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

By Poorya Kabir and Tianyue Ruan

Discussion:
Pulak Ghosh- IIMB

summary

Is it possible to Reduce racial disparities in access to Credit?

- Racial disparities have been an ongoing concern; Policymakers all around the world are trying to reduce it in every field.

- This paper studies this in the context of Credit Access

    - Uses an unique experiment where full names are anonymized at the time of application processing

    - Very interesting Fintech Data

    - Many other tests are conducted

Summary

- Context
  - Interesting and very Important topic
  - Data from Singapore based Fintech- providing short term unsecured consumer loans-
  - Analyze loan offers, origination and performance
  - Post loan offers online, customer need to visit the lender in person before the loan origination--- Unique setting
  - From Septemeber 2021, firm did not use names to screen applications for online offer, but names are being disclosed on subsequent proceedings.
  - Used this as identification to test the effectiveness of anonymizing in reducing racial gap

Summary

- Very Rich Data and Setting

  - October 2020 January 2022

  - Detailed application characteristics including derived race- No Credit score

  - Lending decisions are done by Loan officers– no information on loan officers

  - Loan origination terms-amount, maturity, interest rates and processing fee

  - Loan performance for a subset sample

Summary

- Main findings

  - Racial gap is significantly high at 10%
  - Disappears in the post treatment period- Economically sizable no
  - Decrease in loan origination rate is 8%
  - Average delinquency probability is lower for minority pre treatment
  - Post treatment delinquency probability are same among Chinese and minority borrowers

Summary

- Mechanism
    - Not related to omitted variable bias!
    - Can not distinguish between inaccurate beliefs and taste-based discrimination
    - Statistical discrimination can not explain the results
    - Potentially not due to in-group preferences

Thoughts

- Overall
    - Very topical
    - Excellent paper
    - Great Detail
    - Careful analysis

Thoughts

- Data and Institution
  - Can one lender fund multiple loans? How many and how much?
  - Can multiple lender fund one loan- typical P2P fintech?
  - Credit score?
  - No characteristics about lender
  - Only one product?
  - Interest rates fixed for various products, various tenure and various lender?
  - Does Interest rate changes with maturity period?
  - Majority of the data period covers covid

Thoughts

- Economics

  - Racial disparity reduces drastically. How much money lender loose if this does not happen? Any back of the envelope analysis.

  - Are discriminating returns lower?- should care about loan (expected) IRR. Analysis does not pin down the loan IRR

  - Possible fix:
    - You know the interest rate for each loan
    - Hence, you can test whether the discriminating loans pay lower (or similar interest)
    - E.g., simply regress interest as LHS

Thoughts

- Economics

  - Reject loans

  - What are the characteristics difference between reject loans/borrower and accept loan/borrower

  - Prediction counterfactual on reject loans to figure out how many loans would have been accepted (rejected) if treatment is (not) enforced

  - Aggregate effects:
    - For borrowers: Do more (safe/risky) borrower now get credit?
    - For lenders: do lenders invest (more/less) now? Or, just portfolio effect?

  - Is there Real financial stakes?

Thoughts

- Mechanism

  - Taste vs. Statistical: look at different size loans/different stakes
    - If higher stakes, likelihood of taste lower given cost vs. benefit
    - Either higher or lower, if mistake beliefs same b/c think you are doing the right thing

  - Time trend? Are results robust to time fixed effects?
  - Are delinquencies correlated over time?- Drop recent loans

  - Statistical Discrimination: Lender adverse selection (Balyuk & Davydenko 2019)
  - Taste-based discrimination: Effect on portfolio performance depends on under/over pricing
  - Favoritism: In group bias, home bias (Lin & Viswanathan 2015)

Thoughts

- Mechanism: Alternate Interpretation of Statistical Discrimination

  - Suppose that it is easier to interpret/process the loan applications of the in-or dominant group- In this setting all most all lenders are Chinese

    - For example, I am more exposed to people of my in-group
    - Or, because Minority may be disadvantaged and more constrained to pay, I am more exposed to Non-minority

  - So my personal risk assessment of in(-dominant) group applications will have less noise

  - I use different threshold for each group. I am only willing to lend to higher quality borrowers of out- (disadvantaged) group because of the added classification risk

  - If I know I am not good at processing applications, especially out-group, I happily go by online decisions

Thoughts

- Mechanism: Alternate Interpretation of Statistical Discrimination

  - Such a story can generate differences in profit
  - What about heterogeneity results?

    - Suppose that places with more covid incidence have more homophilic networks (or worst opportunities for minority), then those should eb places where its harder to learn?

  - Finally, which type of borrowers can benefit most by anonymizing? (e.g, smaller loan, low ability to screen, low financial literacy, low education)

Ref

- Chiu,Wolfe,Yoo(2020),

Do Fintech Lenders Fairly Allocate Loans Among Investors? Quid Pro Quo and Regulatory Scrutiny in Marketplace lending

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3281358

Conclusion

- Very topical and Interesting paper
- Should definitely be published and read widely
- All the best!