Reducing Racial Disparities in Consumer Credit: Evidence from Anonymous Loan Applications

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Motivation

- Access to credit is important for consumption, employment, and earnings (e.g., Bos et al. (2018), Van Doornik et al. (2021), Gross and Souleles (2002))
- Racial disparities in access to credit and terms of credit (Ross et al., 2008; Ghent et al., 2014; Bayer et al., 2016; Bhutta & Hizmo, 2021; Blattner & Nelson, 2021; Bartlett et al., 2022; among others)
- Popular policies to reduce racial disparities: restricting the use of information predictive of race.
  - Credit market: U.S. Fair Housing Act prohibits the use of neighborhood racial composition for lending decisions (e.g., Fuster et al., 2022)
  - Insurance market: California's Proposition 103 excludes zip code from variables permissible for insurance pricing (e.g., Pope and Syndor, 2011)
  - Labor market: "'ban-the-box" restricts employers from asking about applicants' criminal histories on job applications (e.g., Agan and Starr, 2018)

Motivation

- A policy proposal that has received considerable attention from policymakers is the removal of a racially identifying variable, applicant names (Behaghel et al., 2015; Bertrand and Duflo, 2017)
- Large body of experimental evidence of discrimination based on name in the labor market (e.g., Bertrand and Mullainathan, 2004), rental markets (e.g., Hanson and Hawley, 2011), credit markets (e.g., Brock and De Haas, 2022)
- FinTech enables cost-effective implementation of anonymous applications (Bartlett et al., 2022; Dobbie et al., 2021; Howell et al., 2021; Fuster et al., 2022; D'acunto et al., 2022)

This paper

- We study the effect of anonymizing loan applications on racial discrimination in personal lending.
- Data: loan applications, approvals, and originations from a leading online personal loan comparison platform in Singapore.
- Setting: Since Sept 28, 2021, this platform stopped showing applicant names to lenders to protect customer privacy.
- Main findings:
  - With names on applications, ethnic minority applicants are 10.6% less likely to receive loan offers than otherwise observably identical Chinese applicants.
  - Anonymizing applications eliminates such disparities.
  - Racial disparities in loan origination also decrease, despite that race is fully revealed before origination.
  - No racial gaps in loan performance either before or after the change.

Advantages of our setting

- We have a comprehensive picture of the key stages of the credit process

- Compared to experimental studies on anonymous resumes (e.g., Behaghel et al., 2015) that rely on *voluntary* participation of hiring firms, our setting is not affected by self-selection into the natural experiment: all lenders receive anonymous applications in the post period.

Online credit comparison platforms across different countries

credible

lendela

Lendo compara+

cashusa.com

MoneyMutual

BadCreditLoans

Zmarta GROUP

Personal loan (aka cash loan or consumer loan) is *unsecured, short-term, high-cost* loan to consumers.

1. Apply for an online loan in a few minutes

2. Receive offers from multiple lenders online

3. Compare offers and select online

4. Visit the lender in person, sign the agreement, and get the money

Lender reviews online application and decides:

- "**reject the application**"
- "**extend an offer**": Each offer specifies the (a) amount, (b) maturity, (c) interest rate, and (d) processing fee.

Data

- Loan applications, approvals, and originations from a leading online personal loan comparison platform in Singapore, from Oct 2020 to Jan 2022
  - Applicant demographic information: **name**, age, nationality, residency status, income, marital status, full postal code, occupation, housing status, existing borrowing
  - Lender's decision: approval/rejection of the initial offer, initial offer terms (amount, maturity, interest rate, and fee)
  - Applicant's choice among multiple offers
  - Final loan contract terms that the applicant receives

Measurement of minority and sample construction

- Singapore is a multiracial city-state with a resident population of 74.3% Chinese, 13.5% Malays, 9.0% Indians

  → We use the term “minority” to refer to non-Chinese races (Malays, Indians, & others)

- We hand-match applicant names to races (Wong, 2013)
- The main sample is restricted to applications whose information is pre-filled directly from the Singapore government database
  - Official records as opposed to self-reported info → higher data quality
  - Applicant consent helps screen out spam applications (like a “captcha” verification)

Application characteristics

Staring from Sept 28, 2021, Platform stopped showing applicant names to lenders.

	Overall mean	$\mu_{MIN} - \mu_{CHN}$ (before)	$\mu_{MIN} - \mu_{CHN}$ (after)
Age	35.65	-1.06***	-1.01***
	[9.46]	(0.18)	(0.30)
Female	0.25	0.06***	0.12***
	[0.43]	(0.01)	(0.01)
Living in public housing	0.89	0.04***	0.04***
	[0.31]	(0.01)	(0.01)
Annual income (SGD)	35,974.42	-8,818.68***	-7,185.09***
	[46,533.08]	(895.42)	(1,278.94)
Number of applications	16,281	11,789	4,492

Unconditional racial disparities

Staring from Sept 28, 2021, Platform stopped showing applicant names to lenders.

	Overall mean	$\mu_{MIN} - \mu_{CHN}$ (before)	$\mu_{MIN} - \mu_{CHN}$ (after)
Average offer probability (%)	43.48	-4.64***	-2.30*
	[30.68]	(0.58)	(0.92)
Average offer amount (SGD)	4,290.71	-931.15***	-801.60***
	[3,160.12]	(63.01)	(103.88)
Average maturity (months)	6.39	-0.51***	-0.26**
	[2.74]	(0.05)	(0.09)
Average annual nominal interest rate (%)	42.44	-0.00	-0.11
	[4.82]	(0.09)	(0.16)
Average processing fee (%)	9.25	0.02	-0.02
	[0.69]	(0.01)	(0.02)
Average annual effective interest rate (%)	99.02	3.98***	1.42*
	[27.20]	(0.54)	(0.71)
Origination probability (%)	16.79	-1.96**	-1.44
	[37.38]	(0.71)	(1.17)
Number of applications	16,281	11,789	4,492

Empirical design

$$y_{i,j} = \pi_t + \alpha_{j,s(t)} + \gamma_{s(t)}X_i + \beta_{pre} \times (Minority_i \times Pre_t)$$
$$+\beta_{post} \times (Minority_i \times Post_t) + \varepsilon_{i,j}$$

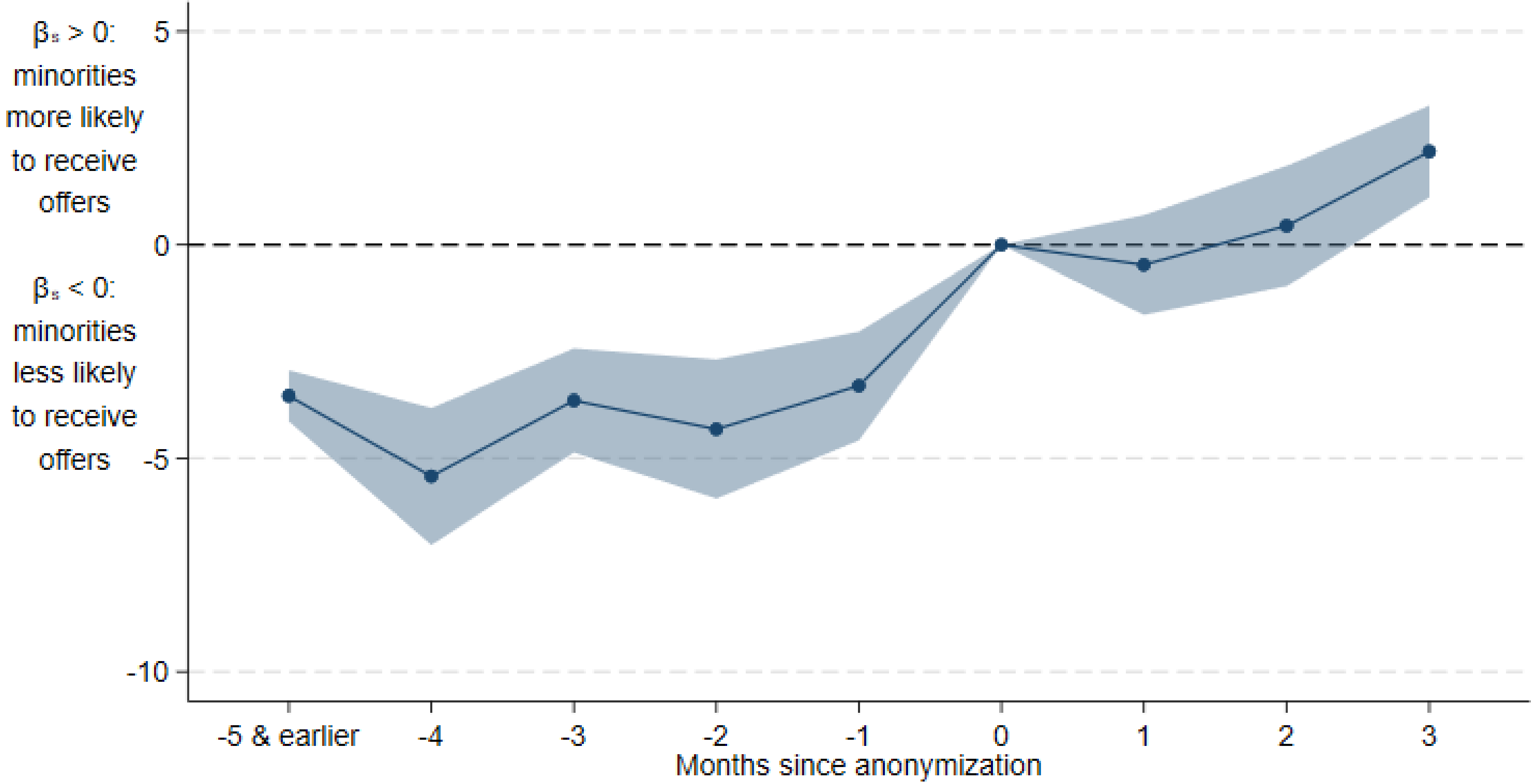
- $y_{i,j}$: credit decisions of lender j for application i whose timing is denoted by t
- $Minority_i$: an indicator for minority applicant
- Pre_t and $Post_t$: an indicator for application is before and after Sept 28, 2021
- β_{pre} and β_{post} reflect racial disparities in the pre- and post-periods, respectively. $\Delta\beta = \beta_{post} - \beta_{pre}$ is the treatment effect in a standard event study setting.
- Control variables and fixed effects:
    - Lender fixed effects separately for the pre and post-periods $\alpha_{j,s(t)}$ with $s(t) \in \{Pre, Post\}$
    - Year-month fixed effects π_t
    - All application characteristics observable to lenders X_i, whose effects are allowed to differ in the pre and post periods $\gamma_{s(t)}X_i$ with $s(t) \in \{Pre, Post\}$
- Robust standard errors clustered at the lender-month level

Disparities in offer rates disappear once names are removed

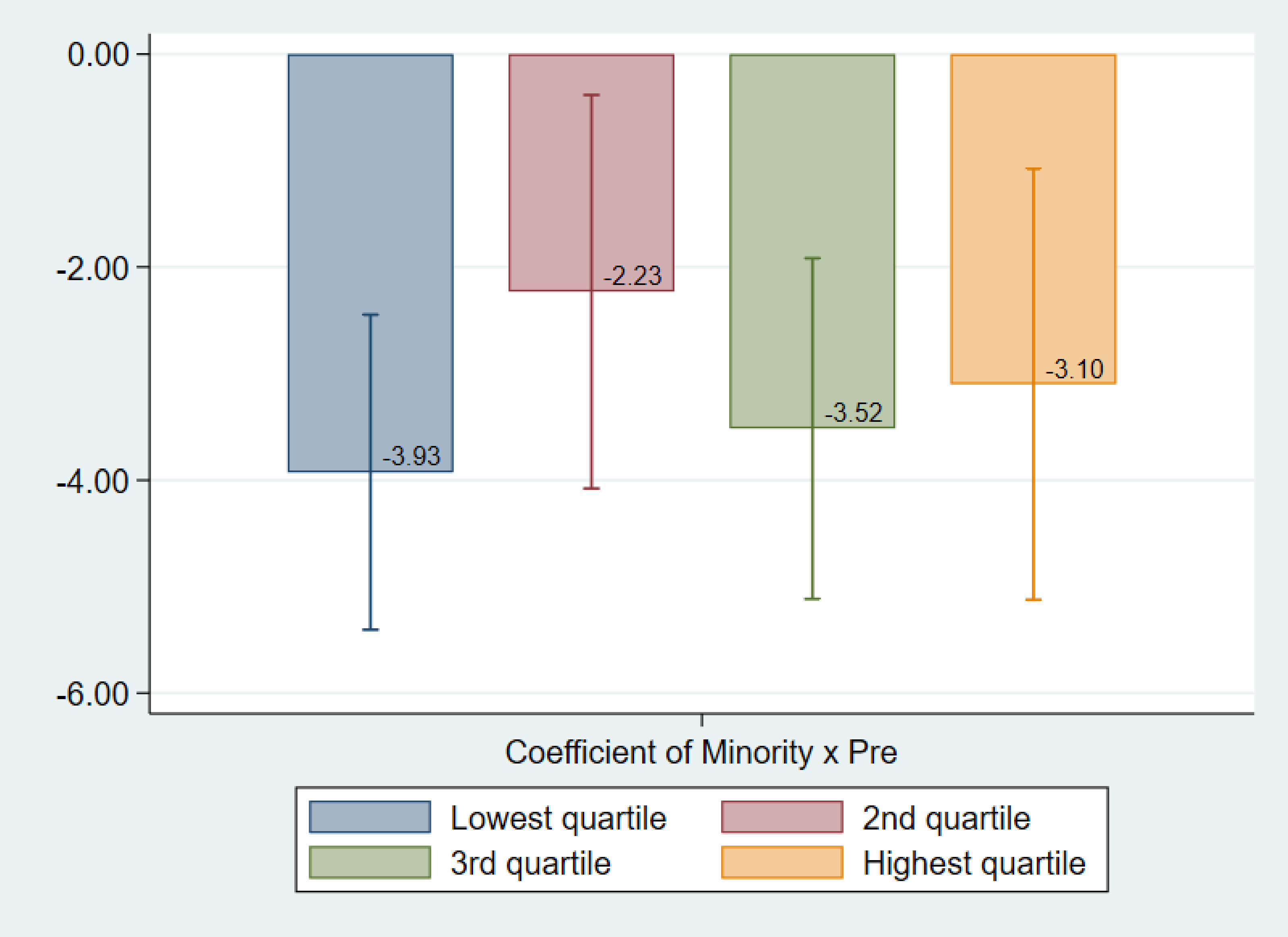
	Application-lender level offer indicator (×100)		Application level average offer probability (%)
	(1) Baseline controls	(2) Alternative controls	(3) Baseline controls
Minority × Pre	-3.810***	-3.096***	-3.969***
	[-16.78]	[-14.08]	[-7.93]
Minority × Post	0.238	0.408	-0.434
	[0.88]	[1.48]	[-0.58]
Δβ	4.048	3.504	3.535
t-stat of Δβ	11.46	9.970	3.910
p-value of Δβ	1.80e-26	4.91e-21	0.00139
Δβ / mean DV	**0.106**	0.0918	0.0813
Year-Month FEs	Yes	Yes	Yes
Lender×Post FEs	Yes	Yes	
Post FEs			Yes
Observable controls	Yes	Yes	Yes
R-squared	0.305	0.291	0.569
No. of observations	322,847	322,847	16,281

Dynamics of racial disparities in offer rate

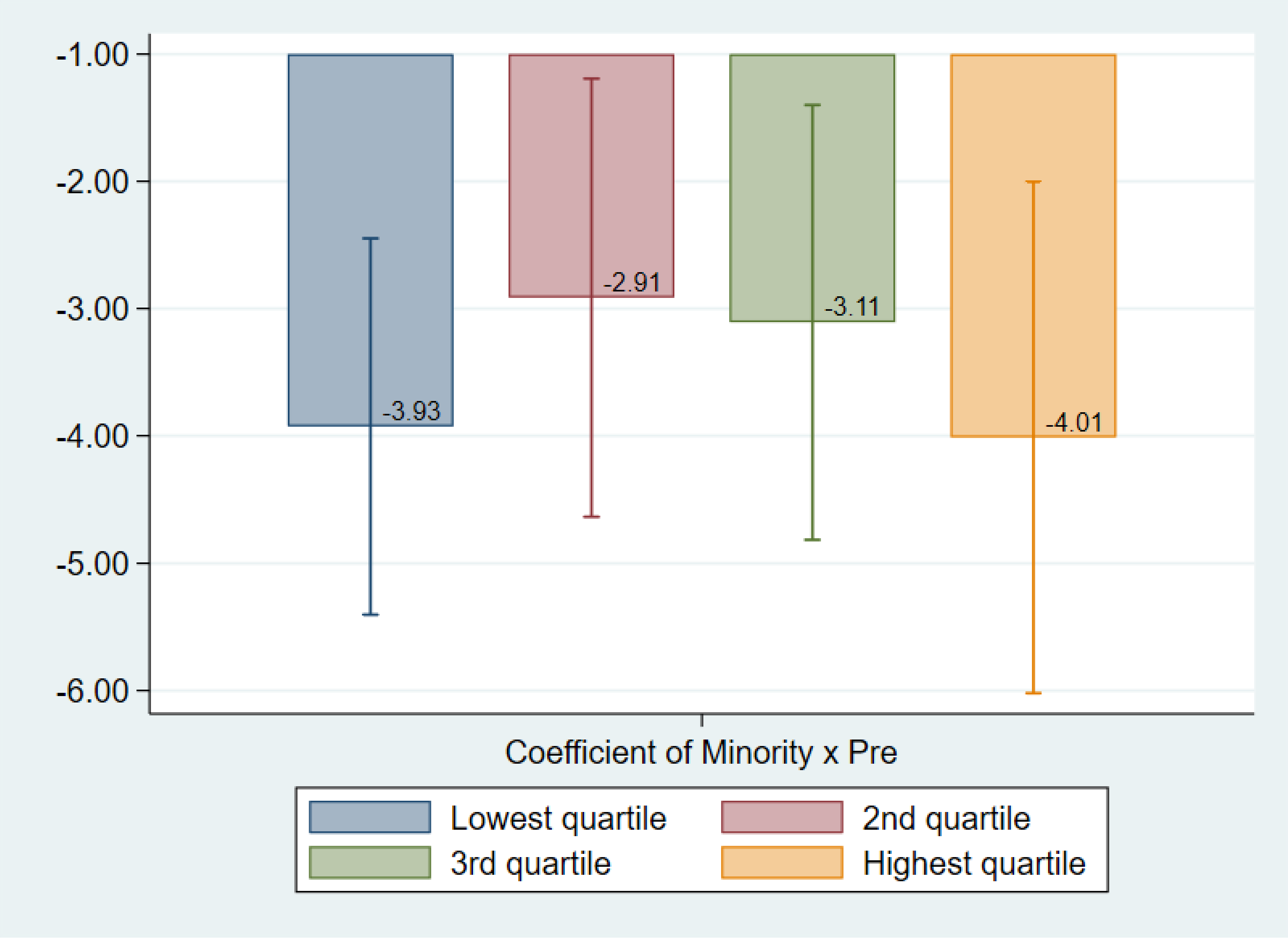
$$y_{i,j} = \pi_t + \alpha_{j,s(t)} + \gamma_{s(t)} X_i + \sum_s \beta_{s\neq 0} \times (Minority_i \times \mathbb{I}_s) + \varepsilon_{i,j}$$



Heterogeneous racial disparities by income



Heterogeneous racial disparities by income-to-debt



Race is revealed at this stage → anonymization does not change lenders’ info set at origination

1. Apply for an online loan in a few minutes

2. Receive offers from multiple lenders online

3. Compare offers and select online

4. **Visit the lender in person**, sign the agreement, and get the money

In-person identity verification & getting the loan

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Partial adjustment by lenders at in-person visits

	Application-lender level offer indicator ($\times$100)	Application-lender level origination indicator ($\times$100)
Minority $\times$ Pre	-3.810***	-0.0910*
	[-16.78]	[-1.68]
Minority $\times$ Post	0.238	-0.0236
	[0.88]	[-0.29]
$\Delta\beta$	4.048	0.0674
t-stat of $\Delta\beta$	11.46	0.692
p-value of $\Delta\beta$	1.80e-26	0.490
$\Delta\beta$ / mean DV	**0.106**	**0.0797**
Year-Month FEs	Yes	Yes
Lender-Post FEs	Yes	Yes
Observable controls	Yes	Yes
R-squared	0.305	0.00792
No. of observations	322,847	322,847

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Partial adjustment by lenders at in-person visits

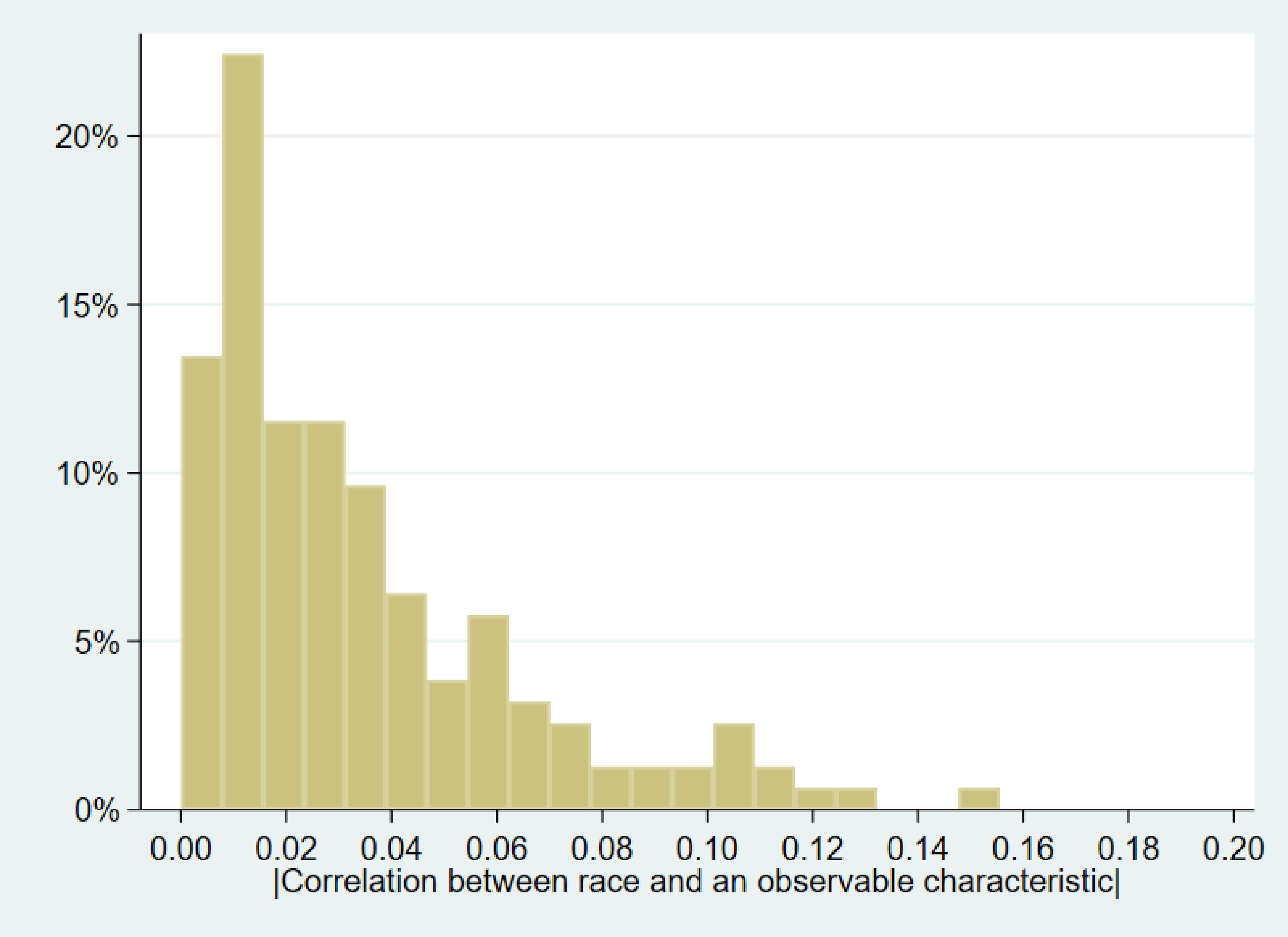
	Application level average offer probability (%)	Application level origination indicator (×100)	Application level conversion rate (%)
Minority × Pre	-3.969***	-1.598*	0.232
	[-7.93]	[-1.89]	[0.97]
Minority × Post	-0.434	-0.500	-0.0764
	[-0.58]	[-0.33]	[-0.14]
Δβ	3.535	1.098	-0.309
t-stat of Δβ	3.910	0.632	-0.517
p-value of Δβ	0.00139	0.537	0.613
Δβ / mean DV	**0.0813**	**0.0654**	-0.0833
Year-Month FEs	Yes	Yes	Yes
Post FE	Yes	Yes	Yes
Observable controls	Yes	Yes	Yes
R-squared	0.569	0.0677	0.0806
No. of observations	16,281	16,281	14,991

Any racial differences in loan performance?

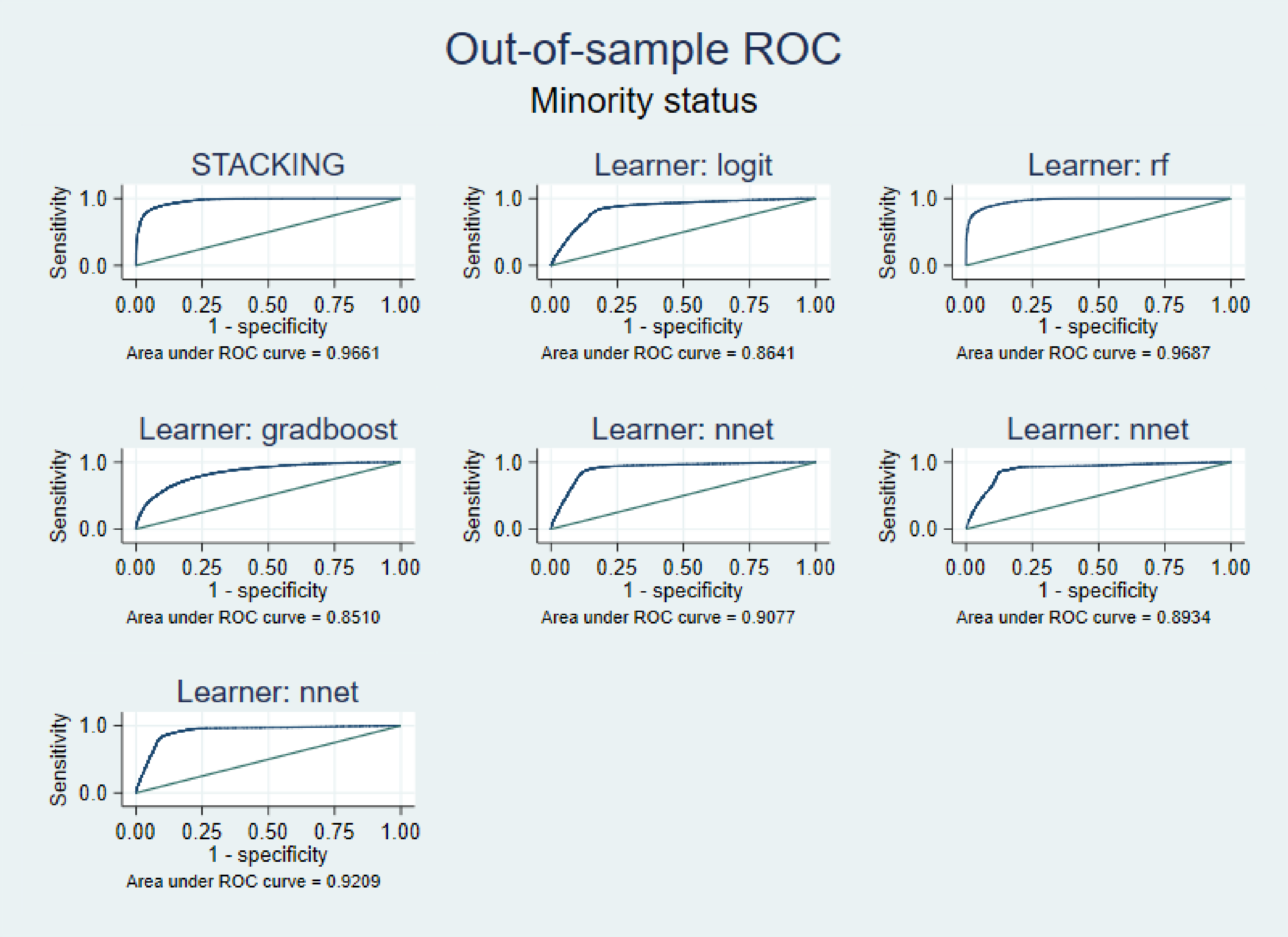
Data on loan performance comes from one lender that originates about 14% of the loans

	Length of coverage	Delinquency indicator (×100)
Minority × Pre	-0.0901	0.151
	[-1.04]	[0.03]
Minority × Post	0.135	-0.319
	[1.42]	[-0.04]
$\Delta\beta$	0.225	-0.471
t-stat of $\Delta\beta$	1.620	-0.0413
p-value of $\Delta\beta$	0.126	0.968
Year-Month FEs	Yes	Yes
Post FEs	Yes	Yes
Observable controls	Yes	Yes
R-squared	0.684	0.406
No. of observations	373	373

Predictability of race from other information



Predictability of race from other information



Discussion

- Strong evidence for discrimination: Before anonymization, minority applicants receive fewer loan offers than otherwise identical Chinese applicants. Once loan applications are anonymized, the racial disparities in offer probabilities disappear.
- Which theory of discrimination best describes our findings?
  - Taste-based discrimination (Becker, 1957)
  - Statistical discrimination (Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977)
- Empirical identification is challenging, even more so in face of inaccurate beliefs (Bohren et al., 2021)

Discussion

1. Similar racial gaps across different quantiles of income and income/debt → repayment ability does not affect racial disparities.
2. Significant discrepancies between the inferred probabilities (based on accurate statistical discrimination model following Agan and Starr (2018)) and empirical probabilities for application characteristics. In particular, the discrepancies do not support stereotypes (Bordalo et al., 2016). → Lenders' beliefs are inaccurate.

→ Accurate statistical discrimination cannot explain our results.

Conclusion

- Focus: Does anonymizing loan applications help minorities and reduce racial discrimination in personal lending?
- Findings: Yes.
  - Racial disparities in loan offer probabilities disappear once names are removed.
  - Racial disparities in eventual loan originations are also decreased by anonymous applications.
- Implications:
  - Anonymization reduces racial discrimination, despite that it merely delays revealing race. It can be a cost-effective way in the digital era to improve equality.

Thank you!

Email me at tianyue.ruan@nus.edu.sg for more questions and comments!