Fintech Lending and Debt Spiral

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1. Motivation: Big Data Enables Targeted Marketing

- How Big Data Is Helping Advertisers Solve Problems ?(a Forbes article)
    - Receiving Data Analysis In Real Time
    - Enabling Targeted Advertising
    - Analyzing Customer Insights
    - Creating Relevant Content

- Such algorithm is widely used in social apps and shopping apps
    - Meta (Facebook) was fined €390m for targeted ads in Europe in Jan 2023

- An example: one customer is chatting with her friend about robo-vacuum in an office chatting app, and later finds the advertisement in her WeChat Moments Circle.

1. Motivation: Big Data

My co-author's personal experience:

He was chatting with us about this fintech lending paper, and a few days later he received the advertisement of lending product in his Moments Circle.

2. Hypothesis: Trapped in debt spiral

- **Technological convenience:** demand minimal effort from consumers and thus induce them to overborrow.
  - Amplify consumers' self-control problem and facilitate impulse-driven expenditures (Berg et al. 2022)
  - Consumers with time-inconsistent taste for immediate gratification (Benton et al. 2007; Heidhues and Koszegi 2010)

- **Promotional mobile messages:** strategically target consumers with strong and urgent demand for credit.
  - typically associated with a high level of poverty, underserved by banks (Hau et al. 2019; Di Maggio et al. 2022)
  - poverty can perpetuate itself by further undermining individuals' self-control capacity (Bernheim et al. 2015)

3. Result Summary

We use a set of loan applications data and the mobile message logs of the borrowers from a leading fintech company in China.

1) **Promotional message.** We find that borrowers obtained the loan from the focal fintech lender receive more promotional messages from other lenders.
2) **New loan registration.** Borrowers who receive more promotional messages are more likely to apply and register new loans from other lenders.
3) **Personal expenditure.** Borrowers who register new loans induced by the promotional messages have higher daily expenditure.
4) **New loan delinquency.** Borrowers who register new loans induced by the promotional messages are more likely receiving debt collection messages indicating loan delinquency.
5) **Social outcomes.** Borrowers who register new loans induced by the promotional messages are experiencing more negative messages such as “divorce”, “breakup” etc.

3. Result Summary : Implications

1) **Financial Literacy.** The results related to debt spiral are more pronounced for the borrowers from areas with lower financial literacy.

2) **Financial Access.** The results related to debt spiral are more pronounced for the borrowers from areas with lower credit access to traditional financial institutions.

3) **Social Insurance.** The results related to debt spiral are more pronounced for the borrowers from areas with lower unemployment insurance coverage ratio.

4. Literature

- **Overborrowing, financial distress, and negative social impact**
  - Allcott et al. (2022, REST), Bernheim et al. (2015, Econometrica), Melzer (2011, QJE), Heidhues et al. (2010, AER), Bertrand and Morse (2011,JF), Skiba and Tobacman (2019,JLE), Lin and Pursiaien (2022,JFE)

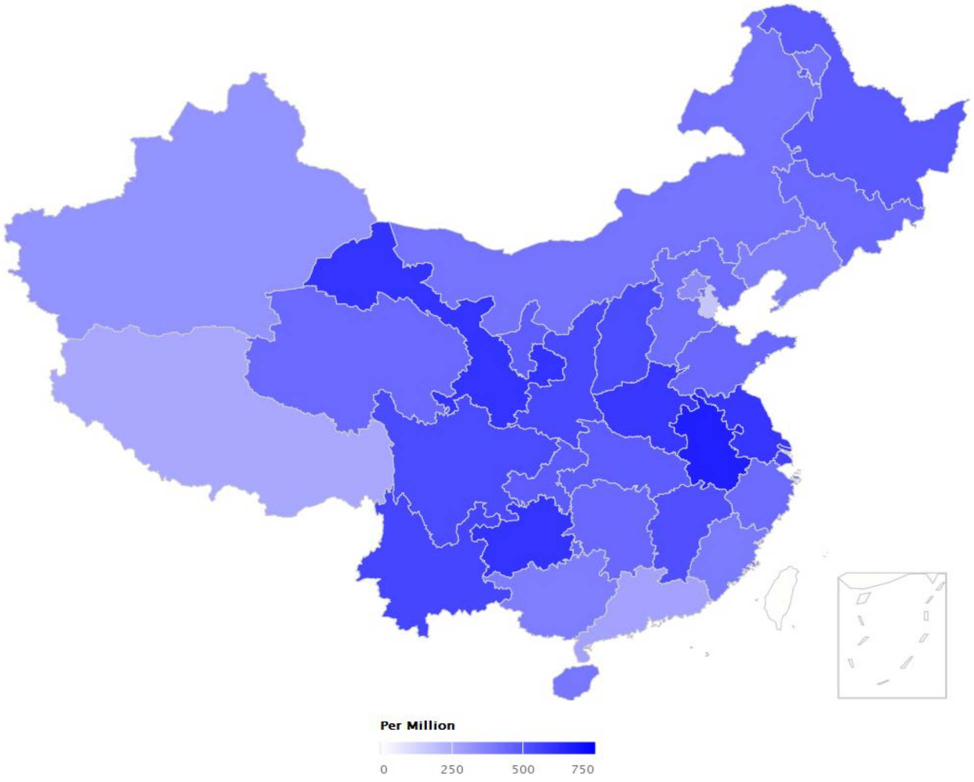
- **Trade-off between personal data privacy and access to credit**
  - Berg et al. (2020,RFS), Chen et al. (2021), Peukert et al. (2022,MS), Tang (2021,RFS)

5. Data

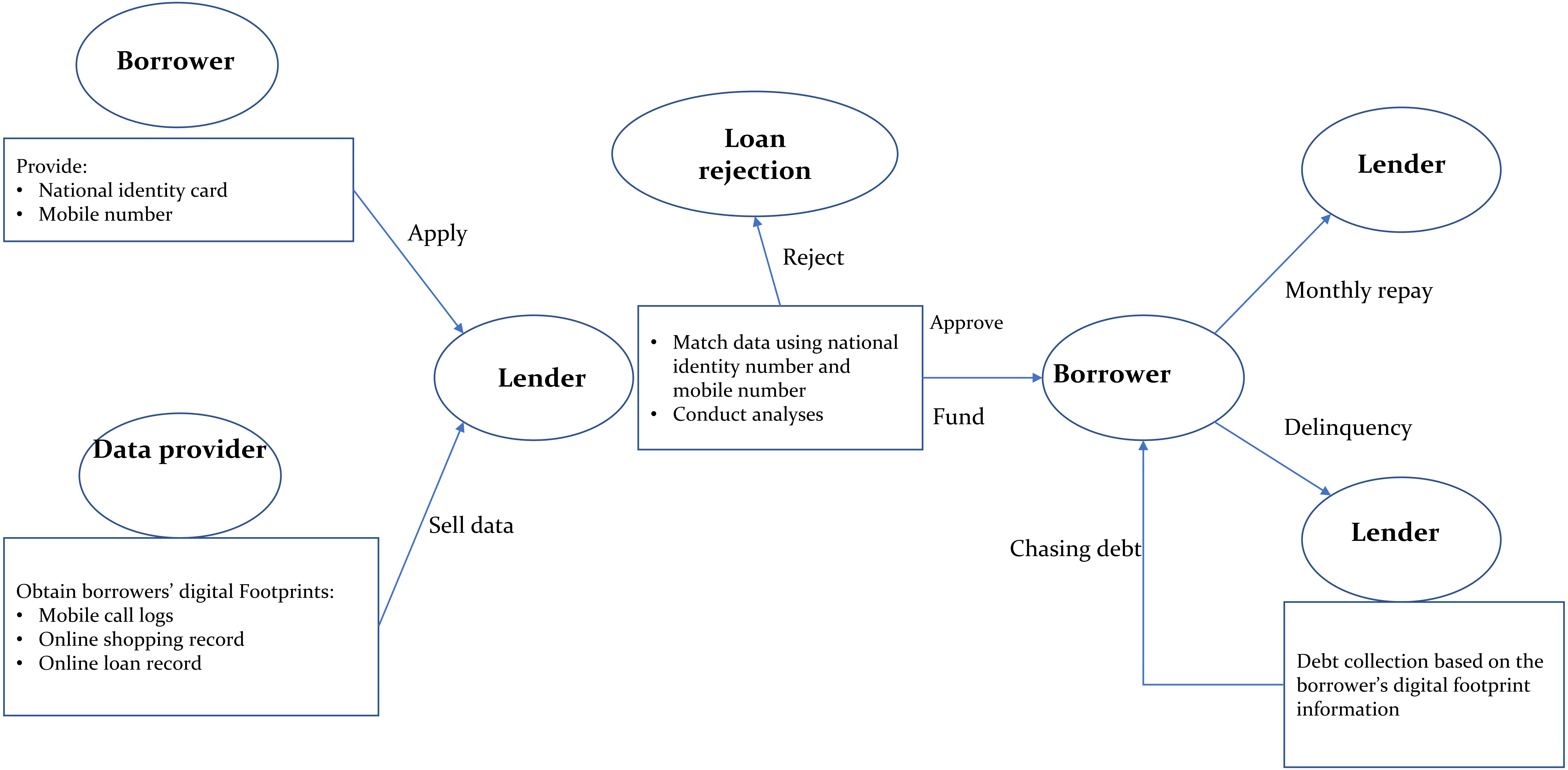
- **52,307 Loan applications** from a leading fintech lender (**focal lender**) in China from 2017-2019.
  - 54.8% are approved
  - Median age 24
  - 12.5% are female
  - 3,000 to 5,000 RMB
  - 1 year

- The applicants' mobile **message logs**, covering before and after the loan application.

- Totally **2,787,505** borrower-day observations relating to **83.6 million** messages.

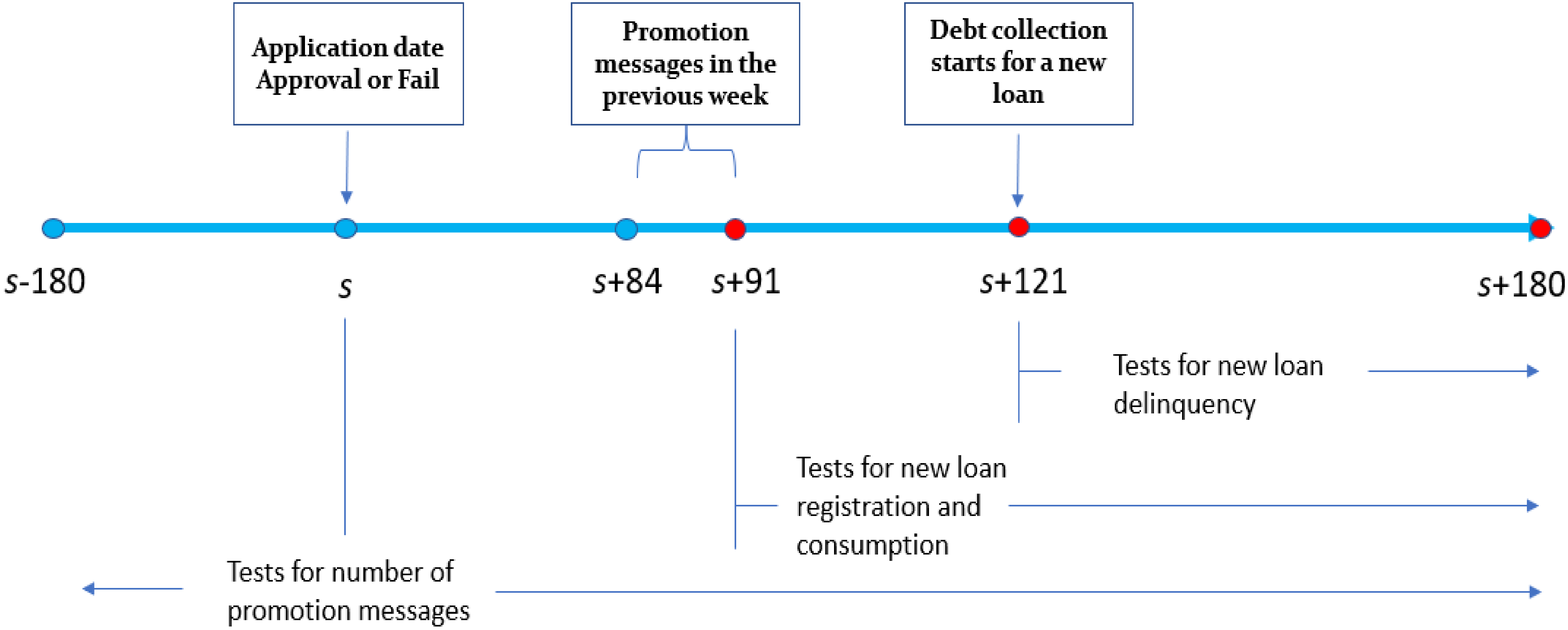


5. Data: the institutional setup



5. Data: research design

Tests of consequences: New loan registration, personal consumption, new loan delinquency



5. Data: Mobile Message Log

- A typical promotion message from a lending platform:

"*[**Ant Credit Pay**] Congratulations! You are successfully included in our whitelist for a credit line of 15,000 yuan! Apply within one hour to get the money. Reply T to **unsubscribe**.*"

- **Identify non-focal lenders**
  - Company name needs to be bracketed, required by regulators (MIIT, 工信部)
  - Applying this rule, we extract all company names from the messages.
  - We manually check whether the company is a lender
  - 4,274 unique non-focal lenders identified from our data.

- **Identify passive promotional messages** (*$Message_{Passive}$*)
  - Promotional messages a borrower passively receive
  - Key words such as "applying and receiving loan immediately," "loan interest waived," and "activate your credit quote."
  - Compulsory keyword "unsubscribe", required by MIIT for marketing messages.

5. Data: Mobile Message Log

- **Identify proactive promotional messages** (*Message* $_{Proactive}$)
    - Promotional messages after the borrower approached the lender
    - Keywords such as "account registered" and "complete personal profile" .
    - Example: "*[Cloud Fast Loan] Congratulations! you have passed the preliminary assessment. Please complete your personal profile to receive the money!*"

- **Identify new loan registration messages** (*Loan Registration*)
    - Messages indicating a new loan registration
    - Confirmation messages **with verification code** for loan registration for verifying identity.
    - Example: "*[360 Fast Loan] Your loan application verification code is 404404. Please do not share with others.*"

5. Data: Mobile Message Log

- **Enticed loan registration** (*Loan Registration* $_{Enticed}$) : apply for a loan from the platform which has sent promotional messages within the previous week.
- **Spontaneous loan registration** (*Loan Registration* $_{Spontaneous}$) : apply for a loan from the platform which did not send promotional messages within the previous week.

- **Identify messages of the expenditure**(*Expenditure*)
  - Transaction record messages from WechatPay and Alipay, sum up the amount
  - Example : *"[WechatPay] Your payment at 2018-03-19 17:03:18 is successful, paid 200.00 yuan"*

- **Identify delinquency messages of the new loans** (*Collection*)
  - Keywords such as "overdue" and "delinquent"
  - Example: *"[Immediate Consumer Loan] Your installment is delinquent. Your overdue amount is 2371.83 Yuan by 11-25. Please repay asap to avoid consequences."*

5. Data: Mobile Message Log

- **Identify negative social outcome** (*Conversation*)
  - Messages indicating negative social consequences
  - Keywords in relation to "divorce," "breakup," "suicide," "detention," "in jail," "curse," "bastard," "fight," "runaway," "fraud," "liar," "call the police," and "home violence."
  - Example: *"I failed. I owe money. If you really want to divorce, I agree. Don't make both of us too tired…"*

6.1 Loan approval and promotional message

- **Difference-in-difference setting** for the impact of focal loan approval on the number of promotional messages:

$Message = \alpha + \boldsymbol{\beta} \times \boldsymbol{Approval} \times \boldsymbol{Post} + \beta_{Control} \times Control\ Variables \times Post + \beta_{FE}\ Fixed$

$Effects + \varepsilon$,

Message : number of passive/proactive promotional messages

Approval : whether the borrower's application to the focal lender get approved

Post : after the loan approval decision

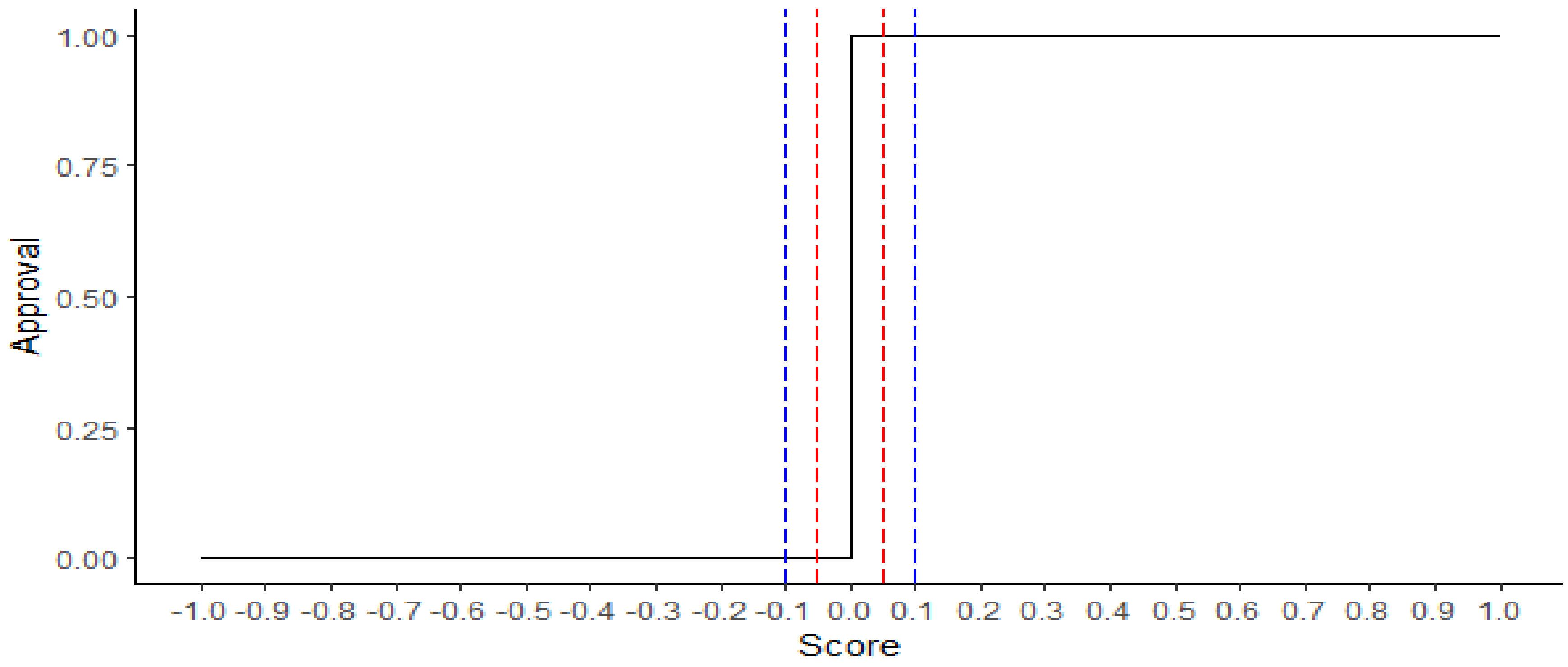
6.1 Loan approval and promotional message

Dependent Variable	*Message* $_{Passive}$		*Message* $_{Proactive}$	
	Full sample	[-180, 180]	*Full sample*	*[-180,180]*
Approval×Post	**0.033*****	**0.037*****	**-0.007****	**-0.007****
	(4.321)	**(4.666)**	**(-2.474)**	**(-2.255)**
Approval	-0.068***	-0.089***	-0.020***	-0.024***
	(-10.470)	(-13.069)	(-9.171)	(-9.345)
Post	0.047	0.119***	0.002	0.028**
	(1.370)	(3.579)	(0.155)	(2.138)
Controls	Yes	Yes	Yes	Yes
Obs	2,787,505	1,741,417	2,787,505	1,741,417

- Coefficients on *Approval* × *Post* are **significantly positive** for passive promotional messages, 7.2%
- Coefficients are negative for proactive promotional messages

6.1 Identification: RDD strategy

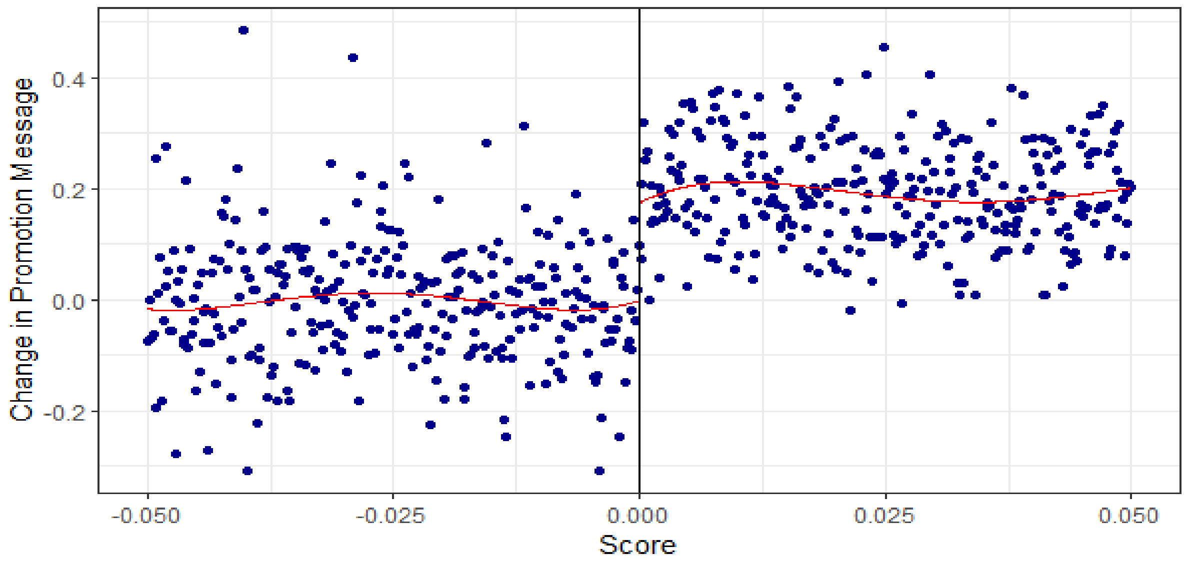
- **Potential endogeneity concern**: borrowers with different credit quality attract ads differently.
- *Sharp Regression Discontinuity Design (RDD)*
  - The loan approval is purely determined by the focal lender's credit model score.
  - Cut the sample close to the cut-off point *Score*=0: [-0.05,0.05];[-0.1,0.1]

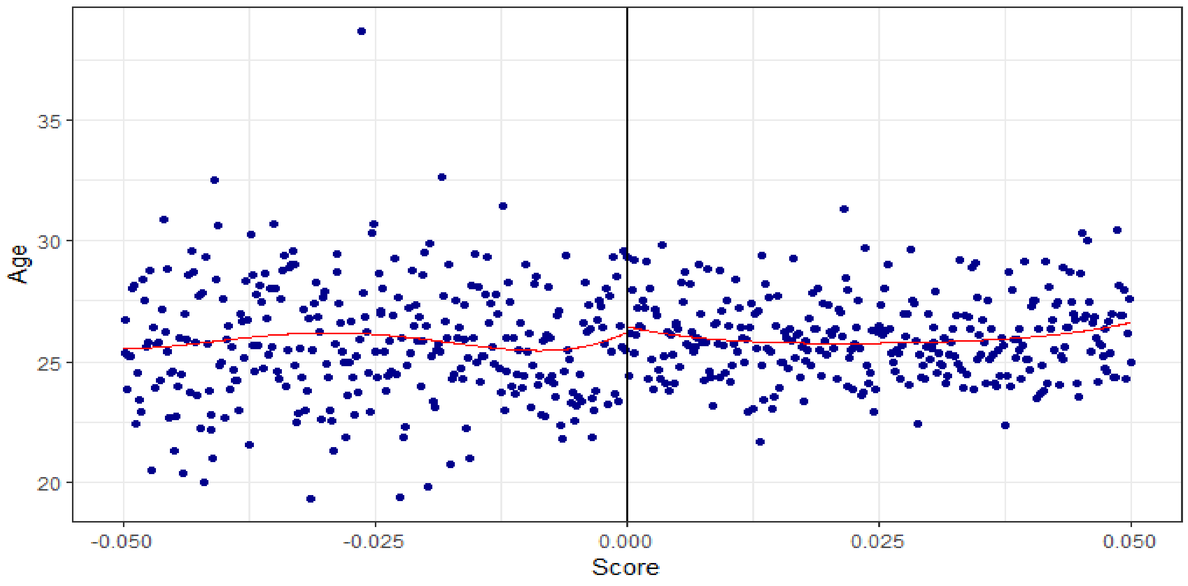


6.1 Identification: RDD strategy

- Preliminary result *Score* at [-0.05,0.05]:

- Change of passive promotional messages **significantly jump** in the cut-off point





- Control variable example *Age* **has no change** around the cutoff point.

6.1 RDD model

- **Sharp RDD test model** for the impact of focal loan approval on the number of promotional messages:

  $Message = \alpha + \beta \times Approval \times Post + \beta_1 \times Score \times Post + \beta_2 \times Score^2 \times Post + \beta_3 \times Approval \times Score \times Post + \beta_4 \times Approval \times Score^2 \times Post + \beta_5 \times Score + \beta_6 \times Score^2 + \beta_{Control} \times Control\ Variables \times Post + \beta_{FE}\ Fixed\ Effects + \varepsilon$

- **Restrict** our sample to the range of *Score* within [**-0.05,0.05**] or [**-0.1,0.1**]

6.1 RDD results

	Message $_{Passive}$		*Message* $_{Proactive}$	
	Score in [-0.05, 0.05]	*Score* in [-0.1, 0.1]	*Score* in [-0.05, 0.05]	*Score* in [-0.1, 0.1]
Approval×Post	**0.023*****	**0.016*****	**-0.007**	**-0.012*****
	(2.805)	**(2.730)**	**(-1.449)**	**(-3.724)**
Score×Post	-1.712***	-0.075	0.006	0.221*
	(-2.940)	(-0.379)	(0.022)	(1.879)
Score²×Post	-43.396***	-0.966	-3.028	1.985*
	(-3.824)	(-0.493)	(0.090)	(1.735)
Approval×Score×Post	3.056***	0.437	-1.496	-0.088
	(4.236)	(1.711)	(-0.199)	(-0.601)
Approval×Score²×Post	11.603	-3.365	-1.496	-4.034***
	(0.792)	(-1.302)	(-0.199)	(-2.773)
Controls	Yes	Yes	Yes	Yes
Obs	633,150	1,296,330	633,150	1,296,330

- The loan approval by the focal lender significantly increases the number of passive promotional messages.

6.2 New loan registration

- Sample starts from day s+91 to day s+180, *Score* range [-0.05,0.05]
- IV approach, taking advantage of sharp RDD

- Stage 1:

$$\boldsymbol{Message}_{\boldsymbol{Passive,\ Week}} = \alpha_1 + \beta_{11} \times Approval + \beta_{12} \times Approval \times Score + \beta_{13} \times Approval \times Score^2 + \beta_{Control} \times Control\ Variables + \beta_{FE}\ Fixed\ Effects + \varepsilon,$$

$Message_{Passive,\ Week}$: passive promotional messages in the previous 7 days

- Stage 2:

$$Loan\ Registration = \alpha_2 + \beta_{21} \times \boldsymbol{Message}_{\boldsymbol{Passive,\ Predicted}} + \beta_{22} \times Approval \times Score + \beta_{23} \times Approval \times Score^2 + \beta_{Control} \times Control\ Variables + \beta_{FE}\ Fixed\ Effects + \varepsilon$$

$Message_{Passive,\ Predicted}$: fitted value of $Message_{Passive,\ Week}$ in stage 1

6.2 New loan registration

Dependent Variable	*Message* $_{Passive,\ Week}$	*Loan Registration* $_{Total}$	*Loan Registration* $_{Enticed}$	*Loan Registration* $_{Spontaneous}$
	First Stage	*Second Stage*		
Approval	**0.087***** **(7.202)**			
Message $_{Passive,\ Predicted}$		**0.186***** **(2.635)**	**0.159***** **(2.264)**	**0.053***** **(6.793)**
Controls	Yes	Yes	Yes	Yes
Obs	262,947	262,947	262,947	262,947

- First stage: Focal lender's approval **significantly increases** the number of passive promotional messages.
- Second stage: The predicted number of passive promotional messages **significantly increases** new loan registrations, for both enticed ones and spontaneous ones. The effect is **stronger** for enticed ones.

6.2 Personal expenditure

- Sample starts from day s+91 to day s+180, *Score* range [-0.05,0.05]
- Daily sum of transaction record messages from Wechat Pay and Ali Pay

- 2nd stage model:

$$Expenditure = \alpha + \beta_1 \times \boldsymbol{Message}_{\boldsymbol{Passive,\ Predicted}} + \beta_2 \times Approval \times Score + \beta_3 \times Approval \times Score^2 + \beta_{Control} \times Control\ Variables + \beta_{FE}\ Fixed\ Effects + \varepsilon$$

- Two sub-samples:
    - Borrowers who have taken a new loan (*Registrant*)
    - Borrowers who have not taken a new loan (*Non-Registrant*)

6.2 Personal expenditure

Dependent Variable	*Expenditures* $_{Amount}$		
	Full Sample	*Registrants*	*Non-Registrants*
Message $_{Passive,\ Predicted}$	**0.447*****	**0.734*****	**-0.042**
	(2.895)	**(3.416)**	**(-0.179)**
Difference		**0.776****	
		(2.439)	
Controls	Yes	Yes	Yes
Obs	262,947	129,909	133,039

- Predicted passive promotion messages **significantly increase** expenditure
- The effect is concentrated in the sample of borrowers who have taken a new loan (***Registrants***)

6.2 New loan delinquency

- Sample starts from day s+121 to day s+180, score range [-0.05,0.05], only observations with borrowers who have taken a new loan (*Registrant*)
- Debt collection messages with keywords "overdue", "delinquent"

- 2nd stage model:

$$Collection = \alpha + \beta_1 \times \boldsymbol{Message}_{\boldsymbol{Passive,\ Predicted}} + \beta_2 \times Approval \times Score + \beta_3 \times Approval \times Score^2 + \beta_{Control} \times Control\ Variables + \beta_{FE}\ Fixed\ Effects + \varepsilon$$

6.2 New loan delinquency

Dependent Variable	$Collection_{\ Indicator}$	$Collection_{\ Number}$
$Message_{\ Passive,\ Predicted}$	**0.315*****	**0.226*****
	(4.561)	**(4.390)**
Controls	Yes	Yes
Obs	56,903	56,903

- Predicted passive promotional message induced new loans have significantly **higher likelihood** of loan delinquency

6.2 Negative social outcome

- Sample starts from day s+91 to day s+180, score range [-0.05,0.05]
- Negative conversation messages with keywords "divorce," "breakup," "suicide," "detention," "in jail," "curse," "bastard," "fight," "runaway," "fraud," "liar," "call the police," and "home violence."

- 2nd stage model:

$$Conversation = \alpha + \beta_1 \times \boldsymbol{Message}_{\boldsymbol{Passive,\ Predicted}} + \beta_2 \times Approval \times Score + \beta_3 \times Approval \times Score^2 + \beta_{Control} \times Control\ Variables + \beta_{FE}\ Fixed\ Effects + \varepsilon$$

6.2 Negative social outcome

Dependent Variable	$Conversation_{Indicator}$	$Conversation_{Number}$
$Message_{Passive,\ Predicted}$	**0.027***	**0.021****
	(1.947)	**(1.962)**
Controls	Yes	Yes
Obs	129,909	129,909

- Sample starts s+91 to day s+180, restricted to new loan registrants
- Predicted passive promotional message induced new loans have significantly **higher likelihood** of experiencing negative social consequences.

6.3 Mechanisms

- **Financial literacy**
  - Borrowers with limited knowledge and experience for personal financial management are more vulnerable to predatory lending(Lusardi and Scheresberg 2013; Allcott et al. 2022)
  - Financial literacy score constructed by 2017 China Household Finance Survey (CHFS) data
- **Credit Access**
  - Borrowers with limited access to traditional financial services are more targeted by fintech lenders.
  - A set of questions related to traditional financial inclusion by 2017 CHFS
- **Social Insurance**
  - Borrowers who face a lower level of unemployment insurance coverage tend to be more vulnerable to the enticement of overborrowing and engage in debt spirals.

6.3 Mechanisms tests

Dependent Variable	*Loan Registration* *Enticed*	*Expenditures* *Indicator*	*Collection* *Indicator*	*Conversation* *Indicator*
	(1)	(2)	(3)	(4)
Message $_{Passive,\ Predicted}$ × *Financial Literacy* $_{Low}$	**0.013**** **(2.988)**	**0.019***** **(2.739)**	**0.022**** **(2.847)**	**0.001** **(0.795)**

Dependent Variable	*Loan Registration* *Enticed*	*Expenditures* *Indicator*	*Collection* *Indicator*	*Conversation* $_{Indicator}$
	(1)	(2)	(3)	(4)
Message $_{Passive,\ Predicted}$ × *Credit Access* $_{Low}$	**0.015**** **(3.407)**	**0.020***** **(2.763)**	**0.015**** **(1.969)**	**0.004**** **(2.442)**

Dependent Variable	*Loan Registration* *Enticed*	*Expenditures* *Indicator*	*Collection* *Indicator*	*Conversation* $_{Indicator}$
	(1)	(2)	(3)	(4)
Message $_{Passive,\ Predicted}$ × *Social Insurance* $_{Low}$	**0.021***** **(4.728)**	**0.020***** **(2.862)**	**0.005*** **(1.667)**	**0.0003** **(0.198)**

7. Conclusion

- We show that a loan from a focal lender **significantly increase** the number of promotional messages of other lenders to the borrowers.

- The promotional messages **entice borrower to apply for new loans**, **expend more money, and more likely to delinquent for new loans**.

- This kind of debt trap has **negative social externality** beyond the financial distress.

- Such effects are stronger for borrowers with **lower financial literacy**, **traditional credit access, and lower social insurance**.

- Policy implications:
  - Regulations on predatory lending strategies such as target ads
  - Improve financial literacy, financial inclusion, and social insurance