How Costly Are Cultural Biases? Evidence from FinTech

by Francesco D'Acunto, Pulak Ghosh, and Alberto G. Rossi
Poorya Kabir
National University of Singapore

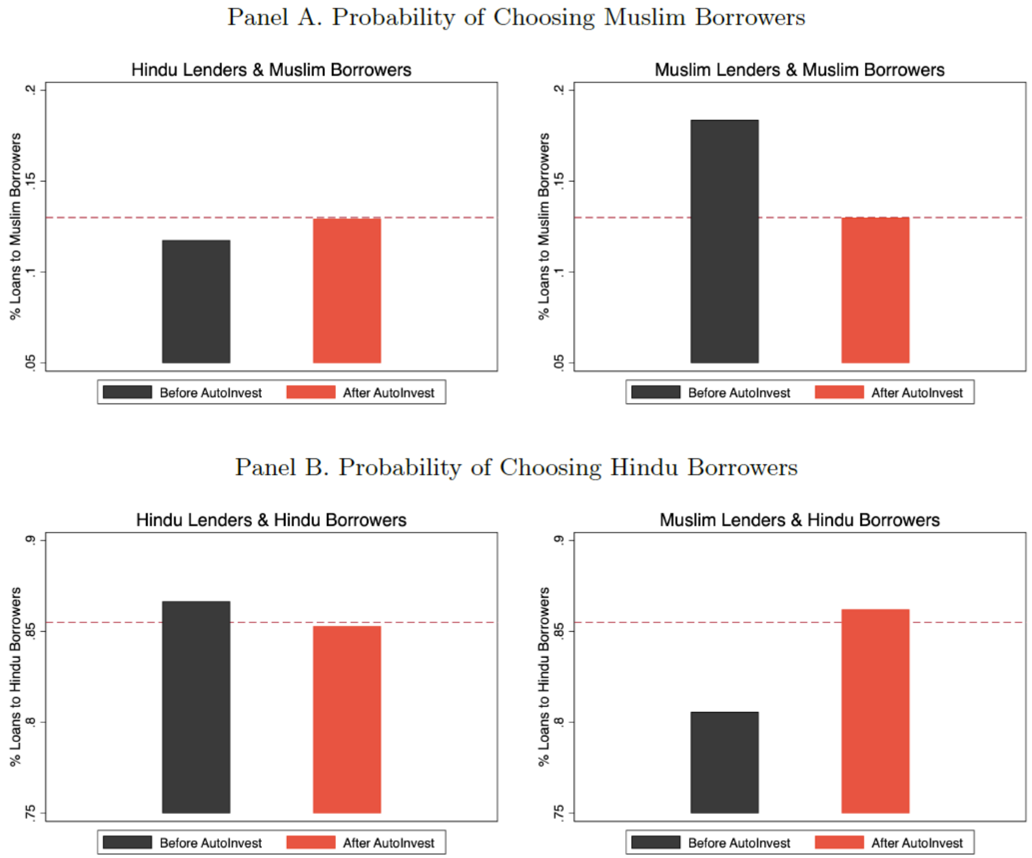
Asian Bureau of Finance and Economic Research Conference
Singapore
May 23, 2023

Summary of the paper

- Question:
  - Do cultural biases exist? i.e., a higher likelihood of lending to co-ethnic borrowers despite lower returns
  - If so, can algorithmic-based suggestions reduce such biases?
- Setting: P2P FinTech lending platform in India.
- Data: applicant-lender pair, loan performance, auto-invest activation date

Lending

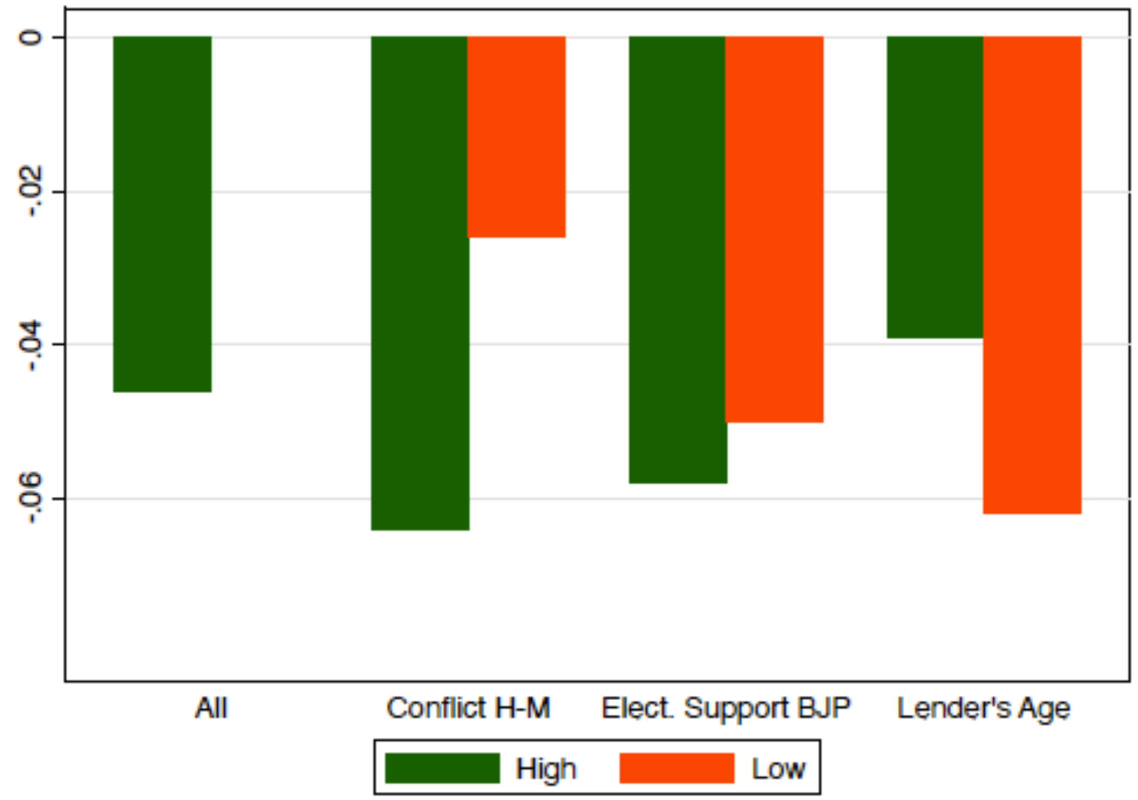
- Existence of biases before auto-invest adoption
- Reduced biases after auto-invest adoption



Default (Hindu lenders)

- Hind borrowers have higher default rates.

Panel A. In-group vs. Out-group Discrimination



Literature

- How can we reduce racial disparities in lending?
- Anti-discrimination enforcement policy
  - Butler, Mayer, and Weston, 2023
- Increase in minority loan officers
  - Frame et al., 2022; Jiang, Lee, and Liu, 2022
- Using FinTech to (1) substitute for human lenders, (2) affect the information set of lenders
  - This paper: D'Acunto et al., 2022
  - Dobbie et al., 2021; Howell et al., 2021; Kabir and Ruan, 2023

Outline

- Fantastic paper that I enjoy reading:
  - A clean setting for identifying cultural biases
  - Excellent empirical execution
  - Novel findings on the existence of cultural biases and the effect of FinTech on reducing biases
- Implications for the existence of discrimination in lending and whether FinTech can reduce discrimination
- Comments and ideas
  - Mechanism
  - Overriding auto-invest
  - Who adopts FinTech?
  - Consequences of adopting FinTech.
  - Another test of inaccurate beliefs

Mechanism

- Two alternative mechanisms:
  (1) auto-invest provides an additional signal
  (2) lenders invest in the auto-invest suggested pool because it is the default option, i.e., status quo bias
- Differentiating between the two is important and could have different policy implications.
- An idea to separate the two mechanisms:
  - Split the sample into “biased” and “unbiased” lenders
  - Does the lending outcome look the same for biased and unbiased lenders after using auto-invest? If so, that favors the status quo bias interpretation.

Overriding auto-invest

- Once a lender chooses to use auto-invest, what characteristics of the suggested applicant pool do they observe?
  - Most importantly, do they observe the last name?
- Do lenders need to manually approve applicants suggested by auto-invest *after the initial setup*?
- If not, can you compare loans approved right after enabling auto-invest to those approved later?
  - If similar, it is further evidence consistent with the lack of overriding auto-invest suggestions by lenders.
- How does auto-invest choose the suggested loan amount?
- Are there some features of loan amount selection that can be used to further argue that lenders do not override the choices of the platform?

Who adopts FinTech?

- FinTech adoption, i.e., who uses auto-invest
  - Is it correlated with (overall/recent) performance?
  - What predicts adoption speed (adoption time – introduction time)?
- I believe that FinTech adoption is orthogonal to differences in in-group biases.
  - Nevertheless, adding a parallel-trend graph might strengthen the claim.
  - New methods of staggered difference-in-differences
  - Limit the sample for in-group bias estimates to those with 20 loans or more.
- Applicants over time (before and after auto-invest introduction):
  - Observable characteristics of Muslims/Hindus over time
  - Differences in observable characteristics of Muslims/Hindus over time

Consequences of adopting FinTech

- How does the use of auto-invest affect observable differences in loan characteristics?
- A quantile regression analysis using these variables as outcome:
  - Credit scores
  - Interest rate
  - Loan amount
  - Maturity
- What is the effect of auto-invest on the amount of money lent?

Another test of inaccurate beliefs

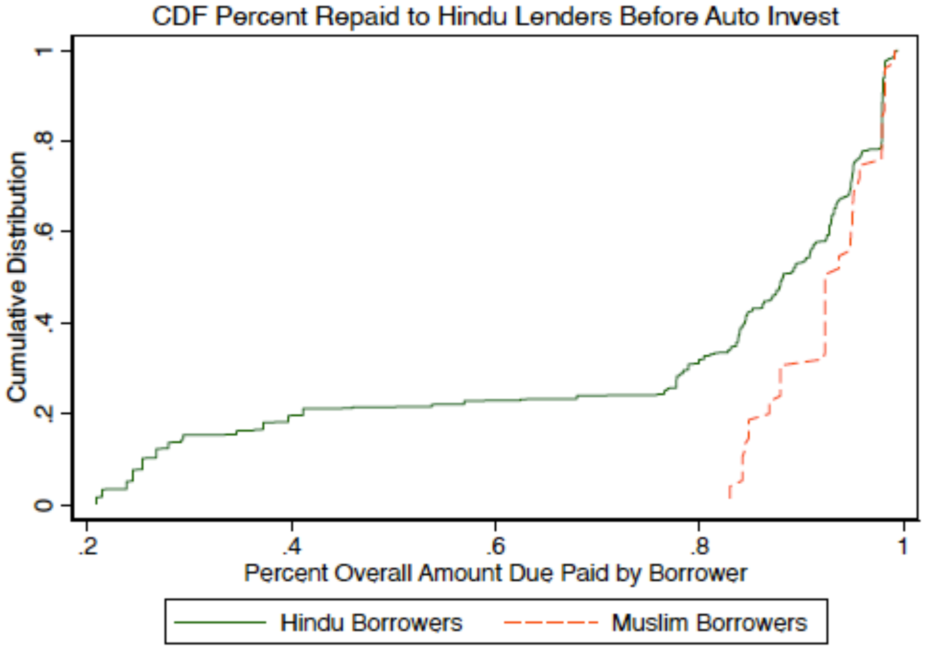
- The probability of belonging to the lowest caste depends on the applicant's location.
  - i.e., the same last name could belong to different castes in different states
- Paper’s current assumption: lenders use the state of the applicant’s residence to infer caste membership (Model 1)
- Assume that lenders use a different model (Model 2):
  - Lenders living in Odisha infer caste based on Odisha’s caste membership and not the state applicant belongs to
- The data can further support inaccurate beliefs if
  - Model 1 is “different enough” from Model 2.
  - The difference in Models 1 and 2 is unrelated to lending decisions.

Conclusion

- Overall, the paper has all the qualities of a top-notch paper
  - excellent execution
  - important topic
  - fascinating data
- Recommend reading the paper to everyone.
- Best of luck publishing the paper.

Learning

- Platform’s pre-screening could pick the best Muslim applicants



- Can you show the screening criteria by the applicant’s religion?
- Do biases weaken over time (presumably after lenders better understand the applicant pool quality in the platform)?

Minor points

- A discussion of infra-marginality Ayres (2002), and how it affects the interpretation of the results.
- A discussion of the data available to lenders not available to the authors and how it affects the interpretation of the results.
- In Table 5, you might want to add another column with Lender and Year FEs without lender characteristics (before columns 3 and 6).
- Differences in religious slurs across different states as another source of cross-sectional variation.
- Names can signal socioeconomic status (Fryer and Levitt, 2004).