How Costly Are Cultural Biases? Evidence from FinTech

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Motivation

Discrimination pervasive in credit markets (Becker, 1957)

- Statistical discrimination (e.g., Phelps, 1965)
  - If asymmetric info, demographics might provide info about quality

  → Improves discriminators' performance, efficient use of information

- Biased discrimination (e.g., Becker, 1971; Akerlof and Kranton, 2000)
  - Taste: dislike certain groups, take costly actions to discriminate
  - Inaccurate statistical discrimination: incorrect beliefs based on demos
  - Cultural biases: such preferences/beliefs shaped by cultural norms

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Empirical Challenges to Disentangle

- Need a measure of discriminators' performance
- Need choices that are costly to discriminating agent
- Need benchmark to assess who, if anybody, is biased

This Paper

- Setting to test for/measure value of cultural biases
  - Peer-to-peer (P2P) lending platform in India
  - AI Robo-advising tool that proposes allocations to lenders
  - Robo-advisor picks randomly conditional on borrower's risk
  - Compare lenders' choices before/after robo-advising

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- Do lenders perform better after switching to robo-advising?
  - NO $\rightarrow$ statistical discrimination
  - YES $\rightarrow$ biased discrimination (taste or inaccurate statistical)

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  - **YES → biased discrimination (taste or inaccurate statistical)**
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  - NO → taste-based discrimination
  - YES → inaccurate statistical discrimination

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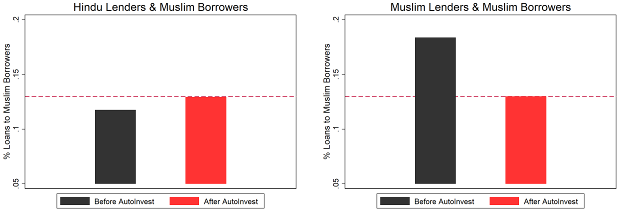
Why India?

Two forms of cultural biases:

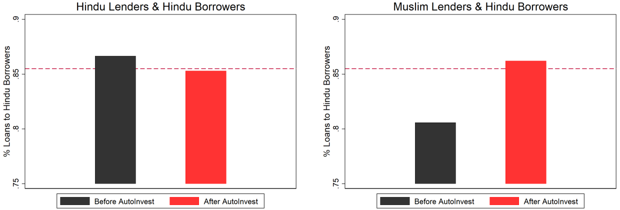
- In-group vs. out-group discrimination: Hindu vs. Muslim
  - Before and after independence (1947), violent conflict
  - Conflict fomented by political parties, regulation
- Stereotypical discrimination: Lower caste (*Shudra*)
  - Centuries-long social discrimination
  - Ingrained in society, no strong opposing forces
    - Not like white vs. minorities in the US

Preview of the Results

Probability of Choosing Muslim Borrowers



Probability of Choosing Hindu Borrowers



- Performance of favored groups improves after debiasing, cut left tail (high risk)

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. biased discrimination

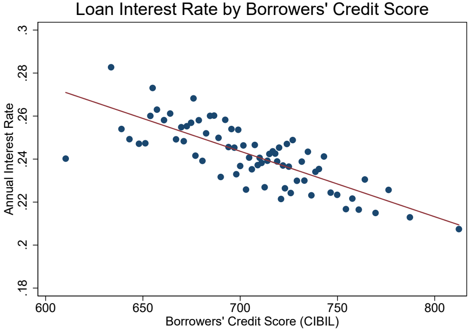
Robo-Advising: Human Choices vs. Algorithmic Choices

- Overview of the area:
  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 assess if decision-making biased

Platform's Screening & Loan Characteristics

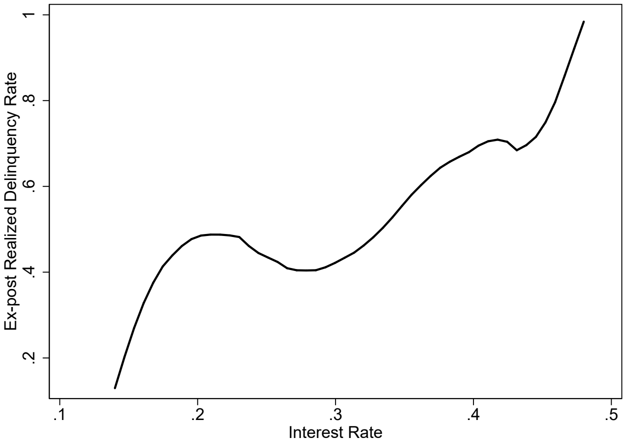
- STEP 1: Prospective borrowers screened (hard info), assigned int. rate, maturity
- STEP 2: (Human) officers verify borrowers' information



Statistical discrimination by platform (probably)

- Decoupling risk assessment from lending decisions
- Platform screens, verifies, monitors borrowers ex post
- Lenders have no role in setting interest rates, maturity, monitoring
- Lenders only choose quantities (if, how much to lend)

Interest Rates and Ex-post Defaults



- Interest rates assigned non-linearly: high defaults pooled just below 50%
- Feature common to other loan pricing (e.g., US mortgages)

Robo-Advising: Auto Invest

My Auto Invest Allocation:

Setup your Auto Invest Allocation here

Total amount to allocate: **₹ 560,465.00**

CATEGORIES	ALREADY DEPLOYED	MAX PROPOSAL AMOUNT (₹)	ALLOCATION (%)	ALLOCATION AMOUNT (₹)
High Range (>26%) Very High, Instant **Min Proposal Amount: ₹ 500**	₹ 8,500.00	500.00	20	112093
Mid Range (18% - 26%) Medium, High **Min Proposal Amount: ₹ 1000**	₹ 21,600.00	1,000.00	35	196162.75
Low Range (<18%) Prime, Minimal, Low **Min Proposal Amount: ₹ 2000**	₹ 38,235.00	2,000.00	45	252209.25

- Lenders decide how much to allocate across three risk categories
- Auto Invest matches them almost randomly with borrowers (order of arrival)
- Instead, unassisted lenders choose very risky borrowers from favored groups

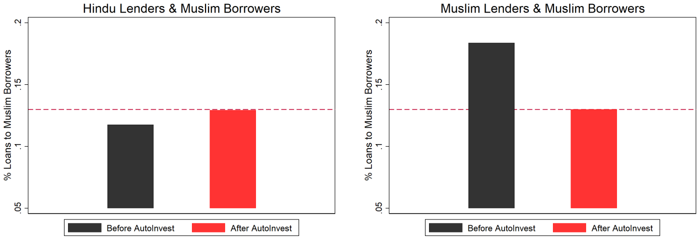
In-group vs. Out-group Discrimination

Two forms of secular cultural biases (discrimination):

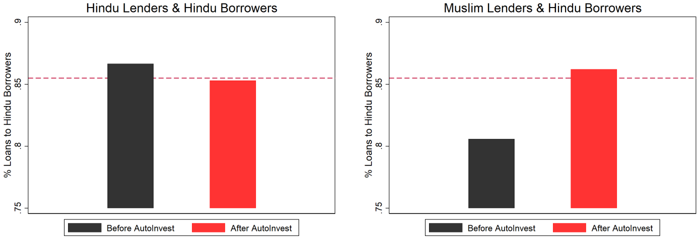
- In-group vs. out-group discrimination: Hindu vs. Muslim
  - Before and after independence (1947), violent conflict
  - Conflict fomented by political parties, regulation
- Stereotypical discrimination: Lower caste (*Shudra*)
  - Centuries-long social discrimination
  - Ingrained in society, no strong 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

In-group vs. Out-group: Extensive Margin

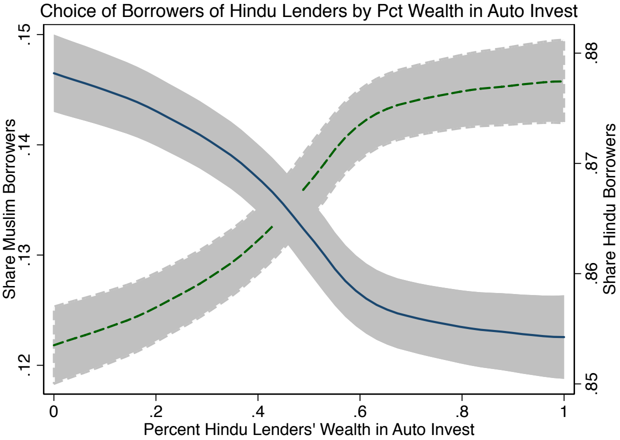
Probability of Choosing Muslim Borrowers



Probability of Choosing Hindu Borrowers



In-group vs. Out-group: Intensive Margin



↑ share funds in Auto Invest (x-axis) → ↑ debiasing (y-axis)

In-group vs. Out-group Discrimination: Multivariate

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

- Unit of observation: Lender-borrower-loan triad
- Loan Risk Measures (X_i):
  Annual interest rate, Maturity (months), Log(Amount)
- Lender fixed effects (η_j): pre-post within lender
- S.e. clustered at the lender level (j), same if double lender-borrower

In-group vs. Out-group: Multivariate

$$\textit{Muslim Borrower}_{i,j} = \alpha + \beta \ \textbf{Auto Invest}_\mathbf{j} + \gamma \ \textbf{Hindu Lender}_\mathbf{j} + \delta \ \textit{Hindu Lender}_j \times \textit{Auto Invest}_j + \zeta \ X_i + \epsilon_{i,j}$$

	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: Salience Hindu-Muslim Animus

- Ideally, exogenous variation salience H.-M. animus by lenders
  see D'Acunto (2020, 2021) on experimental variation salience cultural norms

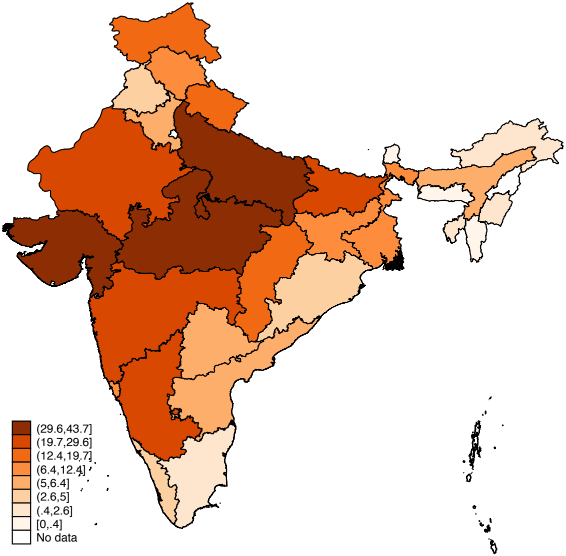
- Instead, XS variation in exposure to ethnic conflict
  - Compare choices of lenders w/ different exposure
  - Vast majority of borrowers in different locations

- Three sources of variation H.-M. animus:
  - City-level Hindu-Muslim riots (1980s onwards)
  - State-level vote shares for nationalistic Hindu party (BJP)
  - Cohort-level exposure to Hindu-Muslim riots
    (younger lenders exposed in formative years)

- Discrimination stronger if higher H.-M. animus

Example: Extent of Hindu-Muslim Conflict

Average Vote Shares Bharatiya Janata Party (BJP), 1977-2015



Heterogeneity: Extent of Hindu-Muslim Conflict

Dependent variable: Muslim Borrower	**Hindu-Muslim Riots** No (1)	Yes (2)	**BJP Vote Share** Low (3)	High (4)	**Lender Cohort** Young (5)	Senior (6)
Hindu Lender × Auto Invest	0.03	**0.05*****	0.02	**0.14*****	**0.07*****	0.01
	(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)
χ^2-test difference		*0.20*		*10.57****		*4.46***
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

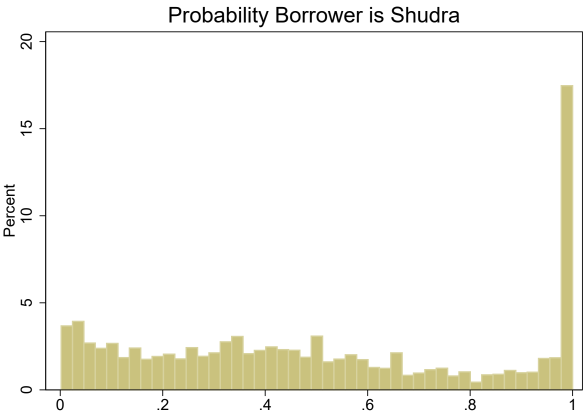
- Traditional, centuries-long Hindu *varna* system (castes)
  - Four hierarchical varnas: *Shudra* bottom group
  - Established segregation: education, jobs, marriages
  - Shudra themselves perceive higher castes as "better" (implicit bias)

- All lenders, <u>including Shudra</u>, should discriminate vs. Shudras

- Unique feature:

  Castes are *not* disclosed. Variation in ease of recognition...

Variation in Lower-Caste Recognizability

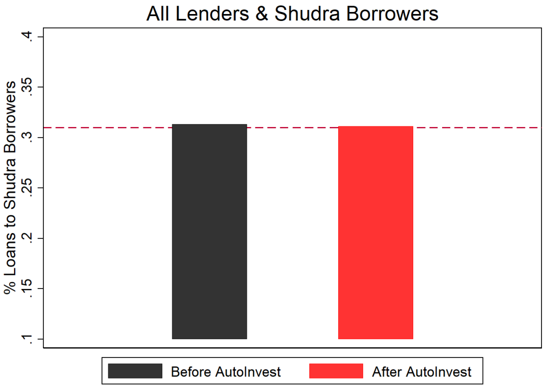


- Algorithm that mimics human assessment of caste (Bhagavatula et al, 2018)
- Based on surname, location, occupation
- Substantial variation in extent Shudra borrowers are recognizable

Stereotypical Discrimination

Choosing Shudra (Discriminated) Borrowers:

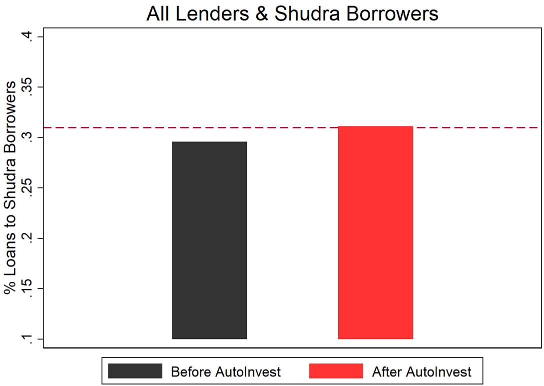
Caste Barely Recognizable (Pr>0)



Stereotypical Discrimination

Choosing Shudra (Discriminated) Borrowers:

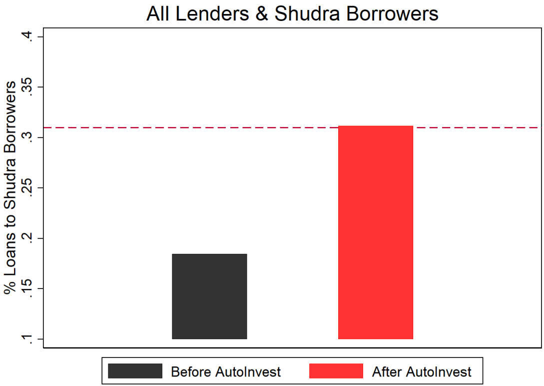
Caste Somewhat Recognizable (Pr>50%)



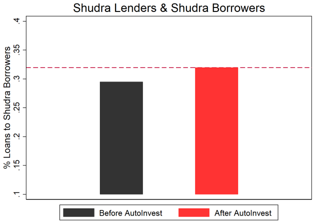
Stereotypical Discrimination

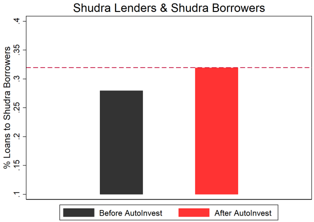
Choosing Shudra (Discriminated) Borrowers:

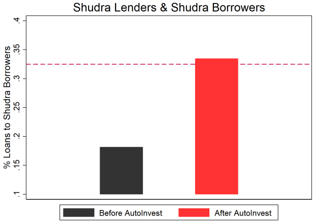
Caste Easily Recognizable (Pr>70%)



Shudra vs. Shudra: Altruism vs. Discrimination

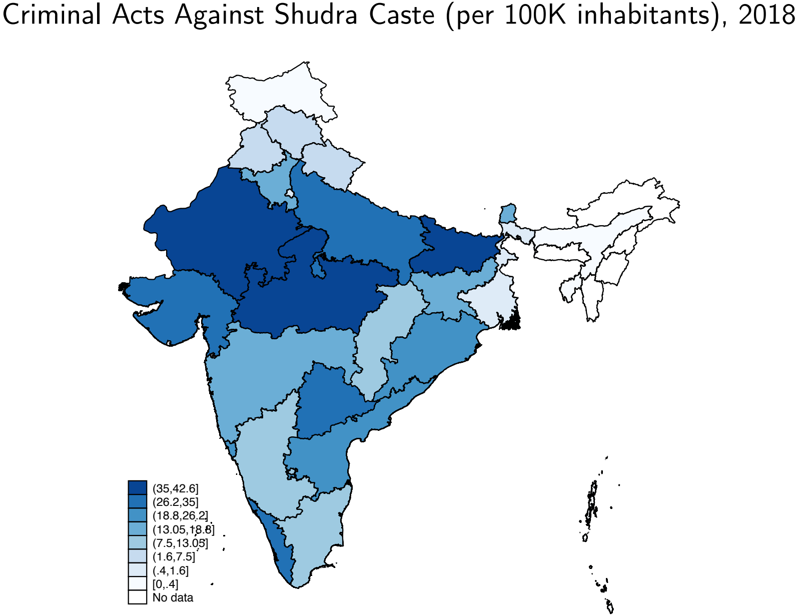






- Shudra lenders discriminate even more against Shudra borrowers
- Result that dismisses a role for kin altruism

Heterogeneity: Local Crime Acts Against Shudras



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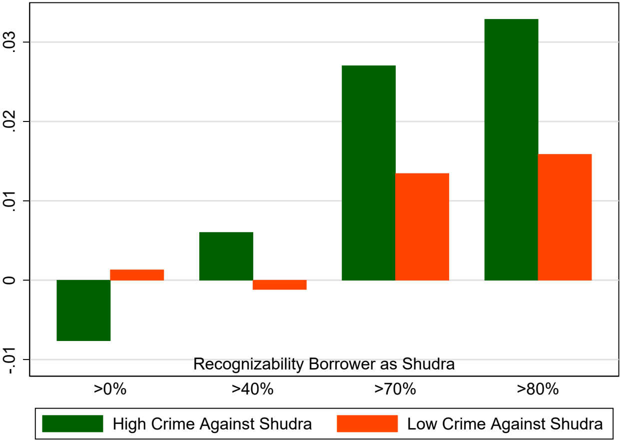
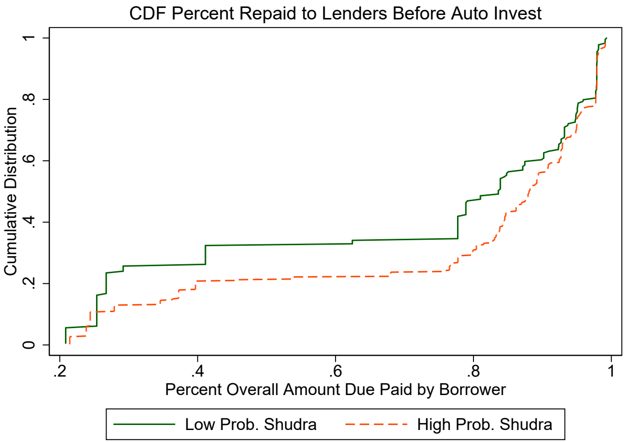


From Debiasing to Performance

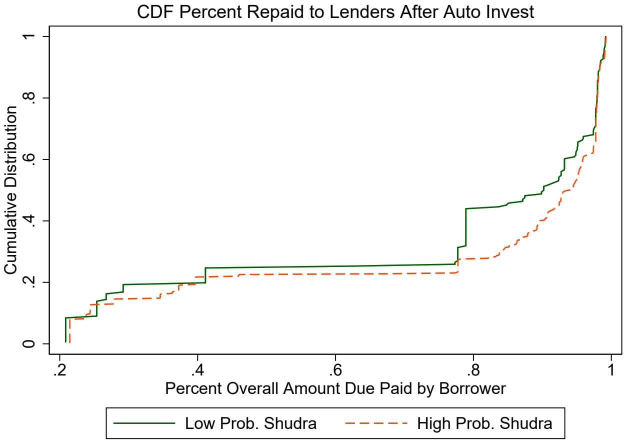
- Positive Effect on Loans' Performance?
  - Culturally Biased Discrimination
    - Lenders dig deeper within the preferred pool
    - Before debiasing, favorite group should perform worse
    - After debiasing, favorite group should perform better
- Negative Effect on Loans' Performance?
  - Screening Channel (Ashraf et al, 2017)
    - Easier to assess the riskiness of borrowers from same religion/caste
  - Monitoring Channel (Fisman et al., 2020)
    - Relationship banking: easier to monitor borrowers from one's community
  - Stigma/Moral Hazard Channel (Burstzyn et al., 2019)
    - Borrowers don't want to default on lenders of same religion/caste

Performance, Intensive Margin: Before Auto Invest



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

Performance, Intensive Margin: After Auto Invest



- **Size loss**: drops by **65%**
- Driven by improvement of favored group, cut left tail very risky borrowers

Change in Performance: Hindu vs. Muslim

Dependent variable:	Lender		Lender	
Delinquent Loan	Hindu	Hindu	Muslim	Muslim
	(1)	(2)	(3)	(4)
Auto Invest	-0.09***		-0.34***	
	(-5.16)		(-3.28)	
Muslim Borrower	-0.05***		0.29	
	(-4.08)		(1.57)	
Hindu Borrower $\times$ Auto Invest				
Muslim Borrower $\times$ Auto Invest				
Loan Risk Measures	X	X	X	X
N. obs.	16,985	16,985	100	100

- **Likelihood default** drops by **40%** for Hindu lenders (=-9pp/22.5pp)

Change in Performance: Hindu vs. Muslim

Dependent variable:	**Lender**		**Lender**	
Delinquent Loan	Hindu	Hindu	Muslim	Muslim
	(1)	(2)	(3)	(4)
Auto Invest	-0.09***		-0.34***	
	(-5.16)		(-3.28)	
Muslim Borrower	-0.05***	-0.07***	0.29	0.44***
	(-4.08)	(-4.02)	(1.57)	(5.63)
Hindu Borrower		**-0.09*** **		-0.33***
× Auto Invest		**(-5.38)**		(-2.79)
Muslim Borrower		-0.05*		**-0.53*** **
× Auto Invest		(-1.79)		**(-2.40)**
Loan Risk Measures	X	X	X	X
N. obs.	16,985	16,985	100	100

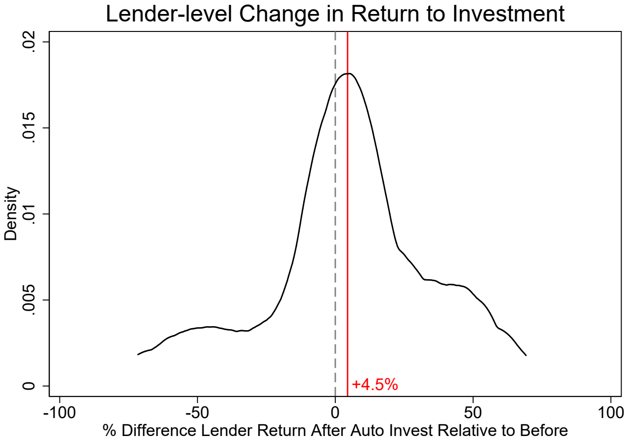
- Drop in defaults driven by homophilic borrowers for each lenders' group

Change in Performance: Shudra vs. Non-Shudra

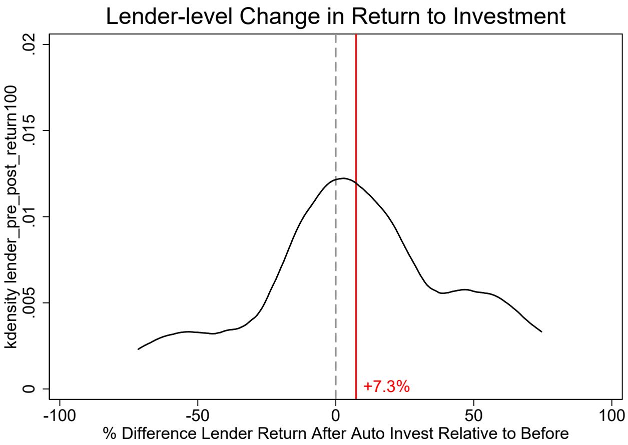
Dependent variable: Delinquent Loan	**All Lenders**	
	(1)	(2)
Auto Invest	-0.033*	
	(-1.72)	
Shudra Borrower		-0.044*
		(-1.80)
Shudra Borrower $\times$ Auto Invest		**0.019**
		(0.42)
Non-Shudra Borrower $\times$ Auto Invest		**-0.043****
		(-2.05)
Loan Risk Measures	X	X
N. obs.	3,457	3,457

- Drop in defaults driven by favorite borrowers for all lenders

Change in Lender-level Returns: Religion



Change in Lender-level Returns: Caste



Conclusion: How Costly Are Cultural Biases?

- High-stakes setting to measure the existence & cost of cultural biases
  - Compare choices pre-post automated robo-advising suggestions
- What form of discrimination?
  - Exclude statistical discrimination: lenders' performance improves
  - Inaccurate statistical discrimination more likely than taste-based
    - Very few lenders override robo-advisor's suggestions
    - Shudra lenders discriminate against their similar
  - Lower bound: robo picks at random. If skilled, even better performance
- Learning?
  - We do not know if lenders learn from robo suggestions...
  - ...is debiasing temporary, permanent? Repeated interventions?

Fraction of Defaulted Loans by Interest Rate Levels