Gradual Optimization Against Heterogeneous Moral Hazard: Evidence from a Fintech Lending Firm

By Chengzheng Li, Xiang Ma, and Kangkai Wang

Sasha Indarte
Wharton, UPenn

January 2024

Big data = big profits?

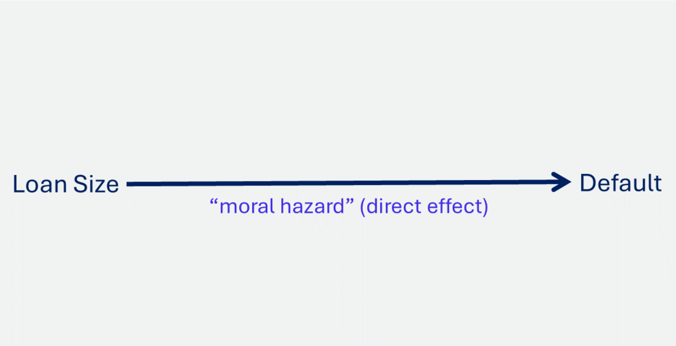
- Are creditors optimizing their lending through their use of data?

- Answer has important implications...
  - Better screening tech can improve credit access for "invisible primes" (Di Maggio Ratnadiwakara Carmichael 2022)
  - But it may also screen out those that would benefit the most from credit access

- Not obvious what to expect! Creditors may fail to optimize for a variety of reasons:
  - Behavioral mistakes and trust (Gertler Higgins Malmendier Ojeda 2023)
  - Technological (e.g., limited ability to interpret data)

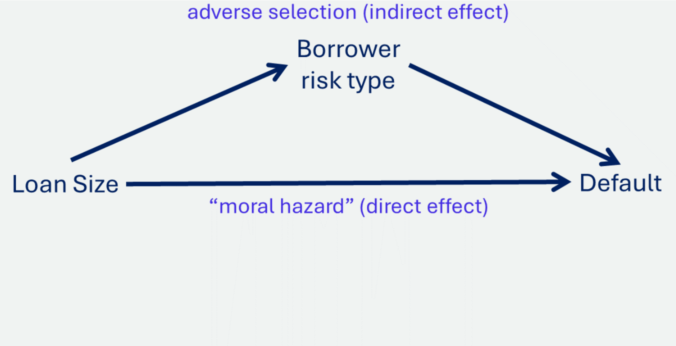
Creditors and authors face a similar identification challenge

- Both seek to know the causal effect of loan size on default



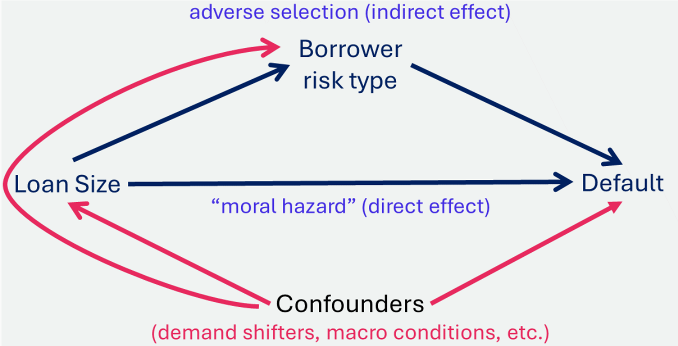
Creditors and authors face a similar identification challenge

- Both seek to know the causal effect of loan size on default



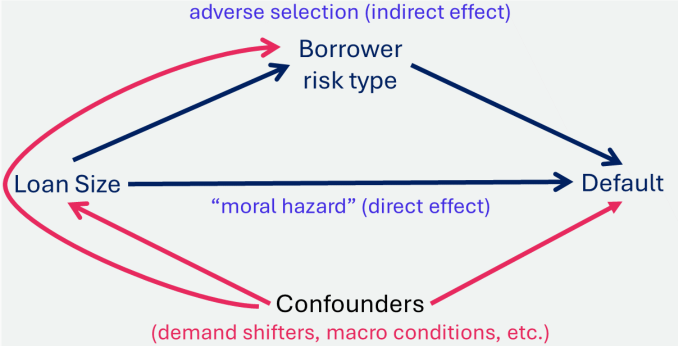
Creditors and authors face a similar identification challenge

- Both seek to know the causal effect of loan size on default



Creditors and authors face a similar identification challenge

- Both seek to know the causal effect of loan size on default



- Generally, creditors can improve predictions about Pr(default | loan size) if they can make good predictions about **both** the direct and indirect effects:

$$\Pr(\text{def} \mid \text{loan size}) = \Pr(\text{def} \mid \text{loan size, bad type}) \Pr(\text{bad type} \mid \text{loan size}) + \Pr(\text{def} \mid \text{loan size, good type}) \Pr(\text{good type} \mid \text{loan size})$$

Comment 1: Identification

Separating adverse selection from "moral hazard"

- Even if loan amount offered is random, those more likely to default may be more likely apply and accept $\Rightarrow$ est. likely reflects both "moral hazard" and adverse selection
  - Even with person FE, if applicant's risk changes over time (e.g., due to job loss), adverse selection may still be reflected in paper's estimates

- Karlan and Zinman (2009) overcome this by randomizing both ex ante offered interest rate and randomly lowering rate ex post after contract has been agreed to

- Authors' data contain applicant's requested loan amount
  - **Suggestion:** can exploit people being "surprised" with a higher offered loan amounts?

Possible confounders for OLS and IV

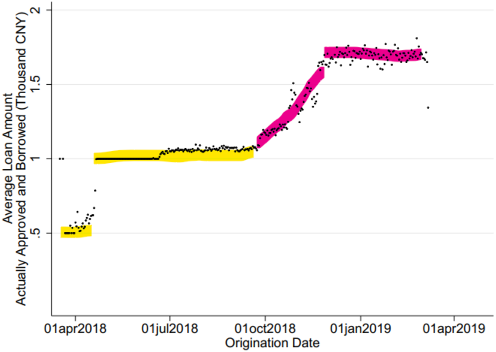
- Omitted variables may affect both loan size and Pr(default)
  - Changes in unemployment risk, firm credit access, borrower outside options, etc.
- Paper’s solution: IV for today’s loan amount with yesterday’s average
  - **Caution:** exclusion restriction may fail if omitted variables persist longer than one day

Possible confounders for OLS and IV

- Omitted variables may affect both loan size and Pr(default)
  - Changes in unemployment risk, firm credit access, borrower outside options, etc.

- Paper's solution: IV for today's loan amount with yesterday's average
  - **Caution:** exclusion restriction may fail if omitted variables persist longer than one day

- Instead, exploit sudden shifts in loan size/growth?
- DID may face similar identification issues...
- **Suggestion:** exploit discontinuity and kink in time RD and RK



Comment 2: Interpretation—is the causal effect of loan size on default "moral hazard"?

Causal effect of loan size on default $\neq$ moral hazard

- "Moral hazard" is often used to describe causal effect of repayment size on default (e.g., Adams Einav Levin 2009 and Gupta and Hansman, 2022)
- **The issue:** the (direct) causal effect of loan size on default embodies both moral hazard and liquidity effects (in the sense of Chetty 2008 and Indarte 2023)
  - Moral hazard: default more because wealth gain from default is larger
  - Liquidity: default more because inability to smooth consumption when repaying

Causal effect of loan size on default $\neq$ moral hazard

- "Moral hazard" is often used to describe causal effect of repayment size on default (e.g., Adams Einav Levin 2009 and Gupta and Hansman, 2022)
- **The issue:** the (direct) causal effect of loan size on default embodies both moral hazard and liquidity effects (in the sense of Chetty 2008 and Indarte 2023)
  - Moral hazard: default more because wealth gain from default is larger
  - Liquidity: default more because inability to smooth consumption when repaying
- Why does this matter? "Moral hazard" suggests inefficiency, where none may exist
  - The rise in default may be an efficient response to a lack of insurance
  - This matters for the welfare consequences of improved creditor screening ability

Causal effect of loan size on default $\neq$ moral hazard

- "Moral hazard" is often used to describe causal effect of repayment size on default (e.g., Adams Einav Levin 2009 and Gupta and Hansman, 2022)
- **The issue:** the (direct) causal effect of loan size on default embodies both moral hazard and liquidity effects (in the sense of Chetty 2008 and Indarte 2023)
  - Moral hazard: default more because wealth gain from default is larger
  - Liquidity: default more because inability to smooth consumption when repaying
- Why does this matter? "Moral hazard" suggests inefficiency, where none may exist
  - The rise in default may be an efficient response to a lack of insurance
  - This matters for the welfare consequences of improved creditor screening ability
- **Suggestion:** the term "moral hazard" is useful for contrasting with Adams et al literature, but discuss the interpretation of the estimated parameter carefully (with welfare implications in mind)

Comment 3: Why only examine heterogeneity in terms of education?

Why not other dimensions of heterogeneity?

- Data has many interesting potential types of heterogeneity to study: income, marital status, "occupation"/industry, stated purpose of loan, gender

- Why education? And how do we interpret this heterogeneity?
  - Paper: education as a proxy for ability to repay
  - But education may also be correlated with patience, preferences, or financial literacy—not just ability to repay

Why not other dimensions of heterogeneity?

- Data has many interesting potential types of heterogeneity to study: income, marital status, "occupation"/industry, stated purpose of loan, gender

- Why education? And how do we interpret this heterogeneity?
  - Paper: education as a proxy for ability to repay
  - But education may also be correlated with patience, preferences, or financial literacy—not just ability to repay
  - High-ed pool may also default less due to less adverse selection, but their moral hazard/willingness to engage in strategic default may be higher
  - Mayer Morrison Piskorski Gupta (2014) found default among wealthy people rose more in response to a lawsuit that made mortgage default force restructuring

Conclusion

To sum up:

- Very interesting paper!
- Important questions for understanding the impact of the rise of big data in lending
- Before inferring welfare implications, need to ask the positive questions about how creditors make use of these technologies
- Are creditors getting better at forecasting default? What limits their ability to do this accurately?