

# Fairness Regularized Risk Assessment Models: Balancing Risk Prediction and Racial and Ethnic Equality

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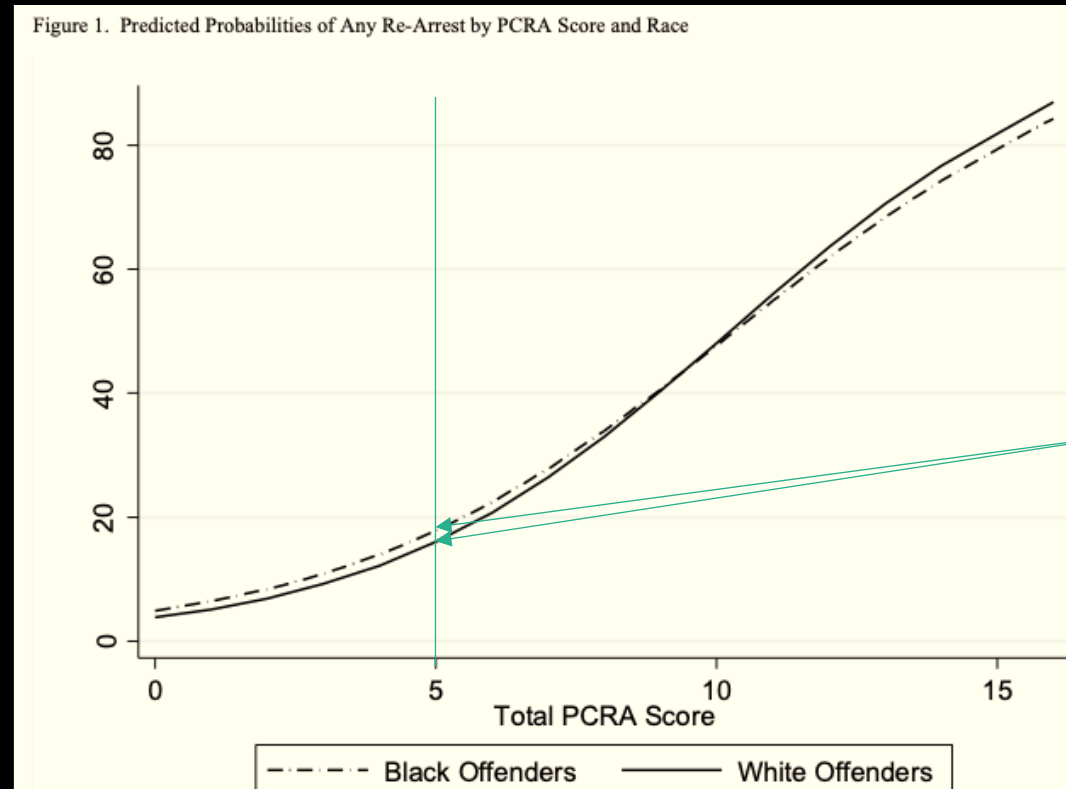
# Overview

- Actuarial risk assessment tools
  - Aim to provide objective measures of risk, but...
  - Generate concerns over racial bias
- Typical process
  - Fit models to maximize prediction accuracy...
  - Then assess racial fairness
- Fairness regularized models
  - Simultaneously optimize predictive performance and minimize racial differences
  - Logistic regression fit with a “lack of fairness penalty” added to the negative Bernoulli log-likelihood

# Background

- Actuarial risk assessment is increasingly prevalent in the justice system
- Several widely publicized critiques
  - Attorney General Eric Holder's Comments (NACDL Speech, 2014)
  - Propublica/COMPAS Controversy (e.g., Angwin et al. 2016; cf. Flores et al. 2016)
  - *Weapons of Math Destruction* (Cathy O'Neil 2016)
- Multiple, conflicting definitions of "fairness" (Chouldechova 2017; Berk et al. 2021)
  - Mathematical proofs that all common fairness measures cannot be satisfied simultaneously

# Calibration Is One Way of Defining Fairness in Risk Assessment



Skeem & Lowenkamp (2016)

**At any PCRA score, rearrest probabilities are similar**

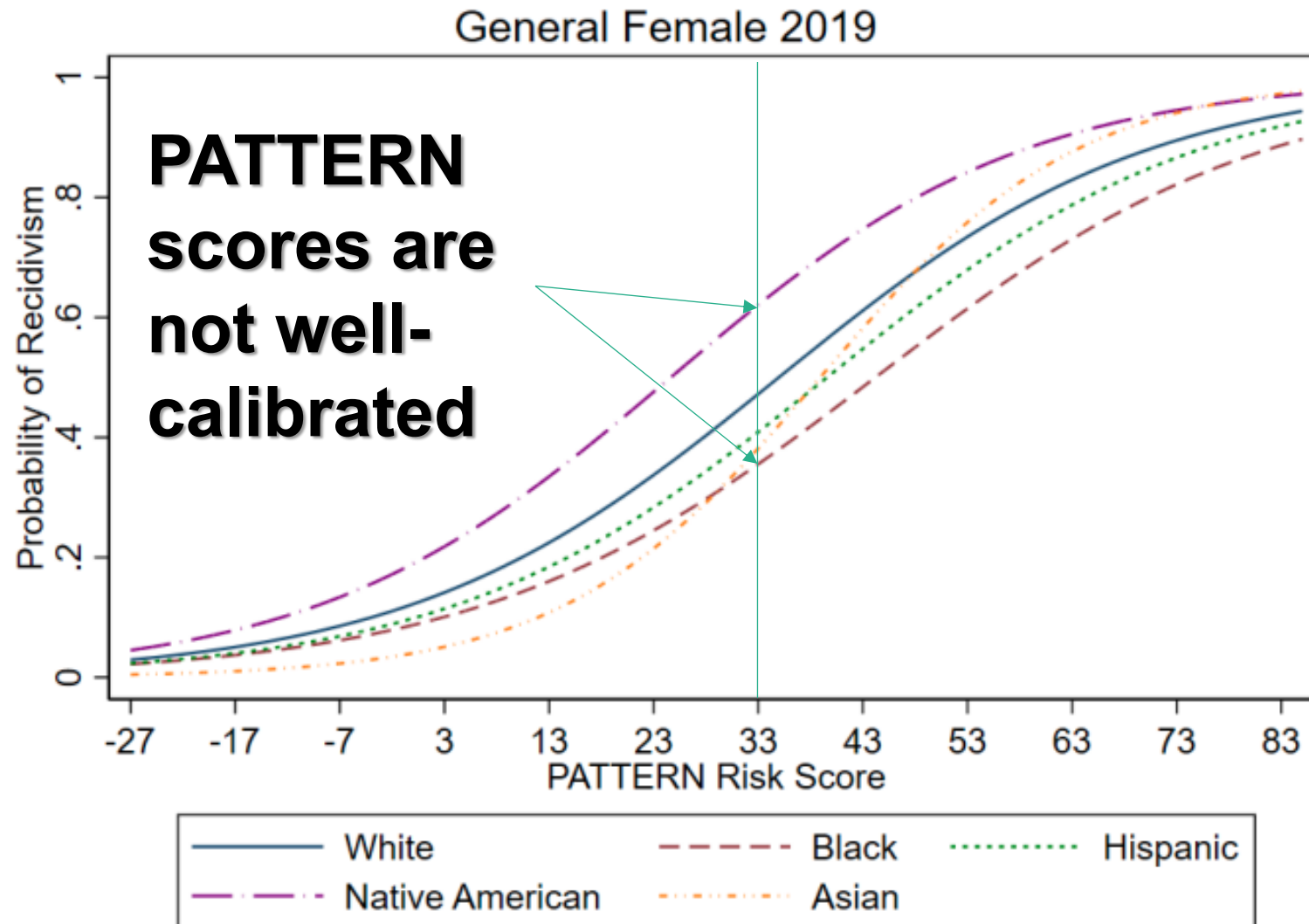
**A score  $S$  is well-calibrated if**

$$P(Y = 1|S = s, R = \text{black}) = P(Y = 1|S = s, R = \text{white})$$

# PATTERN Risk Tool Is Accurate...

- High overall accuracy relative to instruments used in criminal justice
  - Female group AUCs range from 0.73 - 0.86
  - 0.76 and 0.78 for White and Black women

# ...But PATTERN Risk Scores Do Not Seem Fair



# Measure Lack-of-Calibration with F-statistic

- Lack-of-calibration penalty

- Compute score-and-sum predictions as

$$\hat{f}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{1i} + \hat{\beta}_2 x_{2i} + \dots$$

Natural splines allowing  
non-linear relationship  
between score and log odds

$$\log \frac{P(y_i=1)}{1-P(y_i=1)} = \alpha_0 + \alpha_1 ns_1(\hat{f}_i) + \alpha_2 ns_2(\hat{f}_i) + \alpha_3 ns_3(\hat{f}_i) + \alpha_4 ns_4(\hat{f}_i) +$$

$$\alpha_5 \text{black}_i +$$

Main effect for race

$$\alpha_6 \text{black}_i ns_1(\hat{f}_i) + \alpha_7 \text{black}_i ns_2(\hat{f}_i) + \alpha_8 \text{black}_i ns_3(\hat{f}_i) + \alpha_9 \text{black}_i ns_4(\hat{f}_i)$$

- Measure calibration with F-statistic testing

$$\alpha_5 = \alpha_6 = \alpha_7 = \alpha_8 = \alpha_9 = 0$$

Capture difference  
in calibration curves  
across race

# Minimize Deviance with Unfairness Penalty

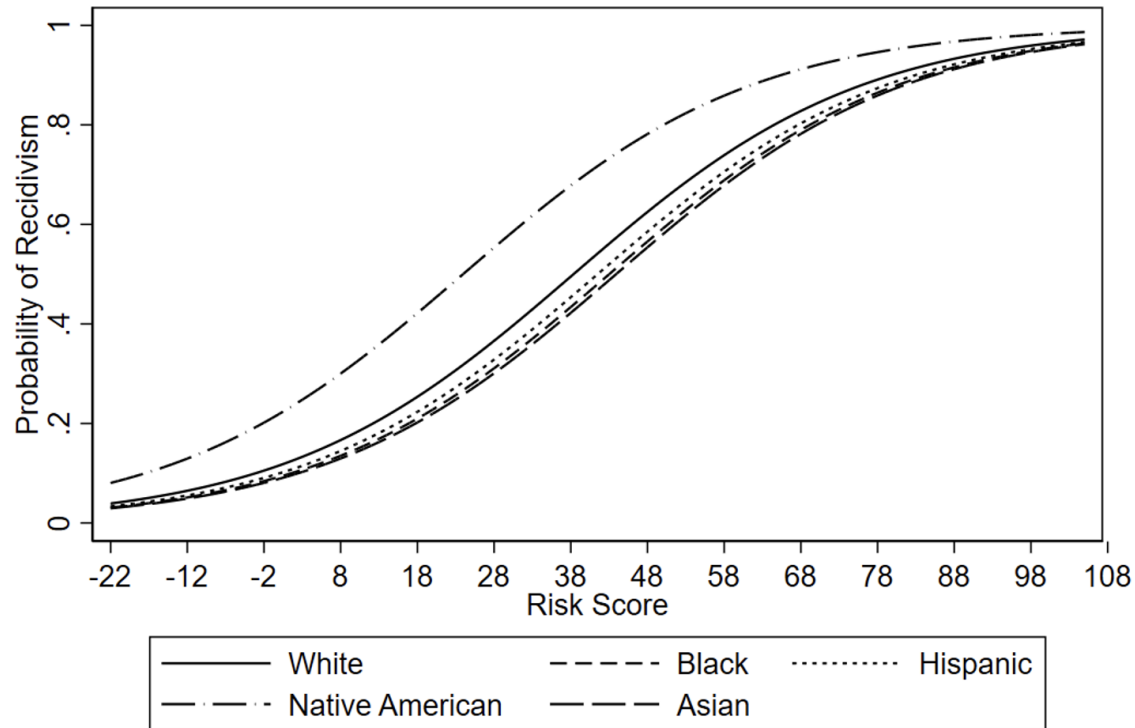
- Finds  $\beta$  to minimize

$$\ell(\beta) = -2 \sum_{i=1}^n y_i \beta' \mathbf{x}_i - \log(1 + \exp(\beta' \mathbf{x}_i)) + \lambda F(\beta)$$

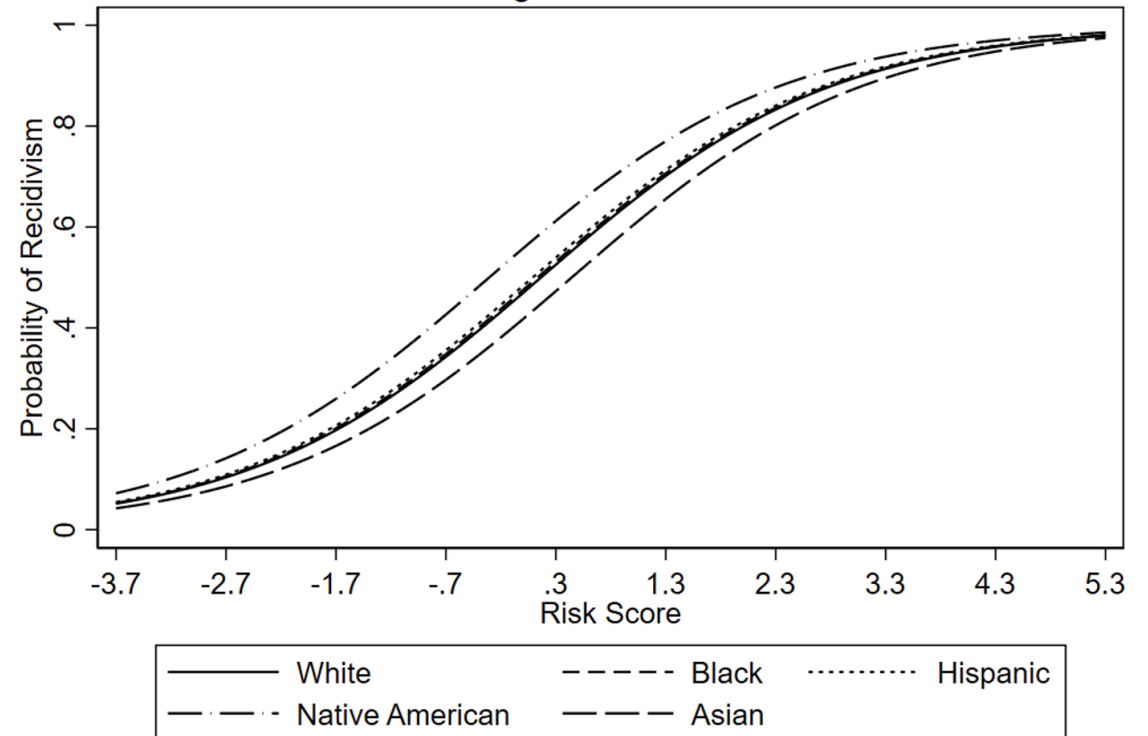
- No differences in calibration by race group,  $F \approx 0$
- Increasing  $\lambda$  focuses optimization focuses on equal calibration
- May create scores that fail to incentive constructive rehabilitation
  - For example, more serious criminal history predicts lower recidivism risk
  - Additional constraints on  $\beta$ 
    - Risk must increase with more serious criminal history
    - Risk must decrease with more participation in rehabilitation programming

# Fairness Regularization Improves Within Race Calibration

PATTERN Risk Tool



Fairness Regularized Risk Tool



# Improving Calibration Slightly Reduces Predictive Performance (AUC)

	PATTERN	FR
White	0.80	0.79
Black	0.75	0.74
Hispanic	0.77	0.75
Native American	0.70	0.70
Asian	0.84	0.84
Overall	0.78	0.77

# Conclusion

- When unconstrained, risk assessments
  - Are not calibrated within groups
  - May encode undesirable incentives
- Fairness regularization improves within group calibration
  - Optimization can also enforce desired incentives
- Improving fairness comes with a price: reduced predictive performance
  - Forcing perfectly calibration reduces the model to predict the baseline rearrest rate for everyone (perfectly fair, but no risk assessment)

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