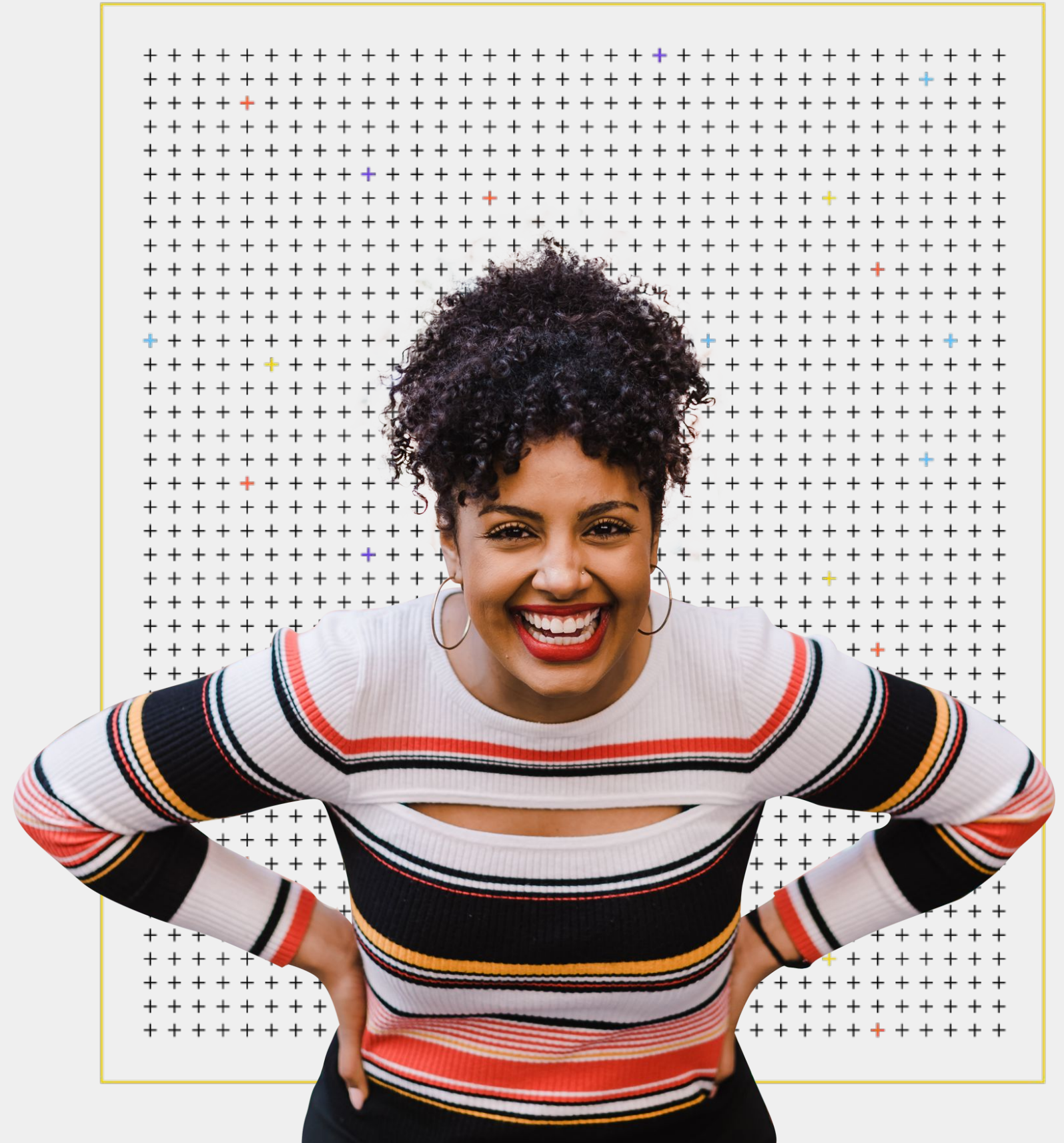# Addressing Fairness Considerations in Recoveries

January 11, 2022

Unprecedented scrutiny of financial services fairness practices

LEGAL AND REGULATORY RISK

Regulators and plaintiff's attorneys are making algorithmic bias a focus of investigations and are imposing massive fines.

ECONOMIC INEQUALITY AGENDA

Policymakers are examining the role algorithmic bias plays in exacerbating the nation's widening wealth and opportunity gaps.

SOCIAL JUSTICE CONCERNS

Consumers and investors are putting racial equity on the corporate agenda, just as they did with ESG issues a few years ago.

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More Fairness Scrutiny is Coming to Collections

CFPB Updates UDAAP Exam Procedures now look at discrimination

Unfair, Deceptive, or Abusive Acts or Practices (UDAAPs) examination procedures

Published Mar. 16, 2022

Download Unfair, Deceptive, or Abusive Acts or Practices (UDAAPs) examination procedures | PDF

This revision of the UDAAP examination procedures guides examiners in evaluating discriminatory practices as potential unfair practices. The revision also guides examiners in evaluating entities' decision-making processes, as well as the safeguards they have in place to prevent discrimination in connection with consumer financial products and services.

New procedures direct examiners to look for discrimination in collections including through Transaction Testing

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CFPB Reaffirms ECOA applies to collections

CFPB Issues Advisory Opinion on Coverage of Fair Lending Laws

Equal Credit Opportunity Act continues to protect borrowers after they have applied for and received credit

MAY 09, 2022

SHARE & PRINT

Washington, D.C. – Today, the Consumer Financial Protection Bureau (CFPB) published an advisory opinion to affirm that the Equal Credit Opportunity Act (ECOA)—a landmark federal civil rights law protecting individuals and businesses against discrimination in accessing and using credit—bars lenders from discriminating against customers after they have received a loan, not just during the application process.

"Equal Credit Opportunity Act continues to protect borrowers after they have applied for and received credit."

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How should entities in the recoveries industry manage this heightened regulatory focus on fairness?

Our Lens For Fairness

Equal Credit Opportunity Act

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Photo by Patrick on Unsplash

Equal Credit Opportunity Act

Overt Discrimination

Disparate Treatment

Disparate Impact

The U.S. has a long history of lending discrimination
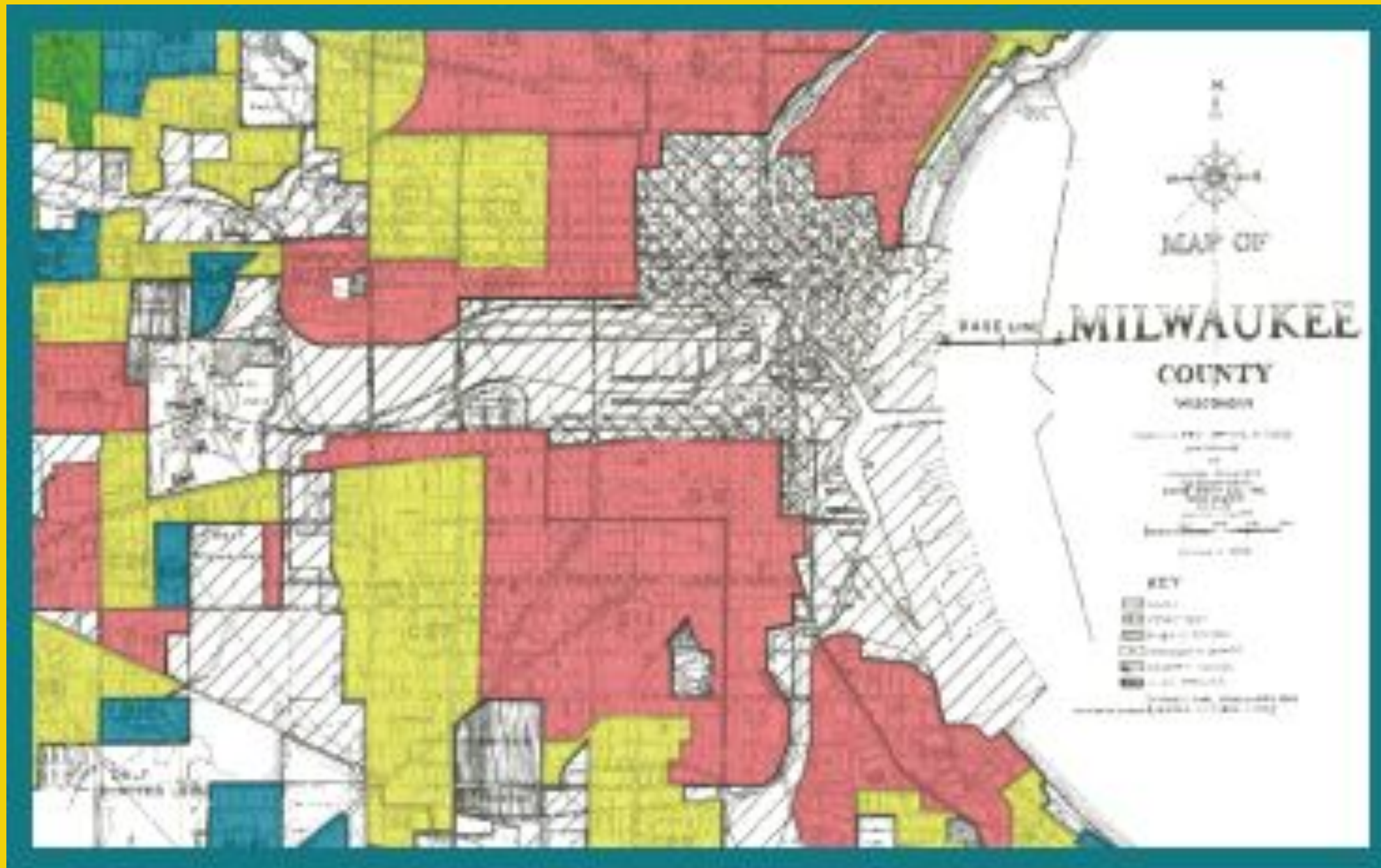
Disparate Treatment

"Are similarly situated people being treated in a similar manner"

Look at where you have discretion:

+ Different collection strategies for different geographies (Amex 2017)

+ How do you work with consumers once you reach them

+ Accounts that are put into litigation/accounts that are sold

Disparate Impact

Look at core collection strategies:

+ Evaluate facially neutral practices through quantitative and statistical analysis to see if there are demographic disparities

+ Example: collections agents spend more time and resources on accounts they will recover from vs those that don't – but what if that creates a statistically significant difference for some groups?

+ Demographic class membership can be estimated with BISG or other techniques

Fairness Through Blindness
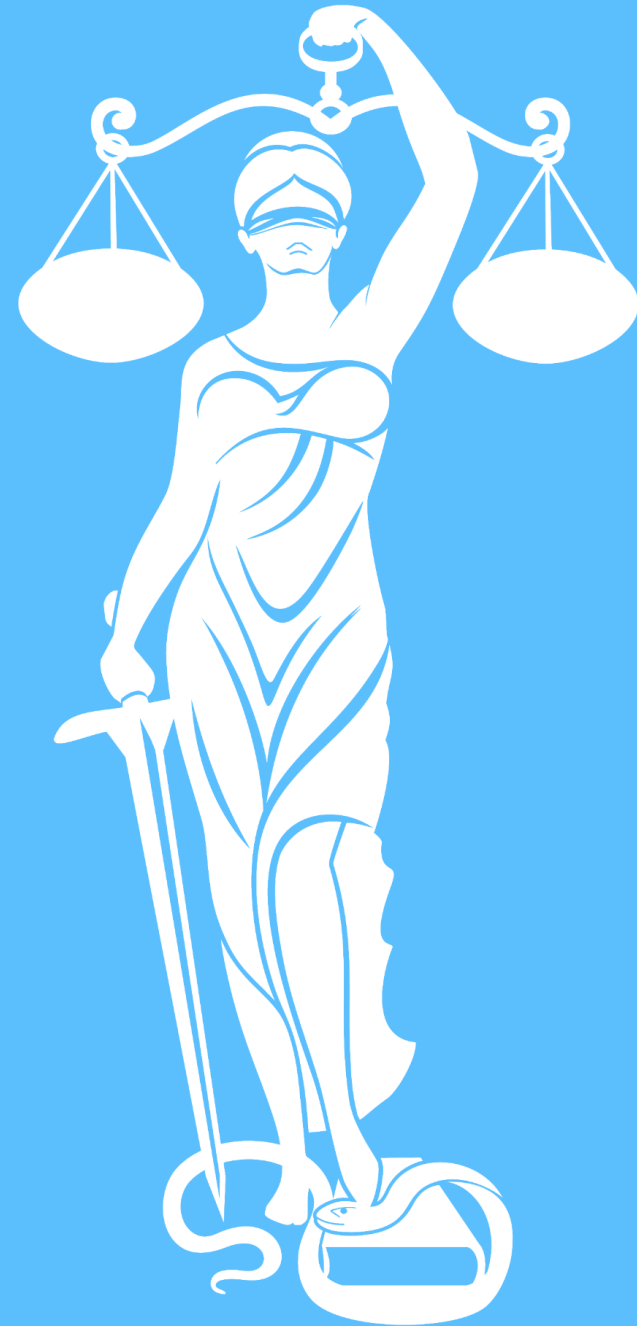
Neutrality is a Fallacy

&

Ignorance of Customer Composition will not protect you

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Variables that appear objective often aren't

A scatter plot with RISK (Predictive of default) on the vertical axis ranging from Low to High, and BIAS (Predictive of protected status) on the horizontal axis ranging from Low to High. Labeled data points include: Primary applicant FICO, Max limit non-authorized user trades, Months since oldest ind card trade, Original amount sum, County FIPS, Trades delinquent in last 12 months, Primary applicant state.

It's time for a new approach:
Fairness through Awareness

FairPlay uses Fairness Through Awareness to identify and remediate algorithmic bias

FAIRPLAY ANSWERS FIVE KEY QUESTIONS

+ Is my algorithm biased?

+ If so, why?

+ Could it be fairer?

+ What is the economic impact of being fairer?

+ Did we give our declines a Second Look to see if they resemble good applicants on other dimensions we haven't considered?

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Fair Lending Analysis

GET DOCUMENTATION

SUMMARY
- ✓ No disparity detected for Female applicants
- ⊘ Disparity detected for Black applicants
- ⓘ Potential disparity detected for Hispanic applicants
- ⓘ Potential disparity detected for API applicants
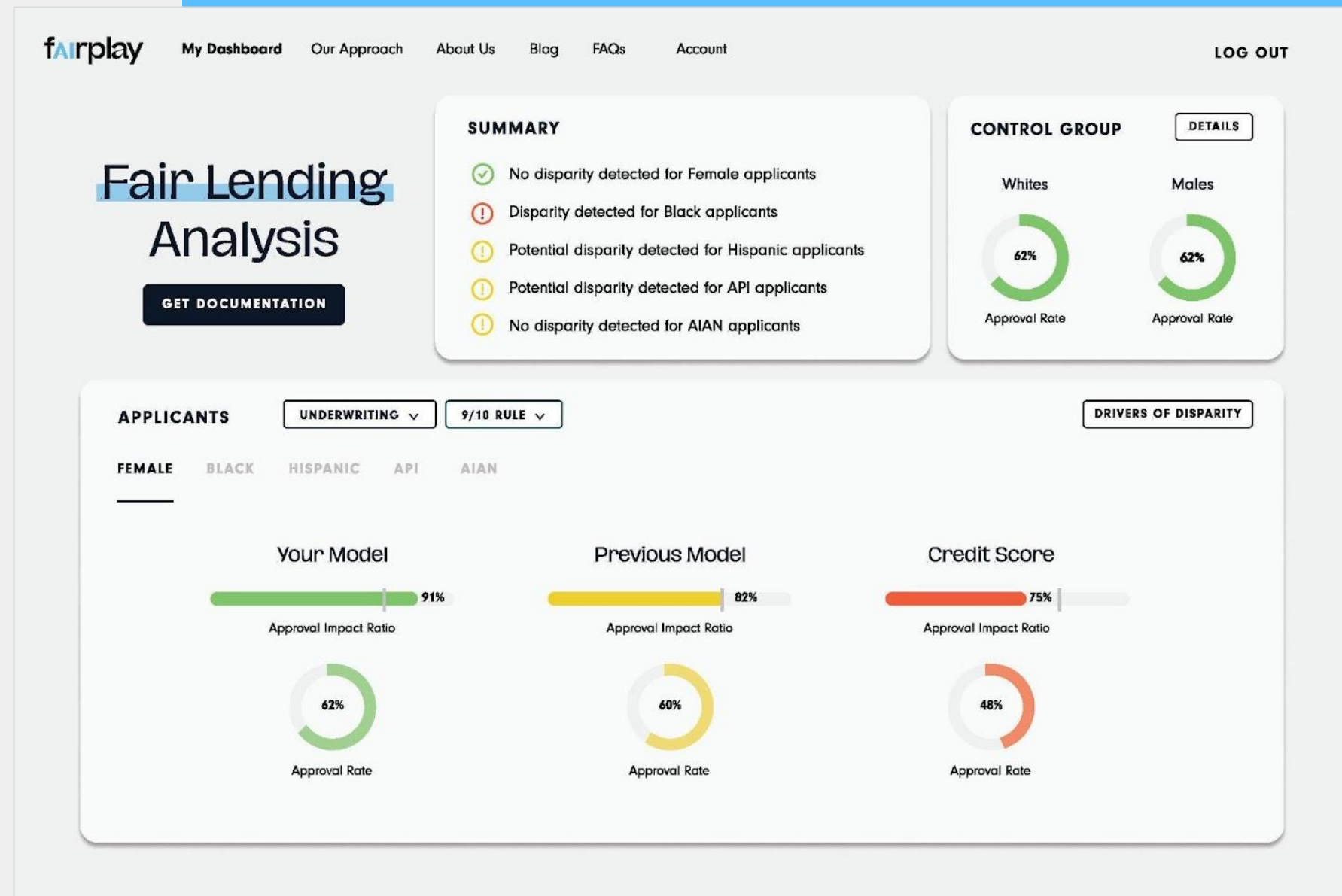- ⓘ No disparity detected for AIAN applicants

CONTROL GROUP   DETAILS

Whites — 62% Approval Rate   Males — 62% Approval Rate

APPLICANTS   UNDERWRITING ⌄   9/10 RULE ⌄   DRIVERS OF DISPARITY

FEMALE   BLACK   HISPANIC   API   AIAN

Your Model — 91% Approval Impact Ratio — 62% Approval Rate

Previous Model — 82% Approval Impact Ratio — 60% Approval Rate

Credit Score — 75% Approval Impact Ratio — 48% Approval Rate

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ML algorithms relentlessly pursue their target to achieve the most accurate outcome

Every algorithm must be given a target

Social media algorithms seek to maximize their target: engagement

**Every algorithm must
be given a target**
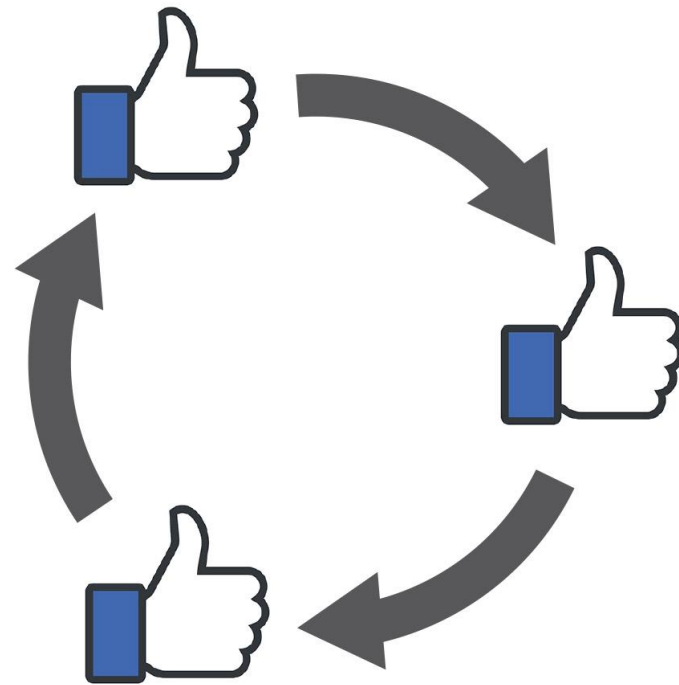
**Social media target:
Maximize engagement**

The algorithm single mindedly focuses on engagement regardless of whether it's good for your health or good for society

Every algorithm must be given a target
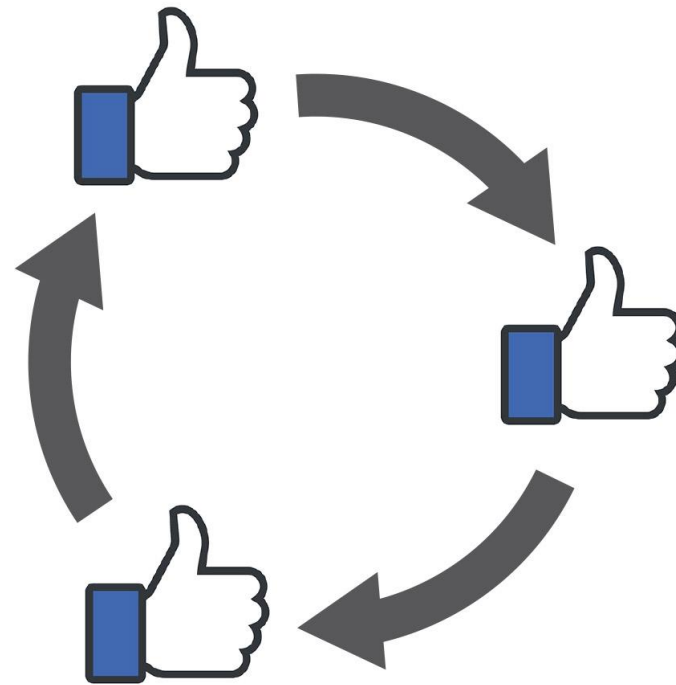
Social media target: Maximize engagement

Without regard for societal harm

Giving an algorithm one target is problematic: imagine a self-driving car whose only target was to get you from point (a) to point (b)

Target: Get from point (a) to point (b)

Self-driving cars have a second target: Safety

Target: Get from point (a) to point (b)

Second Target: Safety (obey traffic laws; avoid accidents with cars, pedestrians, cyclists, etc)

FairPlay Turns Fairness Into a Competitive Advantage

↑ **16%** increase in fairness for Black applicants

↑ **10%** increase in approval rate

↑ **$130** million in additional credit origination with no additional risk

Case Study

+ 680,000 applicants

+ 60,000 approved

+ FairPlay found disparities for Black & Native American consumers

+ $1.5bn portfolio

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10 variables drove 93.4% of [Lender] model's predictive power

Variable	Contribution
CREDIT SCORE *Primary Applicant*	69.9%
Number of trades delinquent in last 12 months	5.0%
Number of inquiries in last 24 months	3.0%
Sum overlimit balance	3.0%
Number of finance companies inquiries in last 24 months	2.8%
Number of auto trades delinquent in last 12 months	2.5%
Number unknown inquiries last month	2.4%
Individual current card trade count	1.9%
Recreational merchandise loan number	1.5%
Original amount sum	1.4%

Contribution percentile
Top 10 Variables
Shapley values

FairPlay identified 7 Second Look models as accurate as the Lender's

	Lender's Model	FairPlay Models						
		1	2	3	4	5	6	7
Accuracy	95.63%	95.97%	95.93%	95.91%	95.91%	95.90%	95.90%	95.81%
Black AIR	75%							
Hispanic AIR	103%							
API AIR	108%							
Female AIR	92%							
Age 62+ AIR	117%							

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... that significantly improved fairness for Black and Female applicants

	Lender's Model	FairPlay Models						
		1	2	3	4	5	6	7
Accuracy	95.63%	95.97%	95.93%	95.91%	95.91%	95.90%	95.90%	95.81%
Black AIR	75%	87%	85%	84%	82%	85%	82%	83%
Hispanic AIR	103%	101%	101%	101%	101%	101%	101%	101%
API AIR	108%	106%	105%	107%	107%	106%	105%	108%
Female AIR	92%	99%	99%	99%	99%	99%	99%	99%
Age 62+ AIR	117%	113%	114%	114%	114%	114%	113%	114%

. . . and produced between 3,700 and 5,200 new loans for approval

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API AIR	108%	106%	105%	107%	107%	106%	105%	108%
Female AIR	92%	99%	99%	99%	99%	99%	99%	99%
Age 62+ AIR	117%	113%	114%	114%	114%	114%	113%	114%
New Loans		5,199	3,714	4,085	3,714	3,714	3,714	3,714

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New Loans		5,199	3,714	4,085	3,714	3,714	3,714	3,714

Fairness Through Awareness Models Make Use of More Variables

Variable	Value
Vehicle type: 1	13.1%
Number unknown inquiries last month	11.6%
Number of auto trades delinquent in last 12 months	10.8%
Revolving percent due	7.9%
CREDIT SCORE *Primary Applicant*	6.5%
Vehicle type: 2	6.3%
Original amount sum	5.7%
Number of finance companies inquiries in last 24 months	5.4%
Vehicle type: 3	5.2%
Individual current card trade count	4.7%
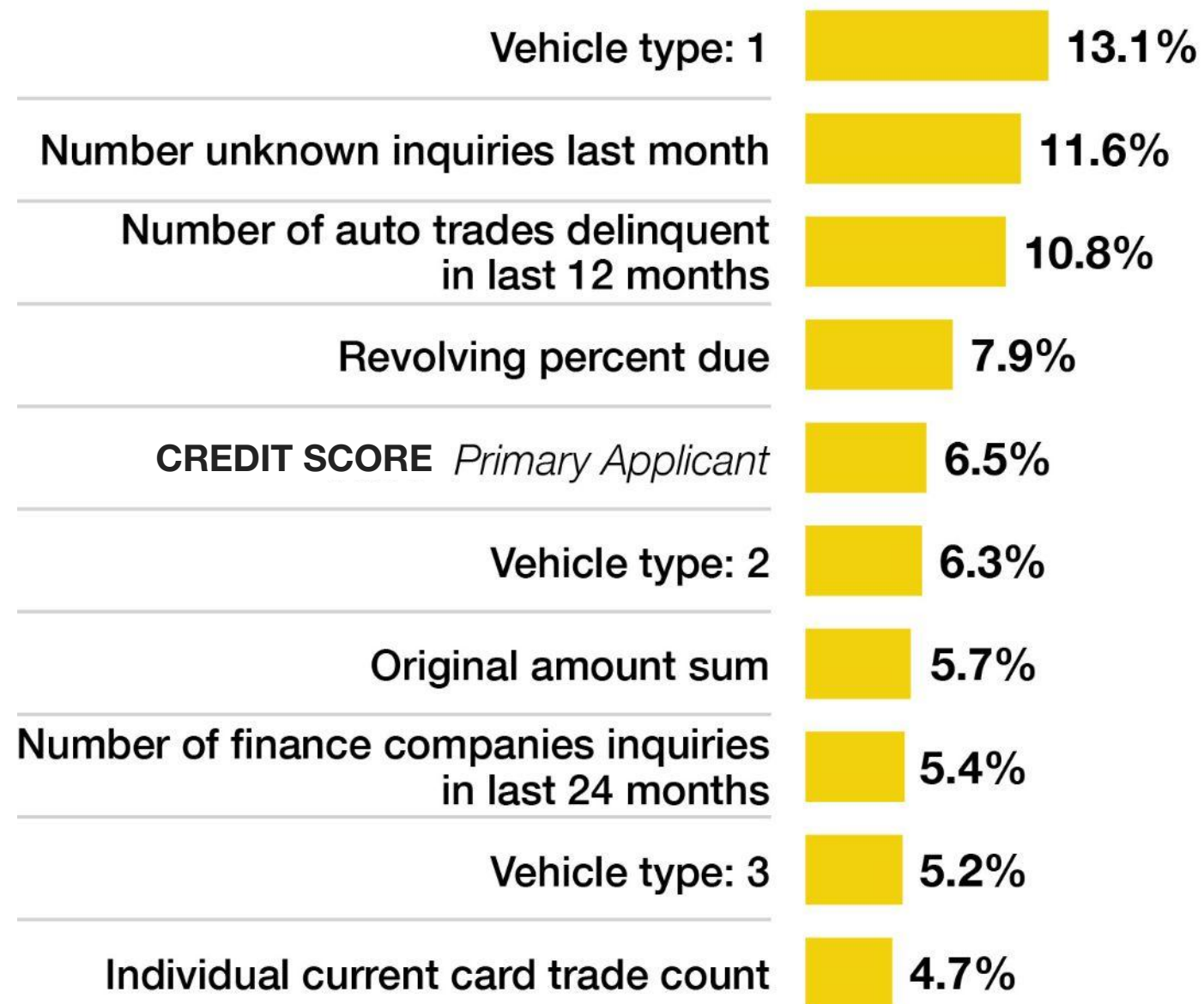
**Second Look
Drivers of Difference
Top 10 Variables**
Shapley values

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Increasing approvals for protected groups ≠ increased risk

Protected Class	Success Ratio								
Female	99.92						●		
Black	99.91						●		
Hispanic	99.93						●		
API	100.03						●		
AIAN	99.98						●		
2+ races	99.89						●		
Under age 25	100.05						●		
Over age 62	99.96						●		
		95%	96%	97%	98%	99%	**100%**	101%	102%	103%

We can do this in collections : Target recoveries while also being fair

Target: Collections objective

Second Target: Fairness

CONTACT

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