumptions and oversights.*

*I understand that my work may have enormous effects on society and the economy, many of them beyond my comprehension.*

*– Emanuel Derman and Paul Wilmott*

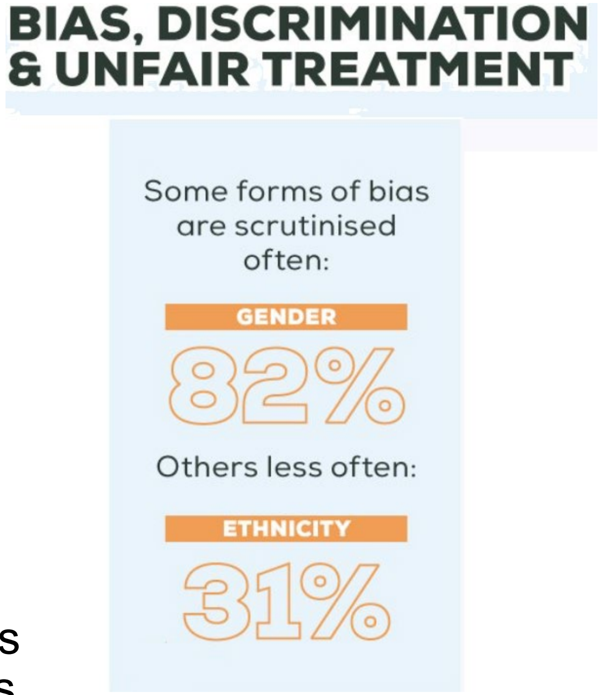


# Does Bias = Unfair Discrimination?

The short answer is …

## No. But it can lead to unfair discrimination & unfair treatment!

- Not all bias is bad. Our brains naturally put things in categories to make sense of the world.
- A sociotechnical approach to resolving algorithmic bias is imperative as a mathematical solution alone will be incomplete.
- A major focus needs to be on the representativeness of training data, modelers, and algorithmic outcomes.



# What can you do to mitigate bias in actuarial work?

- Follow what's happening!
- Work with social scientists to understand the problem
- Review evolving analytics on both sides for misuse
- Review AI/ML governance frameworks
- Conduct consumer related research on premium rates
- Review analytical results produced by computational journalists and comment on approaches
- Aid in synthetic data development for outcome testing
- Educate actuaries and data scientists on Modelers' Hippocratic Oath

Thank You!

Dorothy L. Andrews, MAAA, ASA, CSPA
Senior Behavioral Data Scientist and Actuary, NAIC
Board Member, American Academy of Actuaries (AAA)
Chairperson, Data Science and Analytics Committee, (AAA)