Technology, Online Banks, and Credit Market Segmentation

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What is this paper about?

- **Question:** How does technology affect credit markets?
- Online banks rely only on hard information and cherry pick safe borrowers
- Traditional banks raise loan rates as their borrower pool deteriorates
- FinTech lenders cater to the highest-risk borrowers

View in the literature

- Fuster et al (2019), Buchak et al (2018): technology allows for **faster** processing
- Online banks can then process loans faster and offer better credit terms
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  - Only based on hard information
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  - They offer better credit terms because they picked the safest borrowers
- These two competing narratives are an identification challenge which the authors address

Segmentation in lending

- Conventional view is that **within borrowers**, different lenders offer different terms due to screening
- This paper: online banks and FinTechs **complement** traditional banks by selecting borrowers
- We already know this about FinTech vs banks from Tang (2019)
- Online vs traditional bank selection is new

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- A bank only learns the true type at time $t = 1$
- In equilibrium, banks will only lend to borrowers with the quality above the threshold:

$$\theta_T^\star(M_T) = \frac{I_0(1-p)}{M(S_1 - pR_1) + (M-1)(I_{1S} - S_1)(1-p)}$$

- $\frac{\partial \theta_T^\star(M_T)}{\partial M_T} < 0 \Rightarrow$ banks with higher market power can lend to riskier borrowers

- Because they build relationships over time and gather **soft information**

Adding online banks

- Online banks only use hard information – they do not learn over time, so $M_O < M_T$
- Normalize online banks' market power to $M_O = 1$ and traditional banks' $M_T > 1$
- In the model notation, online banks price each period competitively
- Assuming the same costs of raising funds between online and traditional banks, the threshold is

$$\theta_O^\star(M_O) = \frac{I_0(1-p)}{S_1 - pR_1} > \theta_T^\star(M_T)$$

- Online banks have a higher bar for lending

Segmentation

- As long as $M_T > M_O$, there is full segmentation:
  - Online banks lend to the safest borrowers
  - Traditional banks lend to riskier borrowers
- Online banks charge lower rate, traditional banks' rates decline over time
- Divergence rises as concentration increases, just like in the authors' IV

Comments overview

- The paper's main challenge is identification
- My comments will focus on how we can use theory to strengthen identification
- Hard vs soft information assumption might be too strong
- Welfare and GE analysis would be interesting

Comment 1: Identification

- Current assumption: concentration $\Rightarrow$ loan rates **only** through the demand share of online banks
- Banks do not choose locations randomly. High concentration can mean either

1. low investment opportunities, or
2. presence of banks with high market power

- Both affect loan rates through separate channels (e.g. Drechsler et al (2017))

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- Both affect loan rates through separate channels (e.g. Drechsler et al (2017))
- Selection concern: maybe online banks reject more aggressively
- Paper's falsification tests help but do not kill the problem

Suggestion: Use Petersen and Rajan (1995) predictions

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- Ideal solution: Khwaja and Mian (2008) borrower-time FEs would account for both concerns
- Data limitation: the authors source borrower and lending info from different datasets
- Consider entry of online banks and run event studies
- Petersen and Rajan (1995) derivations predict deterioration of traditional bank borrower quality
- As a result, interest rates change
- Also test if high concentration intensifies the results

Comment 2: Relationships

- It is plausible that initially online banks only use hard information
- But what prevents them from learning over time like traditional banks do?
- The assumption of hard information might be too strong and unnecessary
- The authors can use the online bank entry event study to look into this as well

Suggestions

- Assume no soft information collection by online banks
- Then, all else equal, a new online bank's terms should be indistinguishable from an aged online bank's terms
- The event study can inform us about rate changes within the same borrower

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- Assume no soft information collection by online banks
- Then, all else equal, a new online bank's terms should be indistinguishable from an aged online bank's terms
- The event study can inform us about rate changes within the same borrower
- Also, why doesn't winners' curse hit borrowers? How do online banks distinguish between lemons and peaches?
  - If traditional banks have superior information, why don't online banks systematically attract borrowers that traditional banks are happy to lose?
- Suggestion: use Berg et al (2020)'s digital footprint findings in Germany

Comment 3: General equilibrium

- If traditional banks are unhappy about the consequences, why don't they become online banks?
- Similarly, should FinTechs become regulated?
- FinTechs are also often funded by banks (Acharya et al (2024))
- How do the results explain incentives?
- Prominent example: Nubank in Brazil became an online bank

Suggestions

- Track profitability measures along with other variables
- Maybe segmentation is a profit maximizing decision by traditional banks
- Related concern: default rate mostly treated as exogenous
- However, higher interest rates or lower monitoring can increase default chances

Minor comments

- The current model relies on hardwired assumptions
- κ in the model is ambiguous
- Risk scores can carry a measurement error
- They are also endogenous to the choice of lender
- No direct link between lender and borrower data can be concerning

Conclusion

- Timely and important paper
- Identification discussion can be strengthened using the insights from banking theory

Good luck!