Regulatory Arbitrage or Random Errors? Implications of Race Prediction Algorithms in Fair Lending Analysis

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Motivation

- Major goal of regulators and policymakers is to combat racial discrimination.
  - Check for differential treatment across racial groups
  - Take action against those applying unequal treatment
- In practice, key challenge is that direct information on race often not available
  - Instead, use **proxies** for race to check compliance $\implies$ **classification errors**.
- A key context is lending markets
  - Self-reported race collected for home mortgages (HMDA).
  - But no direct race information for auto, personal, student, or **small business** lending.
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Example: CFPB Action Against Ally

Consumer Financial Protection Bureau

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< Newsroom

CFPB and DOJ Order Ally to Pay $80 Million to Consumers Harmed by Discriminatory Auto Loan Pricing

Ally to Pay Additional $18 Million in Civil Penalties for Harming More Than 235,000 Minority Borrowers

DEC 20, 2013

Example: CFPB Action Against Ally

- What evidence was brought against Ally?
- *The retail installment contracts analyzed by the CFPB and the DOJ* ***did not contain information on the race or national origin of borrowers****. To evaluate any differences in dealer markup, the CFPB and the DOJ assigned race and national origin probabilities to applicants.* ***The CFPB and the DOJ employed a proxy methodology*** *that combines geography-based and name-based probabilities, based on public data published by the United States Census Bureau,* ***to form a joint probability using the Bayesian Improved Surname Geocoding (BISG) method****. The joint race and national origin probabilities obtained through the BISG method were then* ***used directly in the CFPB's and DOJ's models to estimate any disparities*** *in dealer markup on the basis of race or national origin.*

Source: CFPB Consent Order 2013-CFPB-0010.

This Paper

Question: How do prediction errors in proxies for race used for regulatory compliance influence the distribution of lending?

To answer it we need:

1. Data from credit market where race is not collected
2. A replicable algorithm that the regulator uses to evaluate fair lending
3. A measure of actual race that lenders might have access to but regulators do not

Approach:

1. Introduce new small business dataset from Lendio
2. Apply BISG algorithm to generate predicted race probabilities used by regulators
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Main Findings

1. **BISG errors are large.**
   - BISG poorly predicts whether an individual is Black.
   - Twice as many false classifications as correct ones.
2. **BISG errors correlate with socioeconomic characteristics.**
   - High income/education Black borrowers more likely to be misclassified.
3. **BISG errors bias measured disparities in lending.**
   - True approval gap bet. Black, non-Black borrowers 64% larger than implied by BISG.
4. **Average BISG errors vary by lender type.**
   - Fintechs serve high-income Black borrowers missed by BISG.
5. **Counterfactual analysis:** shift to self-reported race would reduce between-race inequality but increase within-race inequality.

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Related Literature

- **Racial disparities in access to financial services:** Tootell, 1996; Bayer et al., 2018; Buchak et al., 2018; Tang, 2019; Fuster et al., 2019; Balyuk et al., 2020; Erel and Liebersohn, 2020; Berg et al., 2020; D'Acunto et al., 2020; Dobbie et al., 2020; Bartlett et al., 2021; Bhutta and Hizmo, 2021; Begley and Purnanandam, 2021; Blattner and Nelson, 2021 Chernenko and Scharfstein, 2021; Fairlie and Fossen, 2021; Giacoletti et al., 2021; Howell et al. 2022.

  Here: How are disparities across groups influenced by how race is *measured*?

- **Racial disparities in entrepreneurship and business lending:** Blanchflower et al. 2003, Robb and Robinson 2018, Asiedu et al. 2012, Bellucci et al. 2013, Fairlie et al. 2022, Arnold et al. 2018, Knowles et al. 2001, Anwar and Fang 2006, Charles and Guryan 2008, Price and Wolfers 2010

  Here: How does regulatory compliance influence the allocation of credit in an environment with *asymmetric information*?

- **Methods to infer race:** Dimmock et al., 2018; Pool et al., 2015; Egan et al., 2022; Frame et al., 2022; Ambrose et al., 2021; Jiang et al., 2021; Athey et al., 2022; Howell et al., 2022.

  Here: New *image-based* method to measure race in lending context.

Simple Model of Lending and Regulation

Simple Model, No Regulation

- Consider a lender who lends to two groups, A and B. Value of lending to individual i of type $j \in \{A, B\}$ is a group-specific mean net of an idiosyncratic cost:

$$v_{i,j} = \mu_j - \varepsilon_i, \qquad \varepsilon_i \sim U[\varepsilon^{min}, \varepsilon^{max}]$$

- We assume $\mu_A > \mu_B$ so that in absence of regulation lenders would provide fewer loans to Group B (motive for regulation).
- Under **No Regulation ("NR")** environment, lender chooses $\{\bar{\varepsilon}_A, \bar{\varepsilon}_B\}$ to maximize:

$$V = \sum_{j \in \{A,B\}} s_j \int^{\bar{\varepsilon}_j} \left(\mu_j - \varepsilon\right) dF_{\varepsilon}(\varepsilon),$$

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Simple Model, Regulation on Actual Race

- Now imagine regulator wants to reduce gap in approval rates across groups, and can observe actual (i.e., self-ID) race.
  - Regulatory constraint: gap between Group A and B approval rates at most κ.
- Under **Actual Race ("AR")** regulation, lender chooses $\{\bar{\varepsilon}_A, \bar{\varepsilon}_B\}$ to maximize:

$$V = \sum_{j \in \{A,B\}} s_j \int^{\bar{\varepsilon}_j} \left(\mu_j - \varepsilon\right) \, dF_\varepsilon(\varepsilon),$$

subject to

$$F_\varepsilon(\bar{\varepsilon}_A) - F_\varepsilon(\bar{\varepsilon}_B) \leq \kappa.$$

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  - Constraint: **predicted gap** between Group A and B approval rates $\leq \kappa$.
  - Let q denote predicted probability that borrower is in Group B.
  - Lender can observe actual race or variables correlated with actual race.
- Under **Predicted Race ("PR")** regulation, lender maximizes:

$$V = \sum_{j \in \{A,B\}} s_j \int \int^{\bar{\varepsilon}_j(q)} \left(\mu_j - \varepsilon\right) dF_{\varepsilon}(\varepsilon)\, dF_{q,j}$$

subject to

$$\sum_{j \in \{A,B\}} s_j \int \left[\frac{1-q}{s_A} - \frac{q}{s_B}\right] F_{\varepsilon}(\bar{\varepsilon}_j(q))\, dF_{q,j}(q) \leq \kappa.$$

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Probability of approval varies by regulatory constraint

- Parameterize ε distribution as uniform: $F_\varepsilon(\varepsilon) = \gamma_0 + \gamma_1 \varepsilon$.
- With **No regulation ("NR")**, probability of approval is:

$$\pi_{i,j}^{NR} = \text{const} + \gamma_1 \underbrace{(\mu_B - \mu_A)}_{<0} \mathbb{I}_{j=B}$$

- With **Actual Race ("AR")**, probability of approval is:

$$\pi_{i,j}^{AR} = \text{const} + \gamma_1 \left[\underbrace{(\mu_B - \mu_A)}_{<0} + \underbrace{\lambda^{AR}(s_A^{-1} + s_B^{-1})}_{>0} \right] \mathbb{I}_{j=B}$$

where λ^{AR} is the multiplier on constraint, s_j is population share.

Probability of approval varies by regulatory constraint

- With **Predicted Race Regulation ("PR")**, probability of approval is:

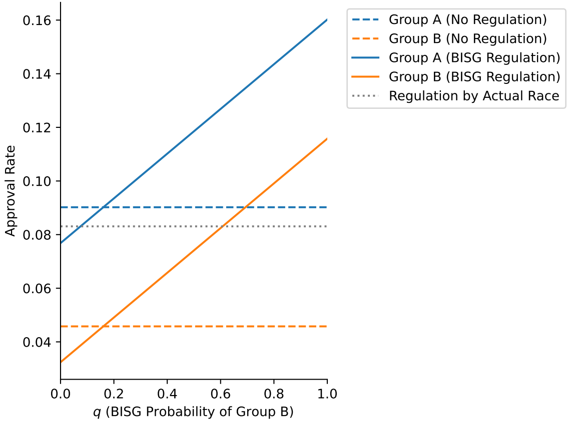
$$\pi_i^{PR} = \text{const} + \underbrace{\gamma_1(\mu_B - \mu_A)\mathbb{I}_{j=B}}_{\text{original term}} + \underbrace{\gamma_1 \lambda^{PR} \left(s_B^{-1} + s_A^{-1}\right) q_i}_{\text{effect of constraint}}$$

- Note: new term loads on q, does not load directly on race.

- Predicted race regulation has no effect on lending by race conditional on q.

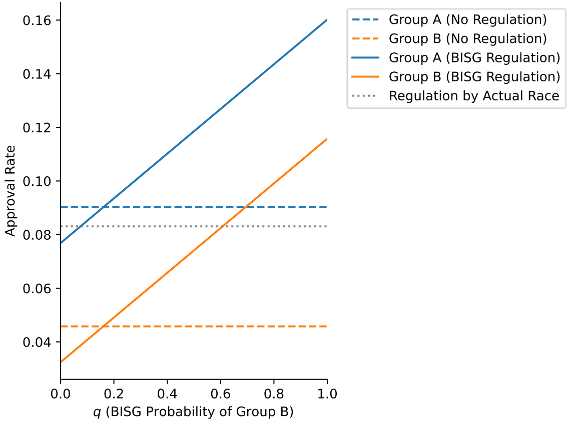
Numerical Example

- Below: approval rates by regulatory regime and q.
- **No Regulation:** large and constant gap between Groups A and B (dashed lines).



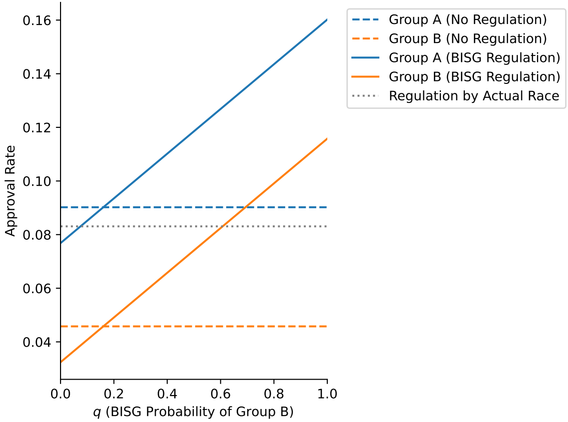
Numerical Example

- **Actual Race Regulation:** equalizes approval rates across groups (dotted line).



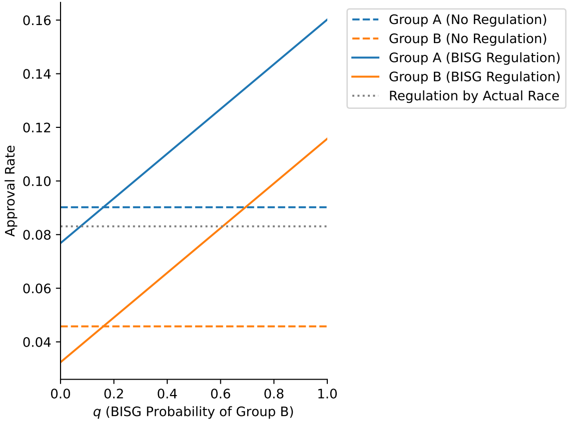
Numerical Example

- **Predicted Race Regulation:** tilts lending toward high q borrowers (relax constraint).
- But gap is equally large conditional on q.



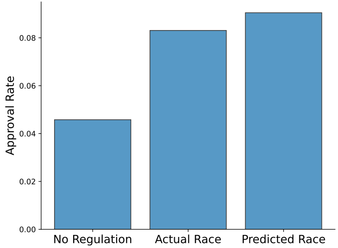
Numerical Example

- PR policy reduces gap because Group B has higher q on average.
- But true approval gap will remain larger than perceived by regulator.

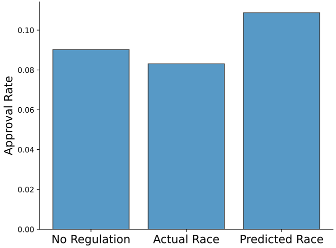


Model: Approval by BISG Classification Type

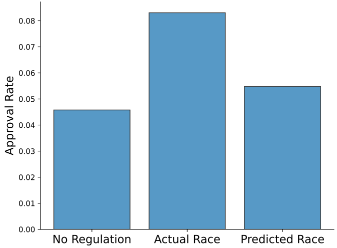
- True positive approval rate is slightly higher under Predicted Race regulation.
- But false pos. approval rate much higher, while false neg. approval rate much lower.



(a) True Positive



(b) False Positive



(c) False Negative

Setting and Data Sources

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- Focus on small business lending
  - Extensive evidence of racial disparities in credit, regulators particularly focused on compliance with fair lending laws
  - Contribute to debate on Dodd-Frank Section 1071: Require small business lenders to collect & report information about race
- We use two samples, neither fully representative, but both useful.
- **Sample 1: Lendio**. Applications and funded loans from online marketplace
  - Enable us to observe lender approval decisions in a real-world context
- **Sample 2: Paycheck Protection Program (PPP)**. Govt-guaranteed, forgivable loans during COVID-19
  - Include self-identified measures of race in a real-world, non-mortgage lending context

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Race Measure 1: Self-Identified Race

- We use three measures of an individual's race.
- *Self-identified*: the race that an individual reports for themselves.
- Available PPP sample, but not in Lendio.
- Note: a person's self-ID race may differ from how they are perceived.

Race Measure 2: BISG

- Bayesian Improved Surname Geocoding (BISG): standard proxy used by regulators.
- Computes probability of each race proportional to product of two components:
  1. **Geography:** fraction of people in your area (ZIP) of that race.
  2. **Surname:** fraction of people in the US with your surname of that race.
- Simple, transparent, and easy to apply, but error-prone for Black Americans.
  - Due to legacy of slavery, huge fraction of Black surnames are ambiguous.
  - Of 10 most common Black American names, only one majority Black.
  - First names would likely help (BIFSG), but data coverage is poor.

Race Measure 3: Image-Based

- Instead of name and geography, we directly infer race from images.
  - May correlate better than self-ID with how individual is perceived.
  - This paper: classify **Black/non-Black** due to name ambiguity, past discrimination.

Step 1: Obtain profile images from LinkedIn.

- Use only profiles that include the company name.

Step 2: Use a pre-trained classifier (VGG-Face/DeepFace) for initial classification.

Step 3: Train random forest model on $\approx$ 170,000 images of entrepreneurs

Step 4: Clerical review of model output.

Comparing Race Measures

- In PPP sample we can compare BISG and image-based proxies to self-ID race.
- Image-based race is highly correlated with self-ID (0.87).
- BISG-based race much less correlated with self-ID (0.54) and image-based (0.56).

	Black (SelfID)	Black (Image)
Black (Image)	0.87***	1.00
BISG Black Percent	0.54***	0.56***
N = 28,990		

Empirical Analysis

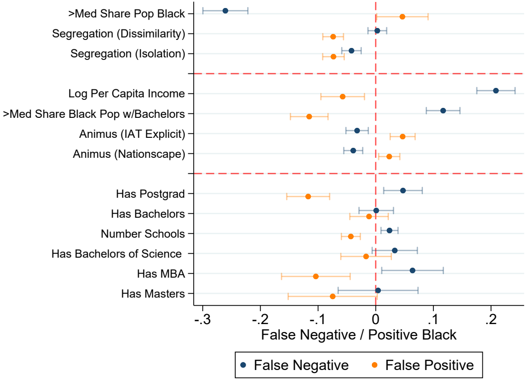
Result 1: BISG Errors are Large

- Below: frequency table of borrowers by BISG and image classification.
- BISG exhibits very large errors classifying Black borrowers.
- Majority of image Black borrowers misperceived by BISG as non-Black.
- Even larger majority perceived as Black by BISG are image non-Black.

	BISG Black	BISG Non-Black
Image Black	3.2%	3.4%
Image Non-Black	5.7%	87.7%

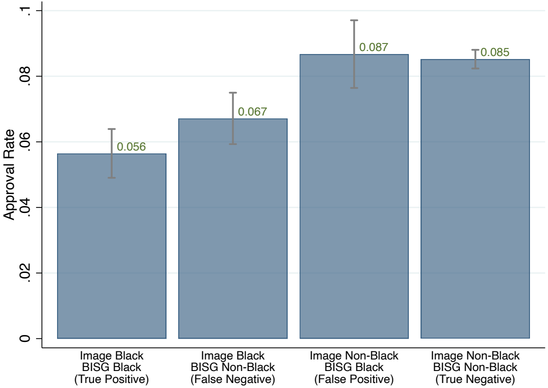
Result 2: BISG Errors are Not Random

- Do errors covary with borrower characteristics?
- Run a sequence of univariate regressions of socioeconomic characteristics on indicators for False Negative and False Positive classification.
- **False Negative:** (Black but BISG believes non-Black) relatively educated, from areas with higher incomes, less segregation/animus.
- **False Positive:** (non-Black but BISG believes Black) show reverse pattern.



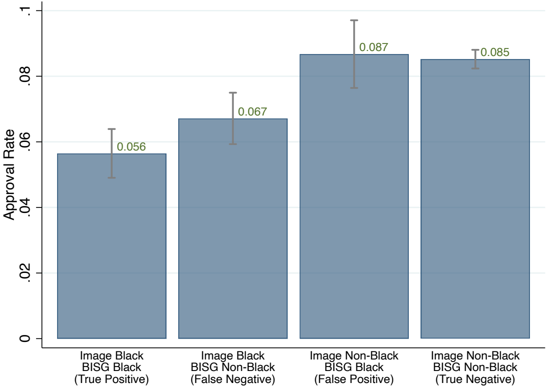
Result 3: BISG Errors Influence Measured Approval Rates

- Loan approval rates vary by BISG classification group.
  - Increasing in q conditional on race, as predicted by theory.



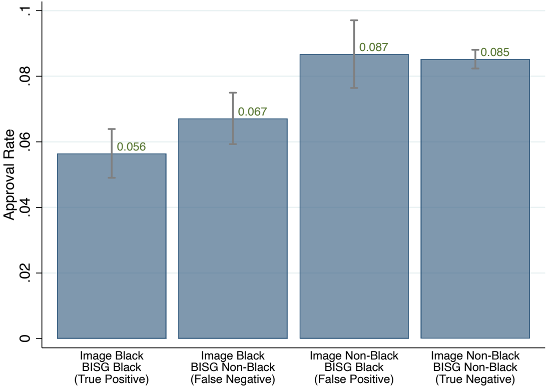
Result 3: BISG Errors Influence Measured Approval Rates

- Regulators compare perceived-Black borrowers (true positive + false positive) to perceived-non-Black borrowers (true negative + false negative).
  - Implied approval gap: **1.1pp**.



Result 3: BISG Errors Influence Measured Approval Rates

- Actual (image-based) approval gap compares image-Black (true positive + false negative) to image-non-Black borrowers (true negative + false positive).
  - Implied approval gap: **1.8pp**. 64% larger!



Measured Approval Rates: Formal Inference

- We next formally test this result.
- In our Lendio sample we run the application-level regression

$$\mathbb{I}(\text{Approved}_{i,l}) = \alpha_l + \gamma_t + \beta\mathbb{I}(\text{Black}_i) + \delta'\mathbf{X}_i + \varepsilon_{il}$$

  where α_i are lender FEs, γ_t are time FEs, and X_i are controls.

- Control for log amount of funding sought and (in some specifications) socioeconomic characteristics.

Measured Approval Rates: Formal Inference

- Columns (1) and (2): our result is robust to fixed effects and controls.

Dependent Variable:	Approved (Mean = 0.08)					
	(1)	(2)	(3)	(4)	(5)	(6)
Black (Image)	-0.018***		-0.016***	-0.016***		
	(0.005)		(0.005)	(0.005)		
Black (BISG)		-0.011**	-0.004	-0.002		
		(0.005)	(0.005)	(0.006)		
True Positive Black (BISG)					-0.023***	-0.021***
					(0.006)	(0.007)
False Positive Black (BISG)					-0.000	0.001
					(0.007)	(0.007)
False Negative Black (BISG)					-0.014**	-0.013**
					(0.006)	(0.006)
Socioeconomic Controls	N	N	N	Y	N	Y

Measured Approval Rates: Formal Inference

- Columns (3) and (4): predictive power of BISG is subsumed by image-based race.
  - Also shows that lenders have information linked to race beyond BISG.

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Measured Approval Rates: Formal Inference

- Columns (5) and (6): bias in approval gap stems from false negative approval rates far lower than those for false positives.

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Result 4: Bias in Approval Rates Varies by Lender Type

- At lender level, construct measure for difference in approval rates using image-based race vs. BISG-based race

$$\Delta_{\text{Share Black Appr}} = \frac{\#\,\text{Image Black Approved}}{\#\,\text{Image Black Applicants}} - \frac{\#\,\text{BISG Black Approved}}{\#\,\text{BISG Black Applicants}}$$

- When $\Delta_{\text{Share Black Appr}} > 0$, lender serving the Black pop at a higher rate than they appear to be with BISG (either more false neg or less false pos)
- When $\Delta_{\text{Share Black Appr}} < 0$, BISG errors make lender appear more compliant with fair lending laws than they actually are

Results: Bias By Lender Type

- Fintechs serve more Black borrowers than predicted by BISG. Consistent with cream skimming or smaller regulatory burden.

	Lendio (Share Approved)			PPP (Share Loans)		
	$\Delta > 0$	Δ	$\Delta >$ 75 Pctile	$\Delta > 0$	Δ	$\Delta >$ 75 Pctile
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech	0.15	-0.00	0.12	0.59^{***}	0.08^{***}	0.64^{***}
	(0.10)	(0.01)	(0.08)	(0.10)	(0.01)	(0.10)
Factoring/MCA/CC	0.02	-0.04^{*}	-0.02			
	(0.15)	(0.02)	(0.13)			
Large Bank				0.22^{**}	0.02	0.21^{**}
				(0.10)	(0.02)	(0.11)
Medium Bank				-0.02	-0.01^{*}	-0.00
				(0.05)	(0.01)	(0.05)
Credit Union/CDFI				0.15^{**}	0.01	0.15^{*}
				(0.08)	(0.01)	(0.08)
MDI				0.01	0.00	0.00
				(0.11)	(0.02)	(0.11)
Y-mean	0.245	-0.006	0.170	0.234	-0.026	0.250

Results: Bias By Lender Type

- Medium and especially small banks (omitted category) serve fewer Black borrowers than predicted by BISG. Consistent with theory under stricter regulation.

	Lendio (Share Approved)			PPP (Share Loans)		
	$\Delta > 0$	Δ	$\Delta >$ 75 Pctile	$\Delta > 0$	Δ	$\Delta >$ 75 Pctile
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech	0.15	-0.00	0.12	0.59***	0.08***	0.64***
	(0.10)	(0.01)	(0.08)	(0.10)	(0.01)	(0.10)
Factoring/MCA/CC	0.02	-0.04*	-0.02			
	(0.15)	(0.02)	(0.13)			
Large Bank				0.22**	0.02	0.21**
				(0.10)	(0.02)	(0.11)
Medium Bank				-0.02	-0.01*	-0.00
				(0.05)	(0.01)	(0.05)
Credit Union/CDFI				0.15**	0.01	0.15*
				(0.08)	(0.01)	(0.08)
MDI				0.01	0.00	0.00
				(0.11)	(0.02)	(0.11)
Y-mean	0.245	-0.006	0.170	0.234	-0.026	0.250

Result 5: Effects of Moving to Actual Race Regulation

- What would happen if regulators collected data on actual (self-reported) race?
  - Major policy rule (Dodd-Frank Section 1071) just finalized in March 2023.
- Theory implies this change in policy would:
  - Tilt lending away from BISG-Black borrowers.
  - Tilt lending toward image-Black borrowers.
- Not clear from the data how large these changes would be.
- However, we can use our data to compute the **direction** of the shift.
  - Vary slope (coefficient) holding total approvals fixed.

Counterfactual Exercise

- Lower weight on BISG-Black would tilt lending away from Black borrowers and false positives, toward true negative (non-Black) borrowers.
- Also tilts lending toward more advantaged, less Black areas.

Characteristic	(1) BISG Weight ↓	(2) Image Weight ↑	(3) Net Change
Panel A: BISG + Image Classification Types			
BISG True Positive Black	-0.590	0.877	0.286
BISG True Negative Black	0.949	-1.728	-0.779
BISG False Positive Black	-0.198	-0.125	-0.323
BISG False Negative Black	-0.161	0.977	0.816
Image Black	-0.751	1.853	1.102
Panel B: Geographic Covariates			
Log Per Capita Income	0.395	-0.273	0.122
Share Pop Black	-0.412	0.369	-0.044
Share Pop w/ Bachelors	0.096	-0.061	0.034

Counterfactual Exercise

- Higher weight on image-Black would tilt lending away from true negatives toward Black borrowers, slightly away from false positives.
- Favors less advantaged, more Black areas.

Characteristic	(1) BISG Weight ↓	(2) Image Weight ↑	(3) Net Change
Panel A: BISG + Image Classification Types			
BISG True Positive Black	-0.590	0.877	0.286
BISG True Negative Black	0.949	-1.728	-0.779
BISG False Positive Black	-0.198	-0.125	-0.323
BISG False Negative Black	-0.161	0.977	0.816
Image Black	-0.751	1.853	1.102
Panel B: Geographic Covariates			
Log Per Capita Income	0.395	-0.273	0.122
Share Pop Black	-0.412	0.369	-0.044
Share Pop w/ Bachelors	0.096	-0.061	0.034

Counterfactual Exercise

- On net, policy would shift more lending toward borrowers who are actually (image-based) Black.
- But also tilts lending toward more advantaged, less Black areas.

Characteristic	(1) BISG Weight ↓	(2) Image Weight ↑	(3) Net Change
Panel A: BISG + Image Classification Types			
BISG True Positive Black	-0.590	0.877	0.286
BISG True Negative Black	0.949	-1.728	-0.779
BISG False Positive Black	-0.198	-0.125	-0.323
BISG False Negative Black	-0.161	0.977	0.816
Image Black	-0.751	1.853	1.102
Panel B: Geographic Covariates			
Log Per Capita Income	0.395	-0.273	0.122
Share Pop Black	-0.412	0.369	-0.044
Share Pop w/ Bachelors	0.096	-0.061	0.034

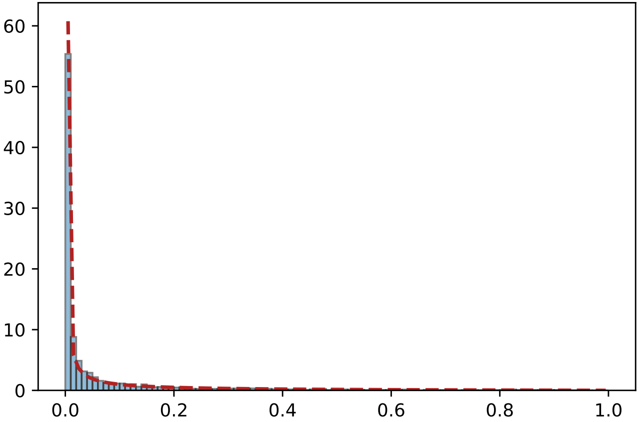
Conclusion

Conclusion

- Regulators want to fight discrimination, but often don't have the data to directly measure it.
  - Instead, rely on imperfect proxies such as BISG.
  - Theory: incentivizes lenders to distort lending, biasing measured approval gaps.
- We use small-business lending data from Lendio and image-based measure of race to measure and analyze BISG errors.
- We find these errors are: (i) large, (ii) correlated with socioeconomic characteristics, (iii) bias measured approval gaps, (iv) vary by lender type.
- Moving to policy based on actual race would reduce between-group inequality, but might increase within-group inequality.

Appendix

Estimated and actual BISG densities for Group A



Estimated and actual BISG densities for Group B

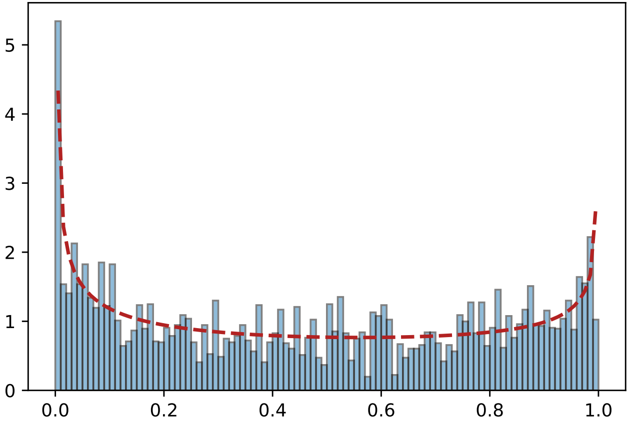


Image-based race is *similar*, not equal, to Self-ID; Image-based race approximates Self-ID, but is not the same

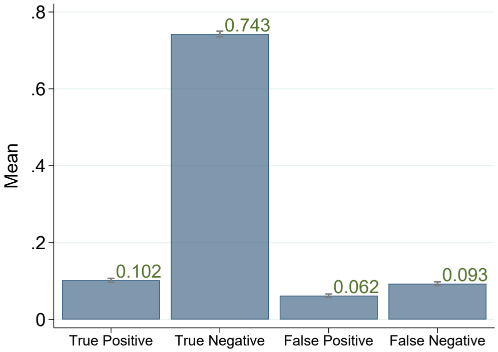
Marcy Ybarra
Self-ID: Black
Image: Hispanic

Daniel Bailey
Self-ID: Black
Image: White

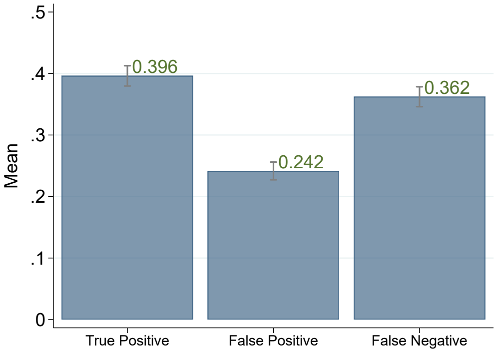
Jessica Williams

Mary Reed

BISG Error Rates (Unique Borrower Level), Lendio Image



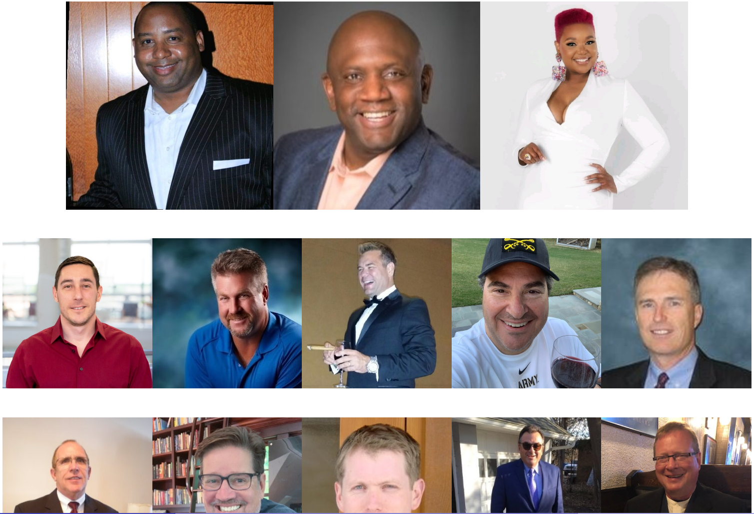
Baseline = Image (Lendio)



Baseline = Image (Lendio, Within Black)

Suppose 25% of *marginal* applicants are Black (Image or Self-ID)

If lenders observe race, a 60% approval rate of all marginal applicants might yield:



We get a different *picture* when we use BISG as a proxy

Why? Sorting on BISG (regulatory motive) likely changes the composition of marginal applicants that are approved

Martin Brown
BISG score: 74

Claudette Hudson
BISG score: 67

Britt Wagner
BISG score: 0.001

Jay Thomas
BISG score: 0.001