Measuring and Mitigating Racial Disparities in Tax Audits

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Hadi Elzayn, 05/2024, Tax Chat!

Disclaimer

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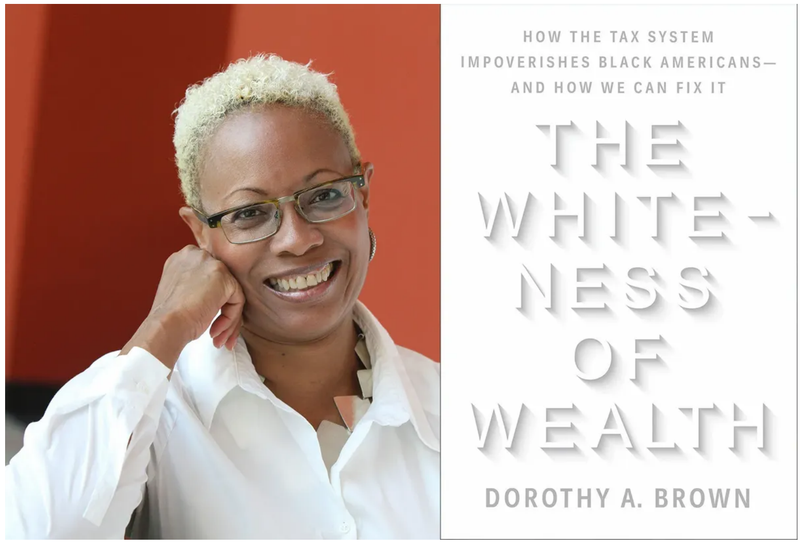
Motivation



Executive Order 13985:

"[E]ach agency must assess whether . . . its programs and policies perpetuate systemic barriers . . . for people of color."

Many Federal datasets are not disaggregated by race, ethnicity, gender, disability, income, veteran status, or other key demographic variables."

Motivating policy question: is there racial disparity in tax audits?

How can we study this topic with limited access to self-reported race?

How does algorithmic design interact with institutional features and policy constraints to shape disparity?

Background

- Income tax is main source of funding for U.S. federal government
    - Increasingly, social policy enacted through the tax code (e.g. Earned Income Tax Credit (EITC))
- Liability is **self-reported** - taxpayer (or preparer) calculates liability and files with govt
- IRS audits taxpayers to verify accuracy of reported tax liability and eligibility for claimed benefits
- Multiple types of audits (single vs. multi -issue, by mail vs. in person, pre vs. post -refund)
    - For EITC claimants, pre-refund, by mail, is vast majority

Background - EITC

- Earned Income Tax Credit - refundable credit designed as social benefit for lower income earners + to incentivize work
- Credit depends on both income and number of qualifying dependents
- Complicated to determine correctly (strict residency length + relationship tests, specific rules on income, etc.)
- Audited at a higher rate than other taxpayers. Previous studies have shown Black taxpayers claim at a higher rate
    - (But we will show that does not account for the disparity)

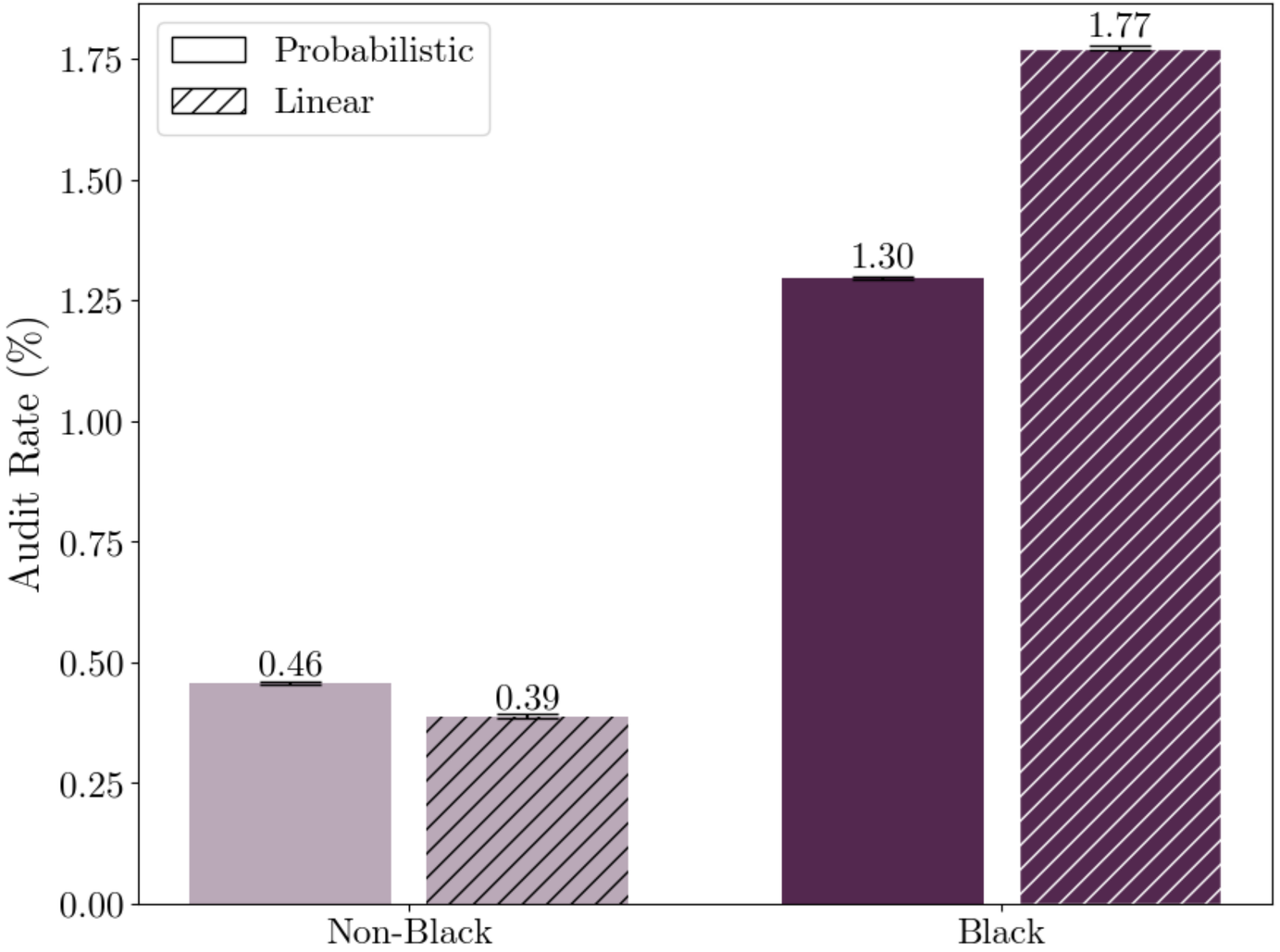
Key idea: Estimated Race + Bounds
(And validating assumptions)

- Use race-correlated information we do have to construct probabilistic estimate of race
    - First name + last name + geography -> BIFSG
- Combine estimated race with audit selection to get estimate of audit rate by race
- Theorem. Under certain conditions:
    - “Linear” estimator -> over-estimate of disparity
    - “Probabilistic” estimator -> under-estimate of disparity
- Validate theorem conditions by analyzing small set of labeled data

Data Sources

1. Tax Return and Operational Audit Data
   - 148M tax returns in 2014, 740k selected for audit
   - Observe filed return + audit outcomes
2. Aggregated Race Data
   - Surname (Census), First name (HMDA), CBG (Census ACS)
3. Matched North Carolina Voter File
   - Includes self-reported race (N=2.5M)
   - Matched on isolated server
4. National Research Program (NRP)
   - 72k returns from 2010-2014
   - Stratified random sample of returns selected for line-by-line audit

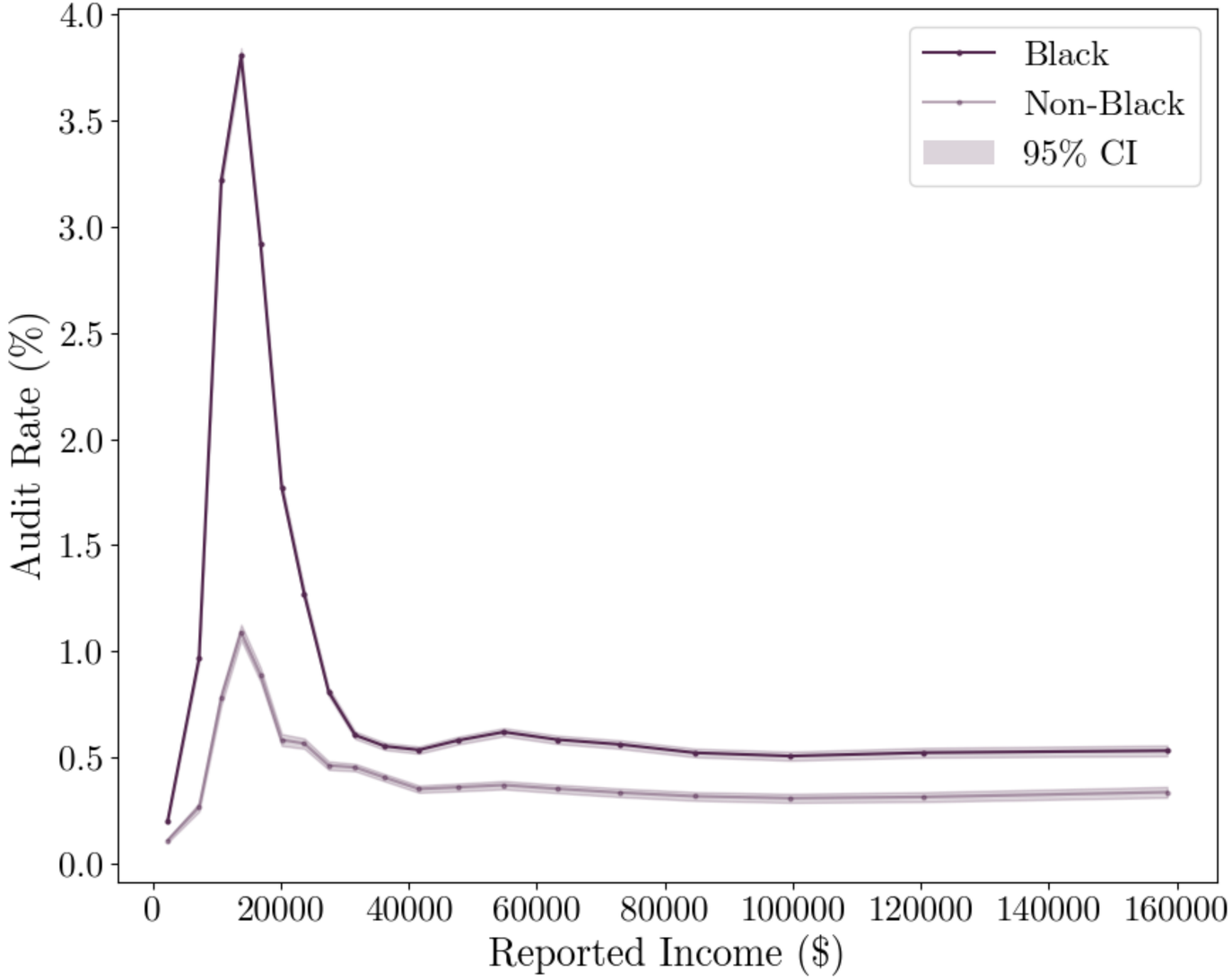
Overall Disparity Results



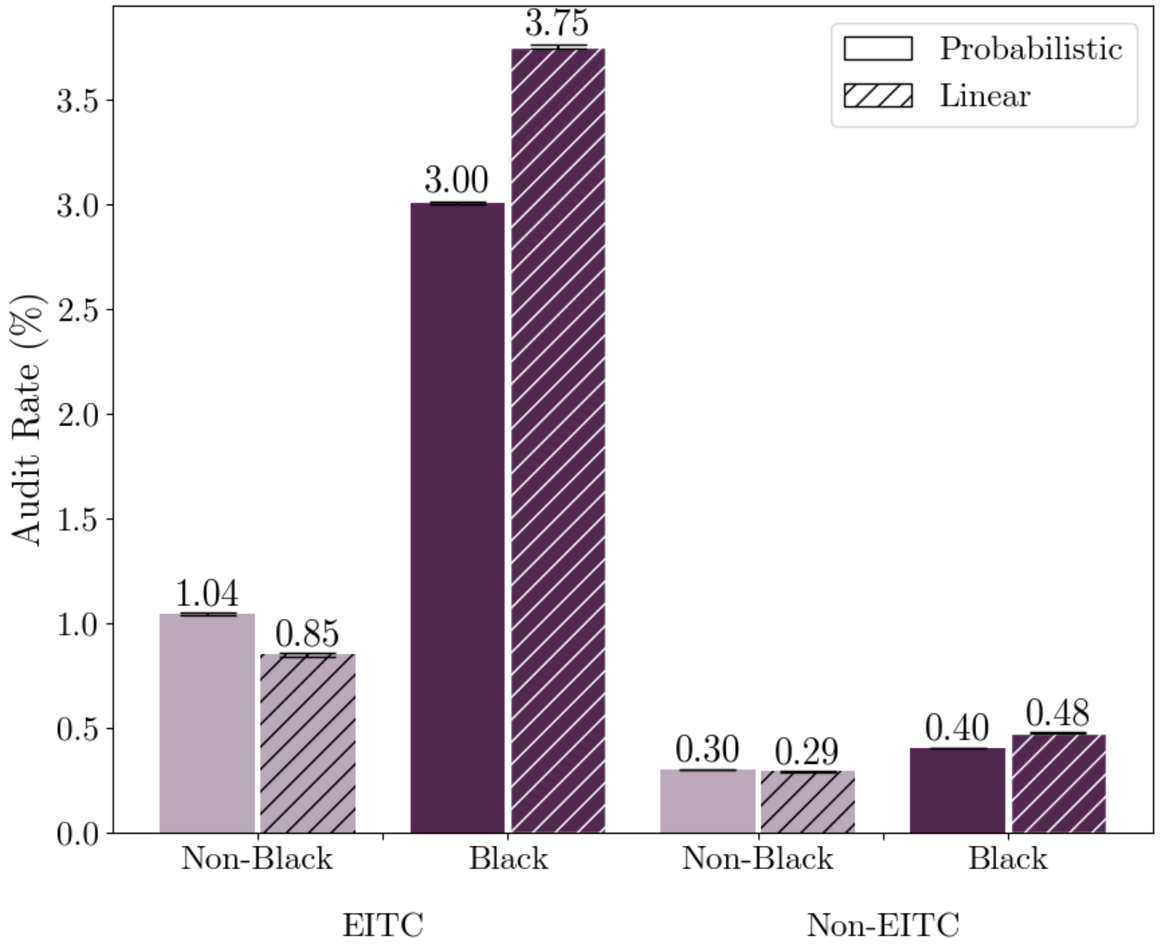
What factors could explain disparity?

- Income?
- EITC Claim rates?
- Filing features?
- Underlying non-compliance?

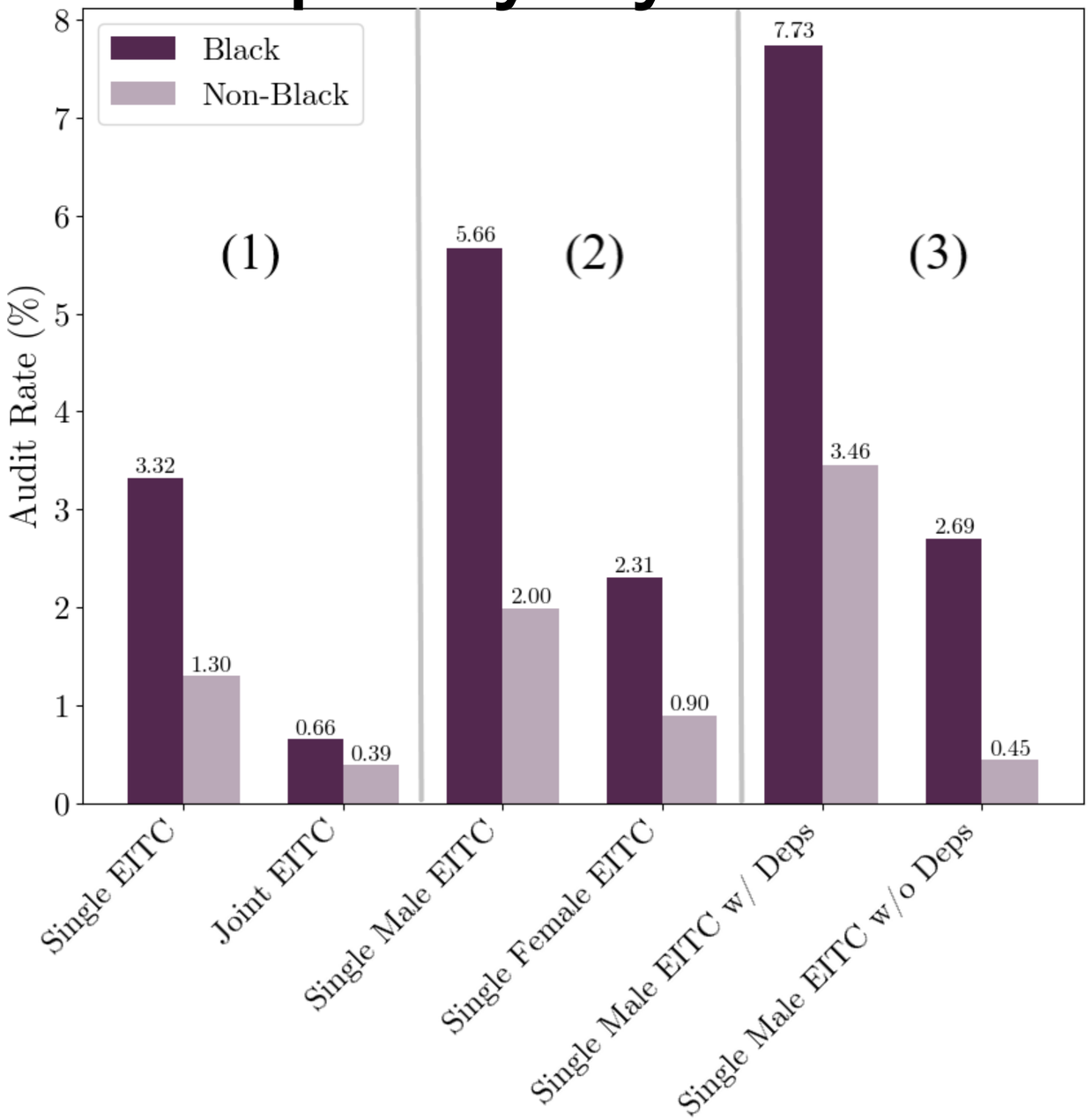
Audit Rate Disparity by Income



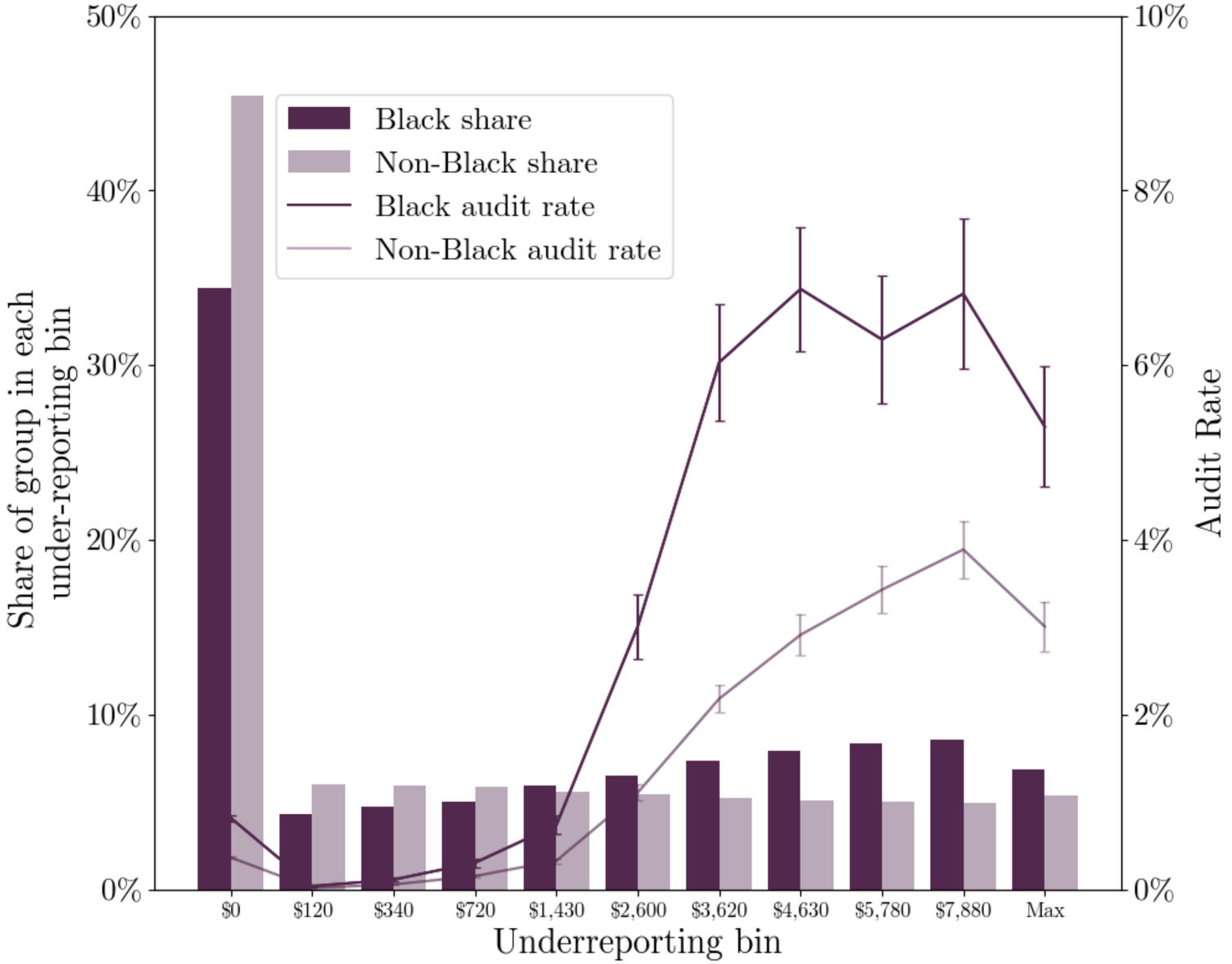
Audit Rate Disparity by EITC status



Audit Rate Disparity by Return Features



Audit Rate Disparity by Underreported Liability



IRS process complicated/secret - how identify contributors to disparity?

Idea: consider counterfactual policies using representative data

Hypothesis?	Test?	Likely Contributor?
Underlying distribution?	Oracle model that “knows” non-compliance perfectly	✗
Prediction?	Model trained to predict *amount* of non-compliance	✗
Focus on refundable credits?	Only include underreporting for refundable credits	✓

Conclusions

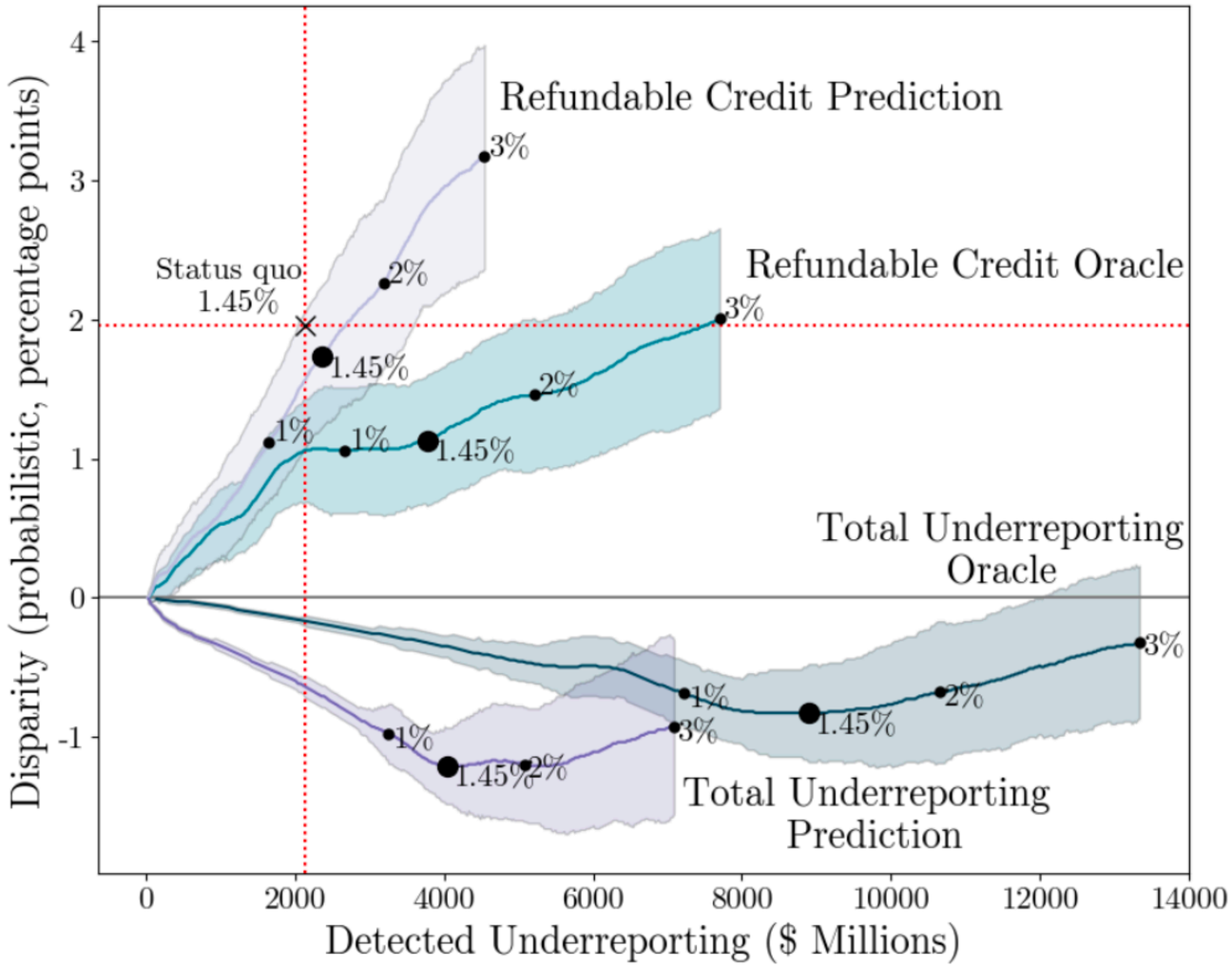
- Methodologically, paper provides a roadmap for disparity assessment without access to self-reported race
    - Use BIFSG (or other) method to obtain probabilistic race estimates
    - Assess whether bound conditions hold via auxiliary dataset
    - Combine estimates with outcome via linear and probabilistic estimators
- Paper provides details about the math

Conclusions

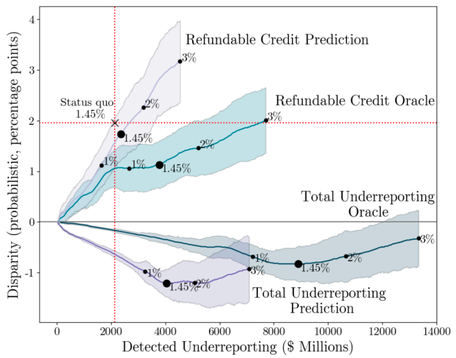
- Substantively: Paper establishes the presence of significant disparities in audit rates between Black/non-Black taxpayers
    - Neither differences in important taxpayer characteristics nor underlying non-compliance appear to contribute to disparity
    - Biggest driver of disparity appears to be focus on refundable credits over other types of underreporting
    - Focusing on total underreporting rather than refundable credits (e.g. focusing on high-risk business/self-employment income) may mitigate disparity

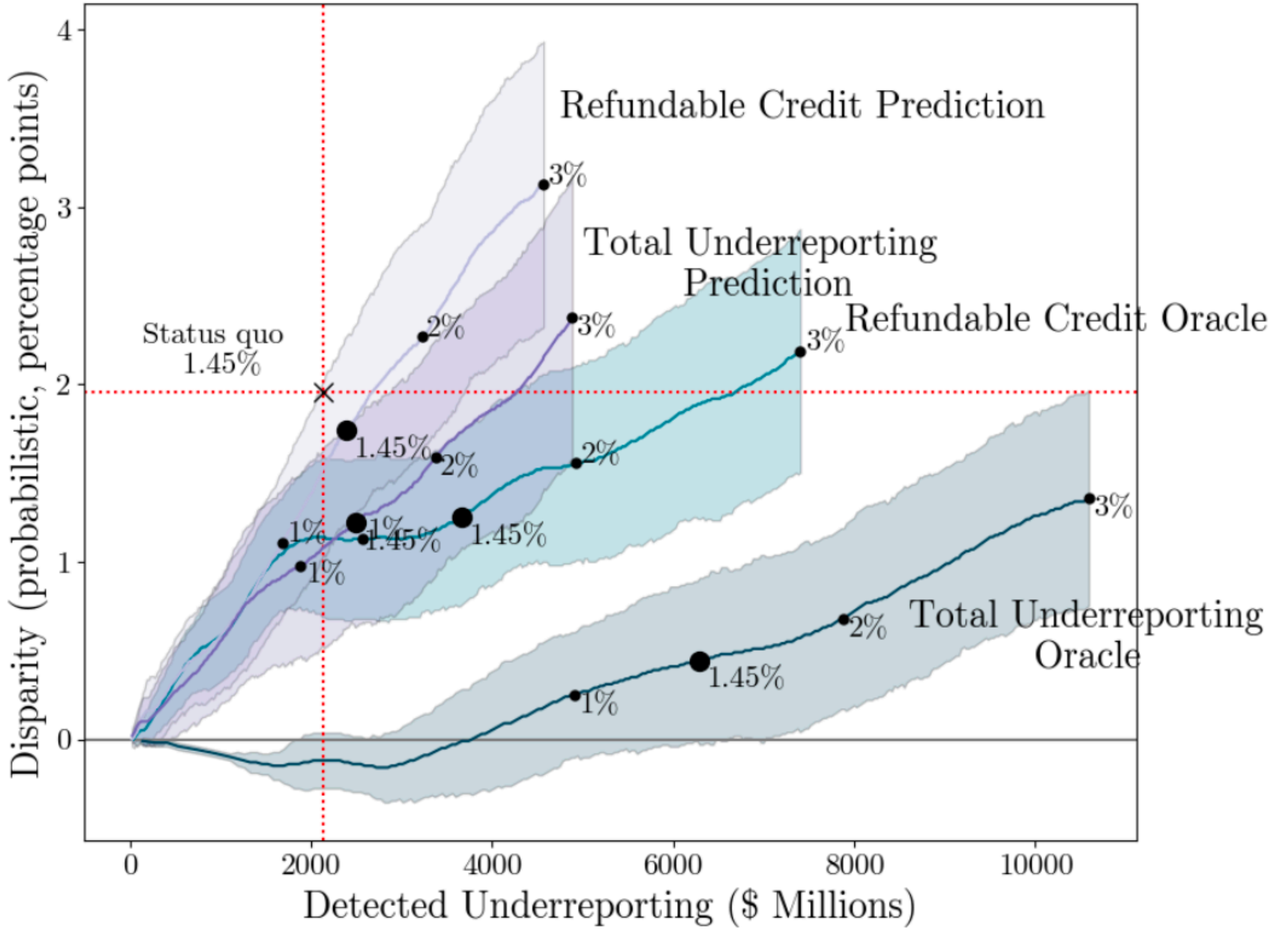
Appendix

Objective: Refundable Credits



Constrain selection by status quo





Formal Notation

- Taxpayers have audit status $Y_i \in \{0, 1\}$ (e.g. based on predicted non-compliance)
- Taxpayers have a first name (F_i), last name (S_i), and geographic location (G_i)
- Taxpayers have an (unobserved, except in NC voter data) race status B_i, corresponding to Black ($B_i = 1$) or non-Black ($B_i = 0$)
- Disparity D is given by:

$$D := \mathbb{E}[Y|B = 1] - \mathbb{E}[Y|B = 0] \tag{1}$$

BIFSG

- Imputations developed using Bayesian Improved First name Surname Geocoding (BIFSG)
- Requires conditional independence assumption: First name, last name, and location independent after conditioning on race
- Imputations given by:

$$\Pr[B|F,S,G] = \frac{\Pr[F|B]\Pr[S|B]\Pr[G|B]\Pr[B]}{\Pr[F,S,G]}$$

Estimators

- *Linear Estimator* $\widehat{D}_l$: Regress Y on b. Estimate disparity as association between audit rate and probability Black.

$$\widehat{D}_l = \hat{\beta}_{OLS} = \frac{\sum_i (Y_i - \overline{Y})(b_i - \overline{b})}{\sum_i (b_i - \overline{b})^2} \tag{2}$$

- *Probabilistic Estimator* $\widehat{D}_p$: Use b as a weight. Estimate Black and non-Black audit rates separately, with each taxpayer contributing to both based on b_i

$$\widehat{D}_p = \widehat{Y}_p^B - \widehat{Y}_p^{NB} = \frac{\sum_i b_i Y_i}{\sum_i b_i} - \frac{\sum_i (1 - b_i) Y_i}{\sum_i (1 - b_i)} \tag{3}$$

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Key Theorem: Bounds

Suppose that b is a taxpayer's probability of being Black given some observable characteristics Z, so that $b = \Pr[B = 1|Z]$. Define D_p as the asymptotic limit of the probabilistic disparity estimator, $\widehat{D}_p$, and D_l as the asymptotic limit of the linear disparity estimator, $\widehat{D}_l$. Then:

1.

$$D_p = D - \frac{\mathbb{E}[\text{Cov}(Y, B|b)]}{\text{Var}(B)} \tag{1.1}$$

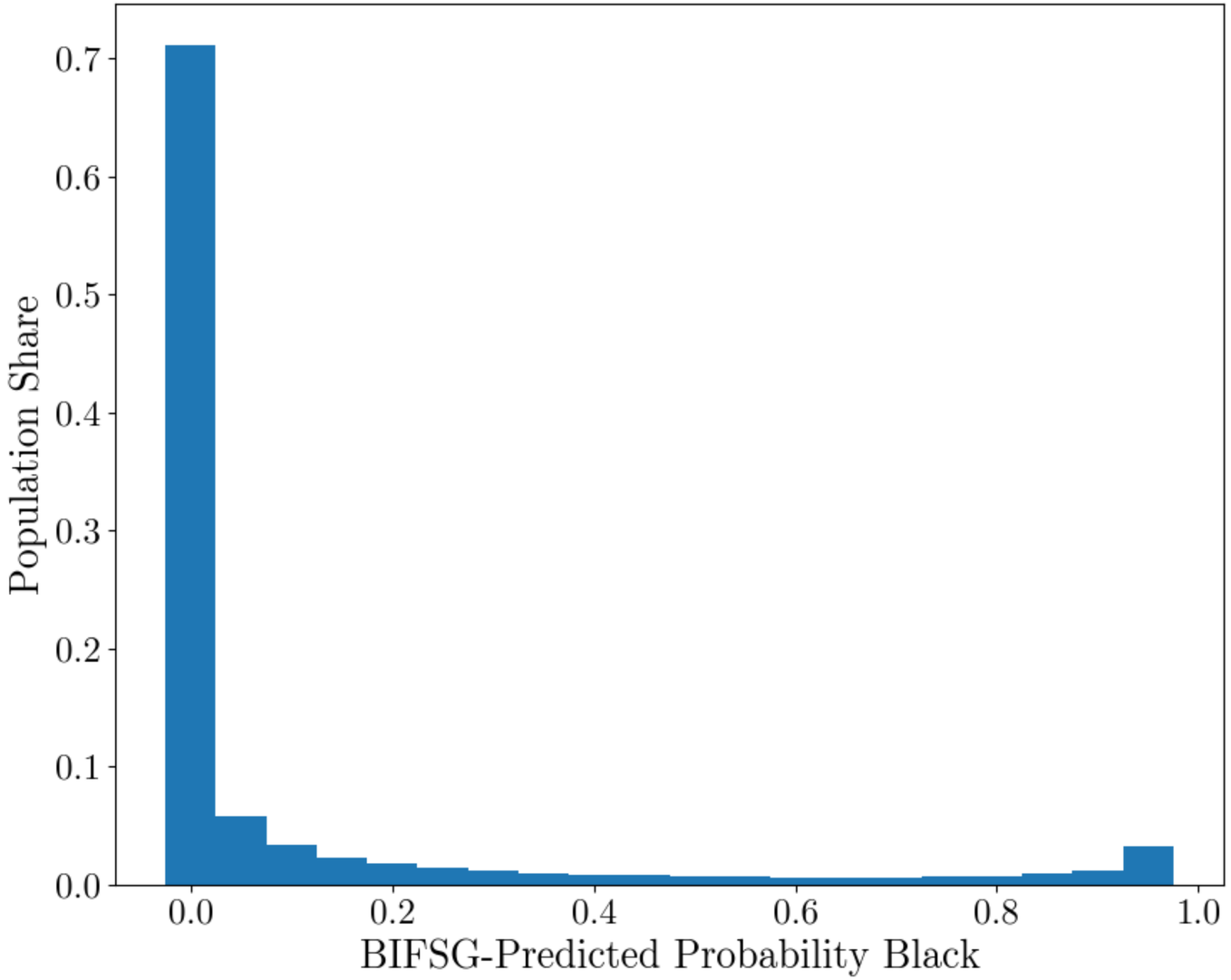
2.

$$D_l = D + \frac{\mathbb{E}[\text{Cov}(Y, b|B)]}{\text{Var}(b)} \tag{1.2}$$

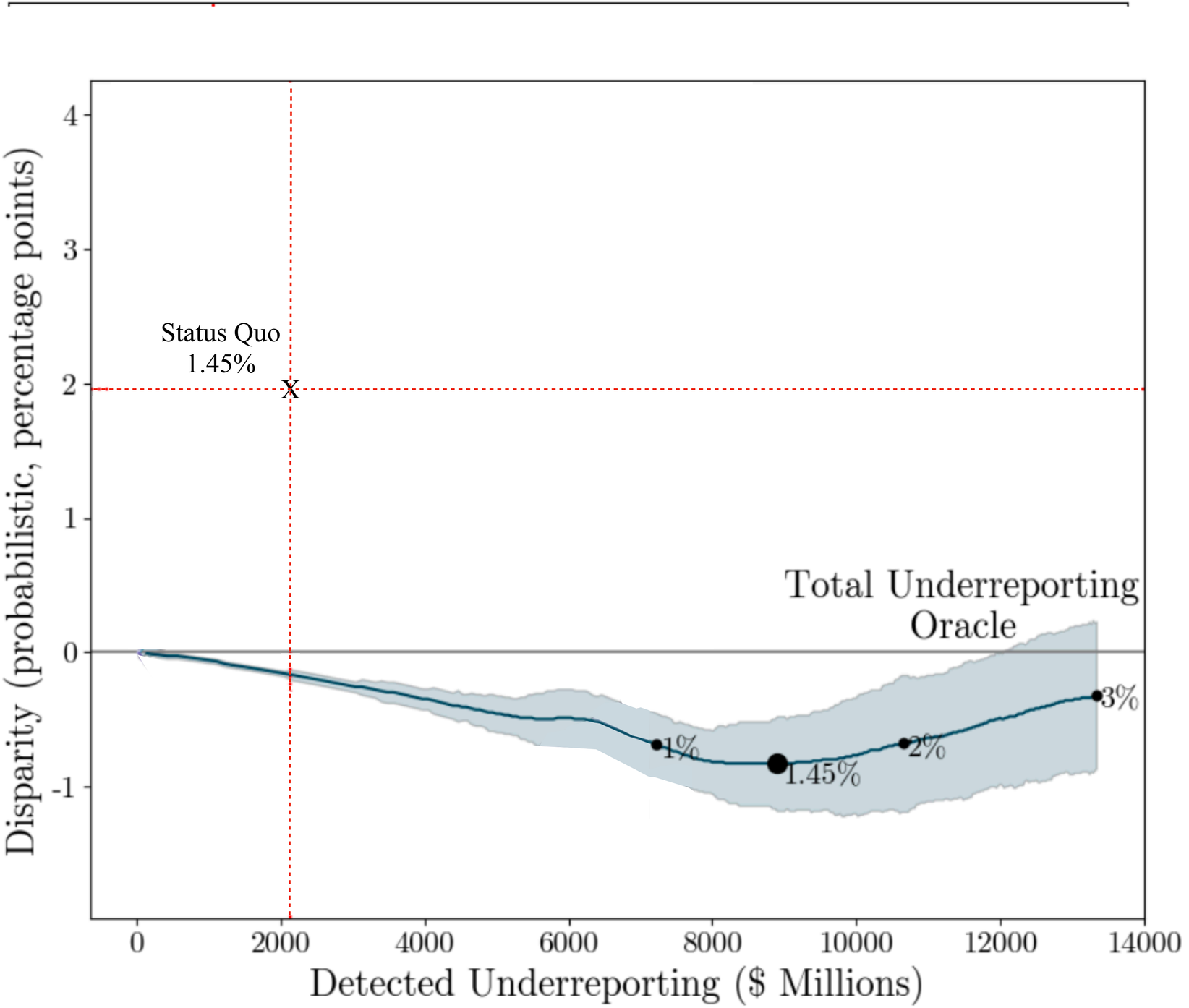
3. Suppose $\mathbb{E}[\text{Cov}(Y, B|b)] \geq 0$ and $\mathbb{E}[\text{Cov}(Y, b|B)] \geq 0$. Then

$$D_p \leq D \leq D_l \tag{1.3}$$

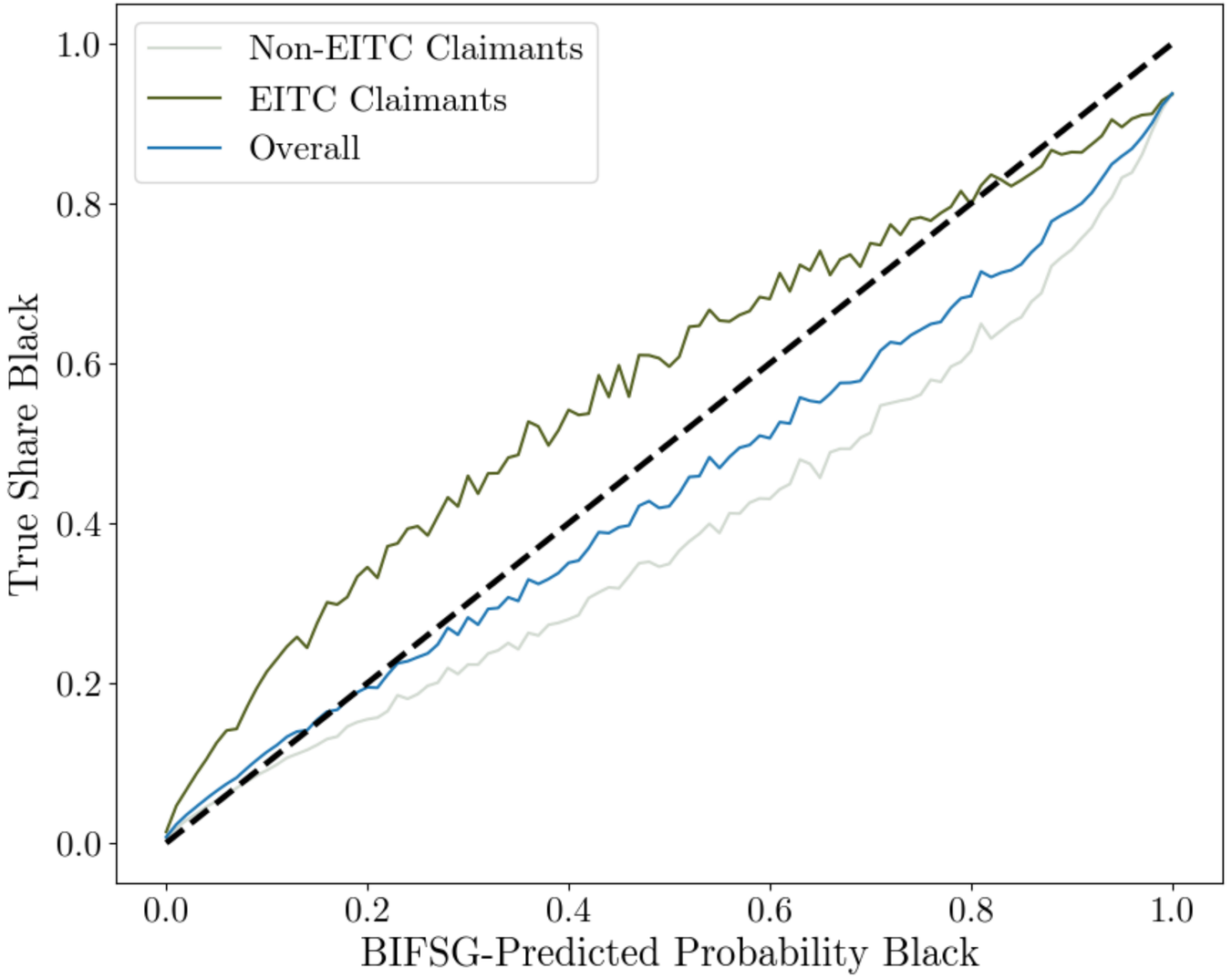
Bimodal BIFSG estimate distribution



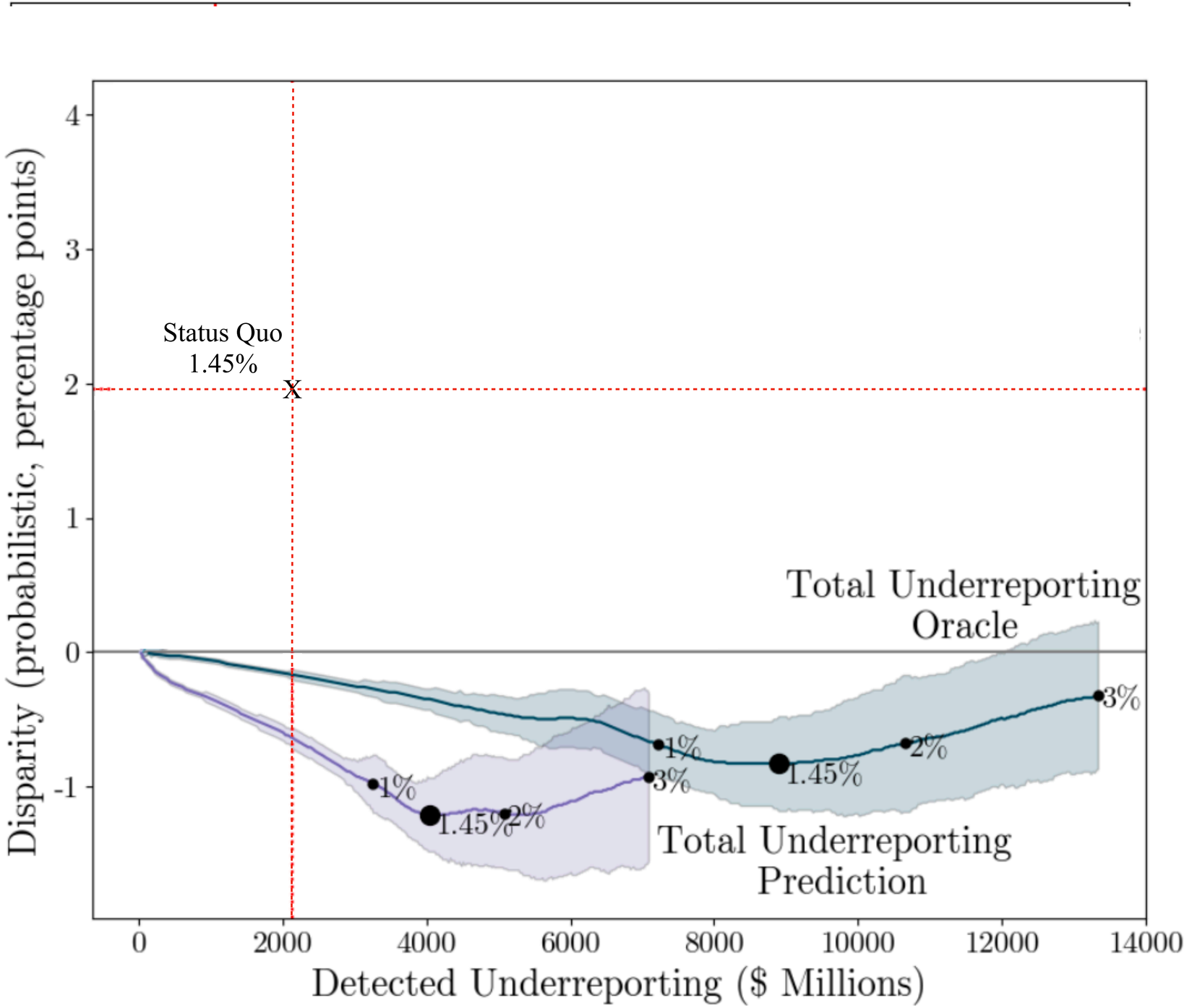
Stanford


Status Quo
1.45%
Total Underreporting
Oracle
1%
1.45%
2%
3%
Disparity (probabilistic, percentage points)
Detected Underreporting ($ Millions)
4
3
2
1
0
-1
0
2000
4000
6000
8000
10000
12000
14000

BIFSG Calibration (vis-a-vis matched NC voter registry)



Stanford


Status Quo
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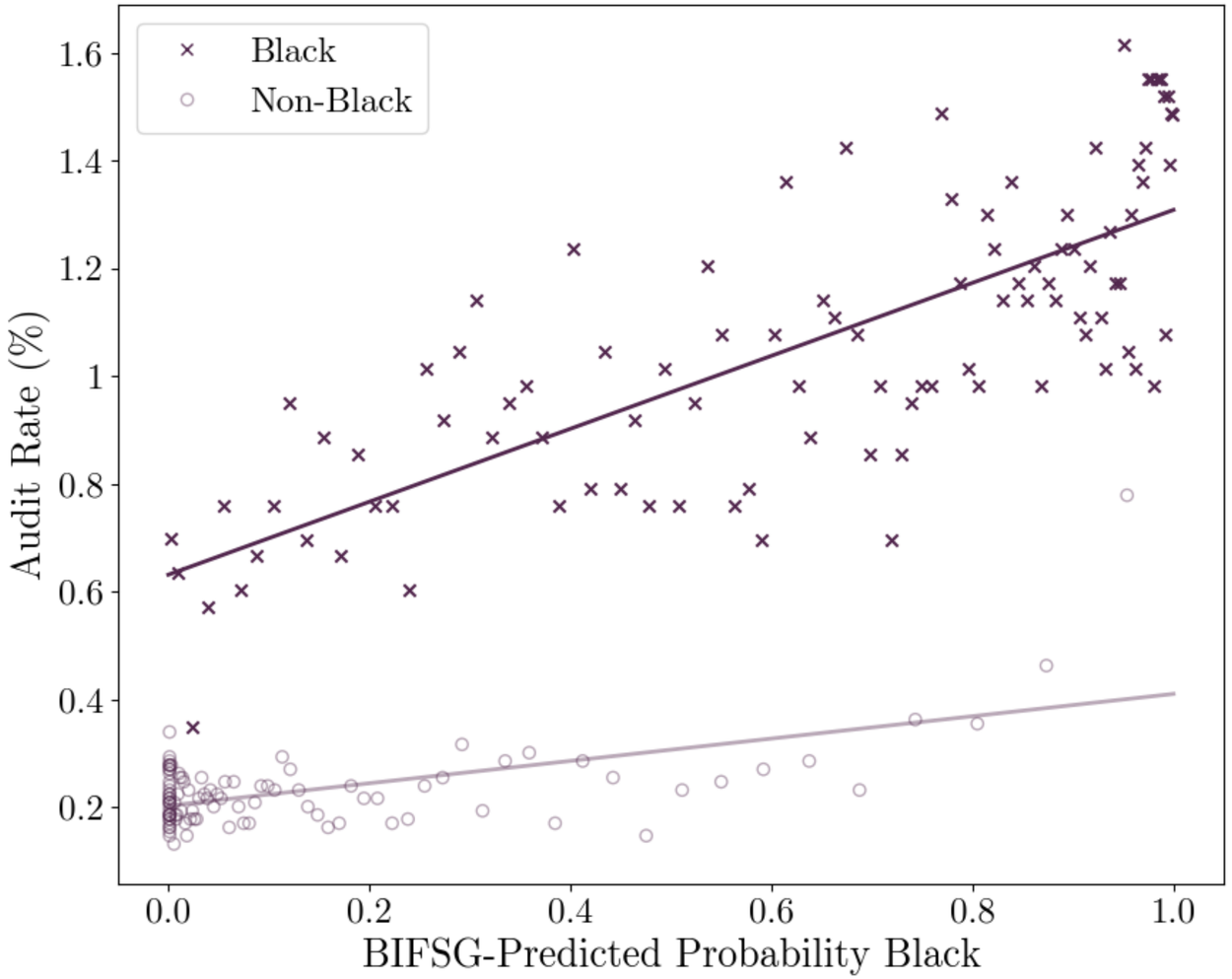
Disparity (probabilistic, percentage points)
Detected Underreporting ($ Millions)
4
3
2
1
0
-1
0
2000
4000
6000
8000
10000
12000
14000

Merged NC data to test for theorem conditions



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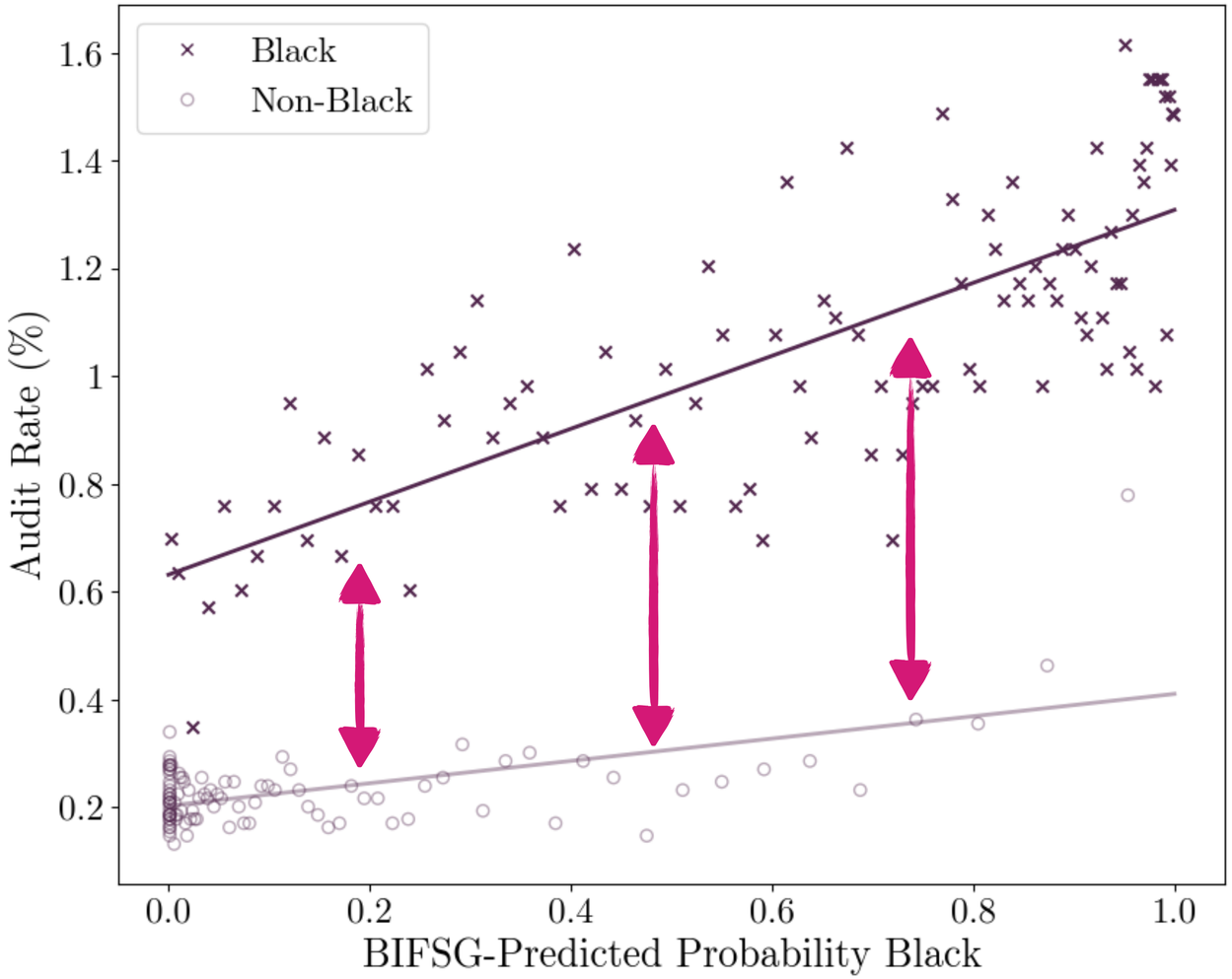
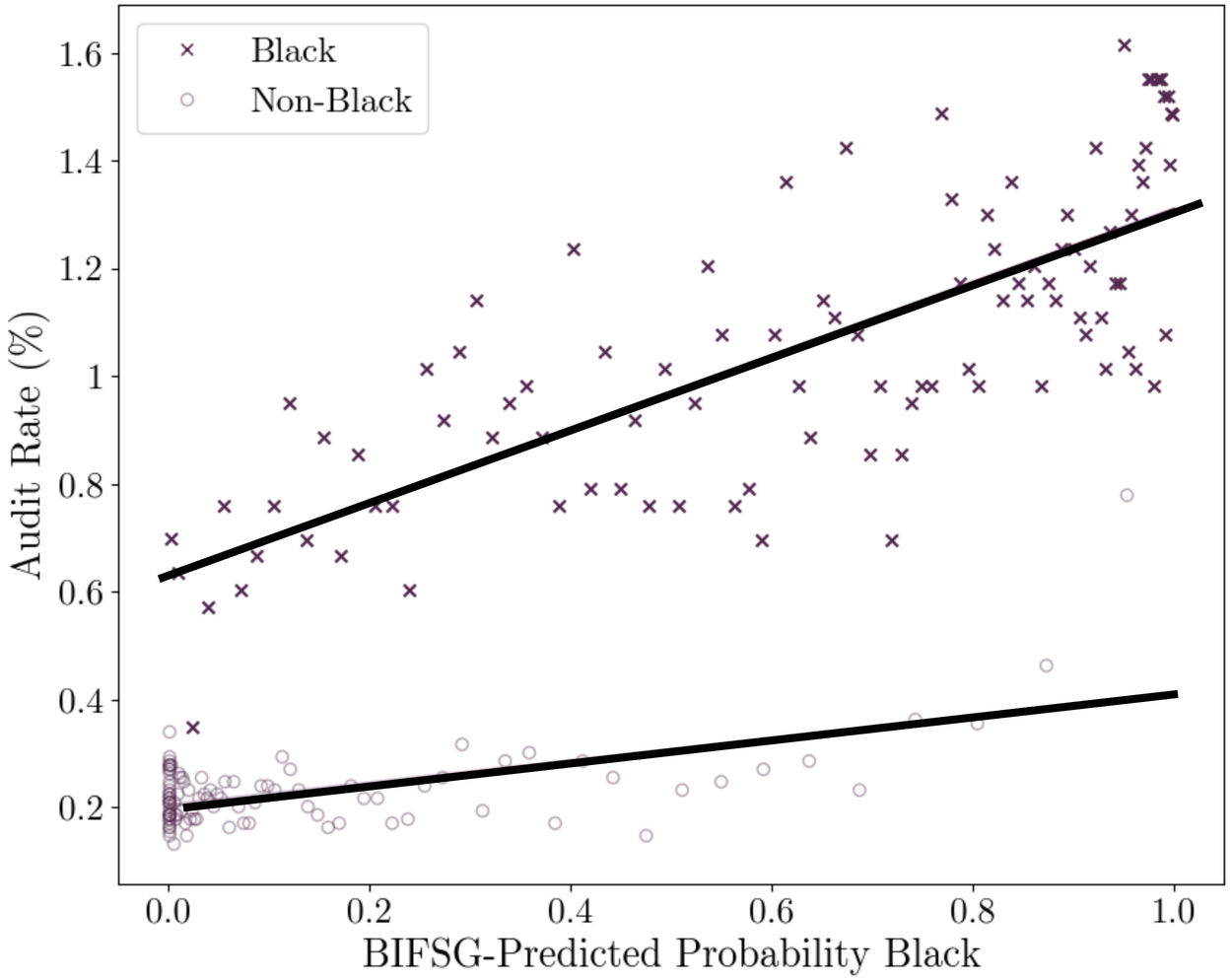


$$\frac{\mathbb{E}[\mathrm{Cov}(Y, B|b)]}{\mathrm{Var}(B)}$$

Merged NC data to test for theorem conditions



$$\frac{\mathbb{E}[\mathrm{Cov}(Y, b|B)]}{\mathrm{Var}(b)}$$