How Costly Are Cultural Biases? Evidence from FinTech

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Motivation

Discrimination pervasive in economic/financial choices (Becker, 1957)

- Agents make choices based on demographics of counterparts
- Statistical discrimination (e.g., Phelps, 1965)
  - Certain demographic groups have average quality below pop. median
  - Absent full information, demographic group provides info about expected quality.
- Taste discrimination (e.g., Becker, 1971; Akerlof and Kranton, 2000)
  - Dislike certain groups, willing to take costly actions to discriminate
  - Bias if performance ex post worse when discriminating
  - Cultural bias: distaste for group due to secular norms and customs

Empirical Challenges

- Need setting that separates statistical vs. taste discrimination
- Need to observe choices that are costly to discriminating agent
- Need benchmark to assess who, if anybody, is biased

This Paper

Propose a setting to test for/measure value of cultural biases

- Peer-to-peer (P2P) lending platform in India
- Robo-advising tool that makes decisions on behalf of lenders
- Can compare lenders' choices before/after robo-advising

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Why is this setting unique to answer the question at stake?

- Little scope for *statistical discrimination*
  - Decoupling risk assessment from lending decisions
  - Platform screens, verifies borrowers. Monitors ex post
  - Lenders choose whom to fund within the (screened) pool

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  - Platform screens, verifies borrowers. Monitors ex post
  - Lenders choose whom to fund within the (screened) pool
- No role for better monitoring/lower moral hazard if discriminate
  - Local-bank lending: lenders might be better at monitoring members of own community, harder to monitor groups against whom they discriminate (e.g., see Fisman et al. 2020)
  - Here, lenders and borrowers all over India. No relationship lending

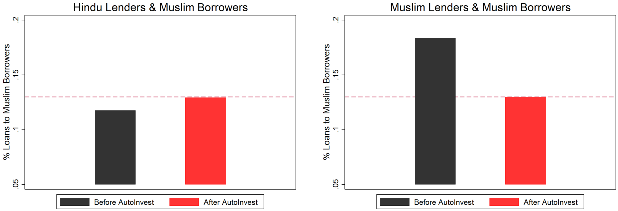
Why India?

Two forms of secular cultural biases (discrimination):

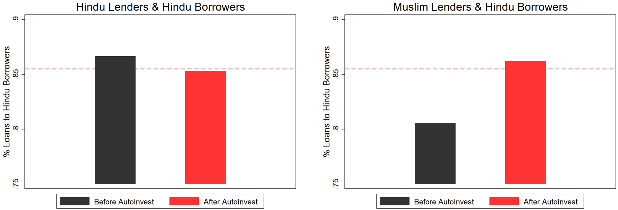
- In-group vs. out-group discrimination: Hindu vs. Muslim
  - Before and after independence (1947), violent conflict
  - Conflict fomented by political parties, regulation
- Stereotypical discrimination: Lower caste (*Shudra*)
  - Centuries-long social discrimination
  - Ingrained in society, no strong opposing forces
    - Not like white vs. minorities in the US
  - Caste not always easy to detect→exploit variation in recognizability
    - Instead, more obvious with minorities in the US

Main Result: Debiasing

Probability of Choosing Muslim Borrowers



Probability of Choosing Hindu Borrowers



- Economically significant extent of discrimination. Drops with robo-advising
- Performance of favored groups improves after debiasing

Related Literature

Discrimination in Economic Choices

- Statistical Discrimination

  Phelps (1972); Borjas and Goldberg (1978) ... and many others
- Taste-Based Discrimination

  Becker (1957); Akerlof and Kranton (2000); Parsons et al. (2011)

→ *Contribution*: Providing a setting to disentangle statistical vs. taste discrimination

Robo-Advising: Humans vs. Machines

- Overview of the field:
  D'Acunto and Rossi (2020), D'Acunto and Rossi (2021)
- Investments:
  D'Acunto, Prabhala, Rossi (2019); Rossi and Utkus (2020); Reher and Sun (2020)
- Consumption/Saving:
  D'Acunto, Rossi, Weber (2020); Lee (2020); Gargano and Rossi (2020)
- Debt Management:
  Golsbee (2004); D'Acunto et al. (2021)

→ *Contribution*: Using robo-advising to create a benchmark for rational decision-making

Data

We use 7 data sets + external aggregate socioeconomic data

- Borrower Characteristics, Lender Characteristics
- Matrimonial registry data
  - Includes religion and caste
- Lender-Borrower-Loan Mapping
  - Each loan is financed by at least 5 lenders
- Loan characteristics data
  - Cross-sectional: Interest rate, Maturity, Log(Amount), Status
- Loan Performance data
  - Panel loan by month, monthly paid amount
- Robo-advising (*Auto Invest*) usage data
  - Date activation, share funds in Auto Invest (intensive margin)

In-group vs. Out-group Discrimination

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In-group vs. Out-group Discrimination

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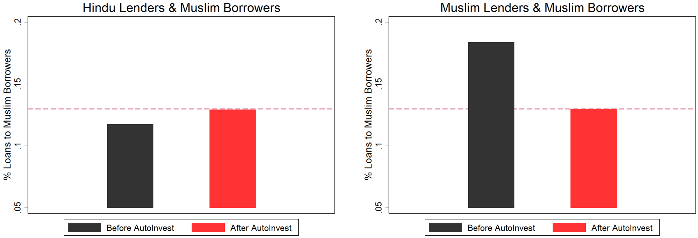

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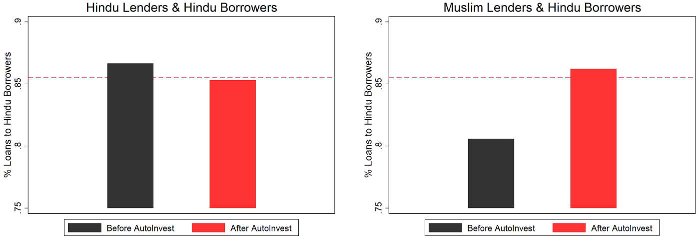
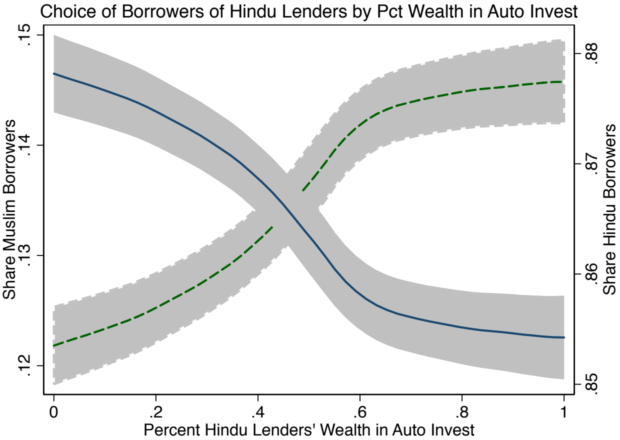


In-group vs. Out-group Discrimination: Intensive Margin



- $\uparrow$ share funds in Auto Invest $\rightarrow \uparrow$ debiasing

In-group vs. Out-group Discrimination: Multivariate

$$\begin{aligned} \mathit{Muslim\ Borrower}_{i,j} =& \alpha + \beta\ \mathit{Auto\ Invest}_j + \gamma\ \mathit{Hindu\ Lender}_j + \\ & \delta\ \mathbf{Hindu\ Lender_j} \times \mathbf{Auto\ Invest_j} + \zeta\ X_i + \eta_j + \epsilon_{i,j} \end{aligned}$$

- Unit of observation: Lender-loan pair
- Loan Risk Measures (X_i):
  Annual interest rate, Maturity (months), Log(Amount)
- Lender fixed effect (η_j)
- S.e. clustered at the lender level (j)

In-group vs. Out-group Discrimination: Multivariate

$$Muslim\ Borrower_{i,j} = \alpha + \beta\ \textbf{Auto Invest}_\textbf{j} + \gamma\ \textbf{Hindu Lender}_\textbf{j} + \delta\ Hindu\ Lender_j \times Auto\ Invest_j + \zeta\ X_i + \epsilon_{i,j}$$

	Baseline	Borrower Char.	Lender FE	Low Use Auto Invest	High Use Auto Invest
	(1)	(2)	(3)	(4)	(5)
Hindu Lender × Auto Invest	**0.04*** (2.51)**	**0.04*** (2.51)**	**0.04*** (2.02)**	**0.009 (0.22)**	**0.05*** (2.05)**
Hindu Lender	-0.06*** (-3.52)	-0.06*** (-3.57)			
Auto Invest	-0.03 (-1.45)	-0.03 (-1.40)	-0.03 (-1.41)	0.01 (0.28)	-0.04 (-1.59)
Loan Risk Measures		X	X	X	X
Lender FE			X	X	X
N. obs.	113,284	113,283	113,283	39,366	72,105

- **Baseline discrimination**: -0.06/0.12 (avg. Muslim share pre) ≈ **50%**
- **Average drop in discrimination**: 0.044/0.06 ≈ **73%**

Heterogeneity: Extent of Hindu-Muslim Conflict

- Ideally, exogenous variation in salience Hindu-Muslim conflict before lenders make their decisions
- Field setting: exploit variation in extent conflict at lenders' locations
- Three sources of variation Hindu vs. Muslim conflict:
  - City-level Hindu-Muslim riots (1980s onwards)
  - State-level vote shares for right-wing Hindu party (BJP)
  - Cohort-level exposure to Hindu-Muslim riots (younger lenders exposed in formative years)

Heterogeneity: Extent of Hindu-Muslim Conflict

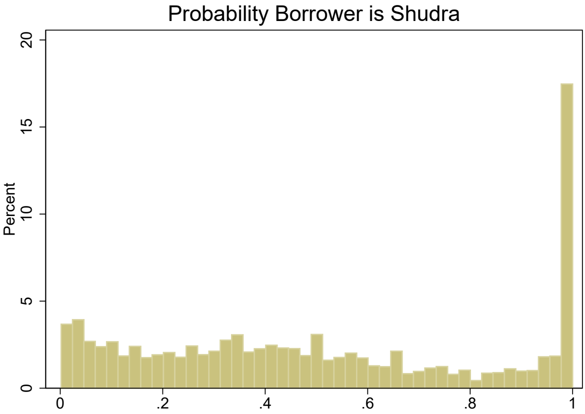
Dependent variable:	**Hindu-Muslim Riots**		**BJP Vote Share**		**Lender Cohort**	
Muslim Borrower	Low	High	Low	High	Young	Senior
	(1)	(2)	(3)	(4)	(5)	(6)
Hindu Lender	0.03	**0.05*** **	0.02	**0.14*** **	**0.07*** **	0.01
× Auto Invest	(0.75)	(2.62)	(0.88)	(4.05)	(3.19)	(0.18)
Hindu Lender	-0.03	-0.06***	-0.04*	-0.09***	-0.07***	-0.03
	(-1.28)	(-3.86)	(-1.94)	(-7.76)	(-4.37)	(-1.29)
Auto Invest	-0.01	-0.03*	0.01	-0.11***	-0.05***	0.02
	(-0.04)	(-1.79)	(0.28)	(-3.22)	(-2.31)	(0.72)
Loan Risk Measures		X	X	X	X	
N. obs.	46,079	67,204	94,909	15,251	44,689	68,594

- **Baseline discrimination** is higher for lenders exposed to Hindu-Muslim conflict
- **Drop in discrimination** is (consequently) higher for those lenders

Moving on to Stereotypical Discrimination

- Traditional (centuries-long) Hindu *varna* system
  - Four hierarchical varnas: *Shudra* bottom group
  - Traditionally segregation, humble jobs
  - Today still discrimination, segregation & set marriages
  - <u>Shudra themselves</u> prefer to interact with higher castes, more prestigious, highly perceived by other Shudras
- All lenders (including Shudra) would tend to discriminate Shudras
- Unique feature:
  Castes are *not* disclosed. Variation in ease of recognition...

Variation in Lower-Caste Recognizability

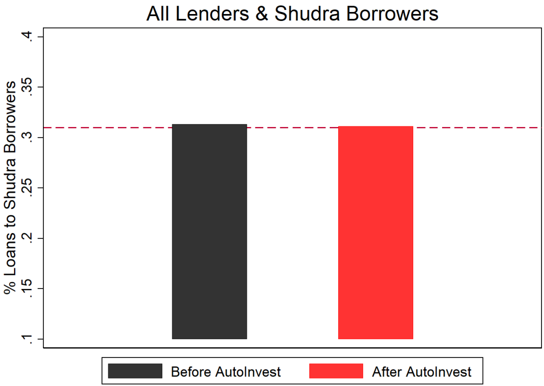


- Algorithm that mimics human assessment of caste (Bhagavatula et al, 2018)
- Based on surname, location, occupation
- Substantial variation in extent Shudra borrowers are recognizable

Stereotypical Discrimination

Choosing Shudra (Discriminated) Borrowers:

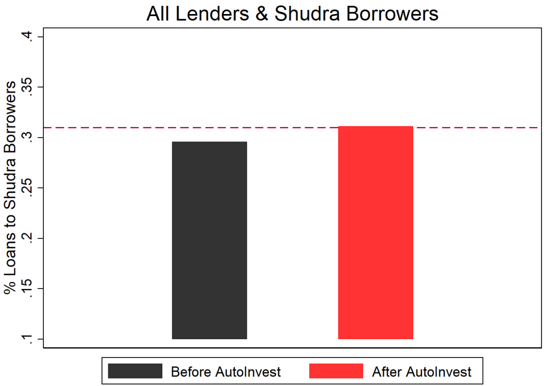
Caste Barely Recognizable (Pr>0)



Stereotypical Discrimination

Choosing Shudra (Discriminated) Borrowers:

Caste Somewhat Recognizable (Pr>50%)



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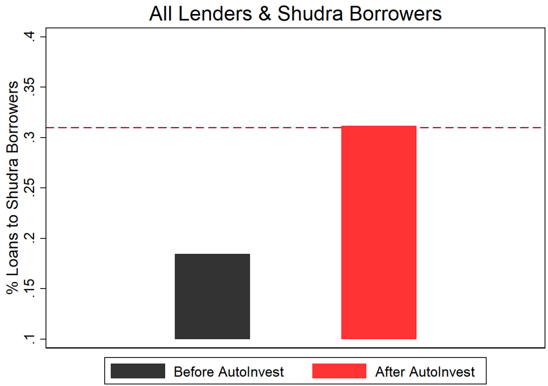
Choosing Shudra (Discriminated) Borrowers:

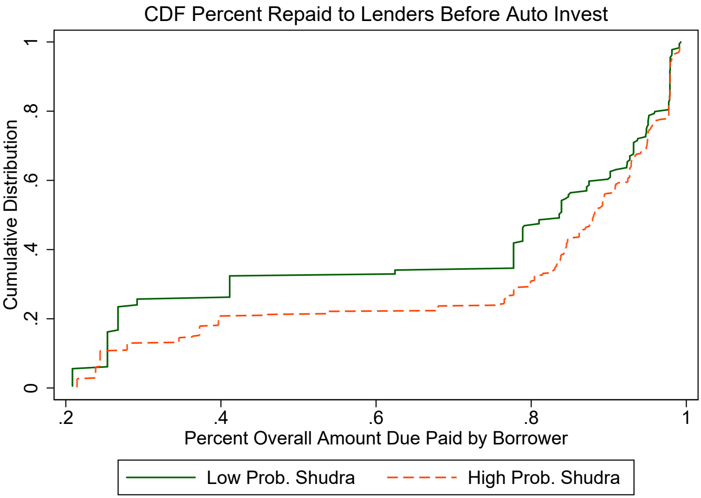
Caste Easily Recognizable (Pr>70%)



From Debiasing to Changes in Performance

- Negative Effect on Loans' Performance?
  - Screening Channel (Ashraf et al, 2017)
    - Easier to assess the riskiness of borrowers from same religion/caste
    - BUT, risk assessment is performed by the platform
  - Monitoring Channel (Fisman et al., 2020)
    - Relationship banking, easier to monitor borrowers from one's community
    - BUT, no local lending here. Lenders and borrowers from all over India
  - Stigma/Moral Hazard Channel (Burstzyn et al., 2019)
    - Borrowers don't want to default on lenders of same religion/caste
    - BUT, no local lending here. No scope stigma default within community
- Positive Effect on Loans' Performance?
  - Taste-Based Discrimination Channel
    - Lenders prefer non-discriminated borrowers, dig deeper in that pool
    - Before debiasing, favorite borrowers should perform worse than others
    - After debiasing, favorite borrowers should be fewer and perform better

Performance, Intensive Margin: Before Auto Invest



- **Size loss**: **130K rupees** ($\approx$ \$1,770) for average lender
- Out of average investment of **1,200K** rupees for average lender

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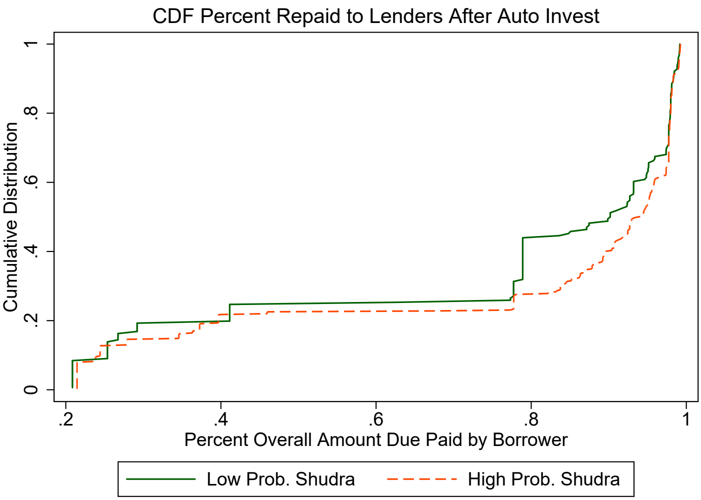


- **Size loss**: drops by **65%**

Conclusion: How Costly Are Cultural Biases?

Unique setting to assess two forms of cultural biases

- In-group vs. out-group discrimination
- Stereotypical discrimination

Empirical Evidence:

- Both forms detected, sizable magnitudes
- Both forms worsen lenders' performance (bad loans)

Policy Implications?

- We do **not** know if lenders are better off with debiasing
- Policy?: provide lenders with information on bias, let them decide if they want to debias by using robo-advising

Platform Pre-Screening of Prospective Borrowers

The P2P platform engages in a two-step screening process of borrowers

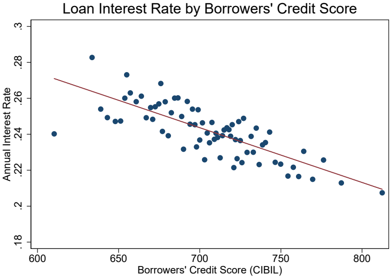
- STEP 1: Prospective borrowers are screened automatically based on hard information
- STEP 2: (Human) officers verify the identity and other information provided by prospective borrowers

$\rightarrow$ If accurate, these steps reduce the scope for statistical discrimination on the part of lenders

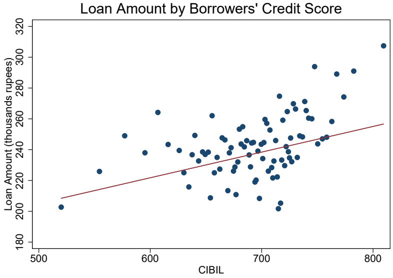
$\rightarrow$ Lenders know about these steps and observe the objective risk proxies the platform attaches to borrowers

Results of Platform's Pre-Screening

Interest Rates by Credit Score



Loan Amounts by Credit Score



- Interest rates and loan amounts are assigned to borrowers based on hard information on risk profile
- If lenders were able to use soft info for statistical discrimination, lenders should perform better when discriminating
- We will see later that lenders perform *worse* when discriminating