

# Cashless Payment and Financial Inclusion

**Shumiao Ouyang**

Saïd Business School, University of Oxford

*SBS Empirical Finance Course  
May 2026*

# Background

- The financial inclusion challenge
  - Extending credit access to the underprivileged
  - The issue has received wide attention but faces a number of challenges

# Background

- The financial inclusion challenge
  - Extending credit access to the underprivileged
  - The issue has received wide attention but faces a number of challenges
- BigTech credit is booming globally, potentially addressing the inclusion challenge
  - BigTech firms usually provide both payment and credit services
  - Mobile cashless payment has accelerated the shift from cash to cashless society

# Background

- The financial inclusion challenge
  - Extending credit access to the underprivileged
  - The issue has received wide attention but faces a number of challenges
- BigTech credit is booming globally, potentially addressing the inclusion challenge
  - BigTech firms usually provide both payment and credit services
  - Mobile cashless payment has accelerated the shift from cash to cashless society

## Research Questions

Is information from payment flows a causal factor behind BigTech credit expansion?  
Does the expansion benefit the underprivileged consumers?

# Causal Link between Cashless Payment and Credit Provision

## Causal Link between Cashless Payment and Credit Provision

- Requires an exogenous shock to the cashless payment activity

## Causal Link between Cashless Payment and Credit Provision

- Requires an exogenous shock to the cashless payment activity
- Requires detailed individual-level data on payment, credit, and so on

# Causal Link between Cashless Payment and Credit Provision

- Requires an exogenous shock to the cashless payment activity
- Requires detailed individual-level data on payment, credit, and so on
- A natural experiment + rich administrative data from Alipay



# The Main Findings

# The Main Findings

- Cashless payment flow facilitates credit provision and take-up
  - Use in-person payment in a month → likelihood of credit access ↑ 56.3%
  - In-person payment amount ↑ 1% → credit line ↑ 0.41%
  - More credit usage for both in-person and online purchases

# The Main Findings

- Cashless payment flow facilitates credit provision and take-up
  - Use in-person payment in a month → likelihood of credit access ↑ 56.3%
  - In-person payment amount ↑ 1% → credit line ↑ 0.41%
  - More credit usage for both in-person and online purchases
- BigTech takes advantage of information in the payment flow
  - Beyond what is in credit usage, repayment, and assets under management (AUM)

# The Main Findings

- Cashless payment flow facilitates credit provision and take-up
  - Use in-person payment in a month → likelihood of credit access ↑ 56.3%
  - In-person payment amount ↑ 1% → credit line ↑ 0.41%
  - More credit usage for both in-person and online purchases
- BigTech takes advantage of information in the payment flow
  - Beyond what is in credit usage, repayment, and assets under management (AUM)
  - I build and estimate a simple model to quantify the value of payment data

# The Main Findings

- Cashless payment flow facilitates credit provision and take-up
  - Use in-person payment in a month → likelihood of credit access ↑ 56.3%
  - In-person payment amount ↑ 1% → credit line ↑ 0.41%
  - More credit usage for both in-person and online purchases
- BigTech takes advantage of information in the payment flow
  - Beyond what is in credit usage, repayment, and assets under management (AUM)
  - I build and estimate a simple model to quantify the value of payment data
- The above effects are present mostly among the financially underserved
  - Stronger credit provision effects on the less educated and older

## Two Closely Related Papers

## Two Closely Related Papers

- Parlour, Rajan, and Zhu (2022)
  - A model of competition between financial intermediations for payment processing
  - Key premise: payment flow data contain information on consumers' credit quality

## Two Closely Related Papers

- Parlour, Rajan, and Zhu (2022)
  - A model of competition between financial intermediations for payment processing
  - Key premise: payment flow data contain information on consumers' credit quality
  - **My paper**: Provides direct evidence supporting the premise



## Two Closely Related Papers

- Parlour, Rajan, and Zhu (2022)
  - A model of competition between financial intermediations for payment processing
  - Key premise: payment flow data contain information on consumers' credit quality
  - **My paper**: Provides direct evidence supporting the premise
- Ghosh, Vallee, and Zeng (2022)
  - Uncovers the synergy between FinTech small-business lending and cashless payment

## Two Closely Related Papers

- Parlour, Rajan, and Zhu (2022)
  - A model of competition between financial intermediations for payment processing
  - Key premise: payment flow data contain information on consumers' credit quality
  - **My paper**: Provides direct evidence supporting the premise
- Ghosh, Vallee, and Zeng (2022)
  - Uncovers the synergy between FinTech small-business lending and cashless payment
  - **My paper**: Shows causal effect of cashless payment on consumer credit provision

## Two Closely Related Papers

- Parlour, Rajan, and Zhu (2022)
  - A model of competition between financial intermediations for payment processing
  - Key premise: payment flow data contain information on consumers' credit quality
  - **My paper**: Provides direct evidence supporting the premise
- Ghosh, Vallee, and Zeng (2022)
  - Uncovers the synergy between FinTech small-business lending and cashless payment
  - **My paper**: Shows causal effect of cashless payment on consumer credit provision
  - Better firms benefit more from cashless payment adoption

## Two Closely Related Papers

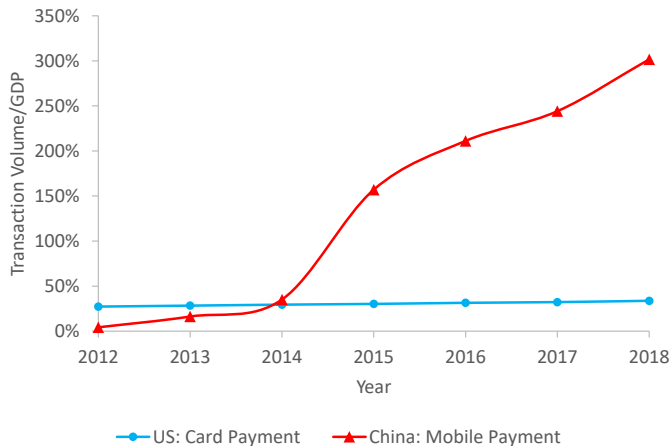
- Parlour, Rajan, and Zhu (2022)
  - A model of competition between financial intermediations for payment processing
  - Key premise: payment flow data contain information on consumers' credit quality
  - **My paper**: Provides direct evidence supporting the premise
- Ghosh, Vallee, and Zeng (2022)
  - Uncovers the synergy between FinTech small-business lending and cashless payment
  - **My paper**: Shows causal effect of cashless payment on consumer credit provision
  - Better firms benefit more from cashless payment adoption
  - **My paper**: The underprivileged get more credit access after payment adoption

## Two Closely Related Papers

- Parlour, Rajan, and Zhu (2022)
  - A model of competition between financial intermediations for payment processing
  - Key premise: payment flow data contain information on consumers' credit quality
  - **My paper**: Provides direct evidence supporting the premise
- Ghosh, Vallee, and Zeng (2022)
  - Uncovers the synergy between FinTech small-business lending and cashless payment
  - **My paper**: Shows causal effect of cashless payment on consumer credit provision
  - Better firms benefit more from cashless payment adoption
  - **My paper**: The underprivileged get more credit access after payment adoption
- See the paper for a more comprehensive list of references

# Data and Identification

# Observation 1: Rise of Cashless Payments



Source: US Federal Reserve, PBOC, World Bank

## Observation 2: Rise of BigTech Credit

- *Alipay*: the largest mobile wallet with more than 1 billion users Alipay's Business Structure
- *Huabei* credit line: the largest consumer finance product Huabei's Product Features



## Observation 2: Rise of BigTech Credit

- *Alipay*: the largest mobile wallet with more than 1 billion users Alipay's Business Structure
- *Huabei* credit line: the largest consumer finance product Huabei's Product Features
- In a representative sample of Alipay users
  - 72% have access to Huabei credit line

## Observation 2: Rise of BigTech Credit

- *Alipay*: the largest mobile wallet with more than 1 billion users Alipay's Business Structure
- *Huabei* credit line: the largest consumer finance product Huabei's Product Features
- In a representative sample of Alipay users
  - 72% have access to Huabei credit line
- Among those with Huabei access
  - 95% have used the credit, with an average monthly usage of 533 CNY ( $\sim 80$  USD)

## Observation 2: Rise of BigTech Credit

- *Alipay*: the largest mobile wallet with more than 1 billion users Alipay's Business Structure
- *Huabei* credit line: the largest consumer finance product Huabei's Product Features
- In a representative sample of Alipay users
  - 72% have access to Huabei credit line
- Among those with Huabei access
  - 95% have used the credit, with an average monthly usage of 533 CNY ( $\sim 80$  USD)
- Even among those who do not have a credit card on file
  - 64% have access to Huabei credit line

# Data

- Representative Random Sample from Population
  - 41,485 Alipay users with in-person cashless payment activities
  - Individual-level monthly panel data with detailed information
    - Personal characteristics
    - Payment, credit, investment, and other digital footprints

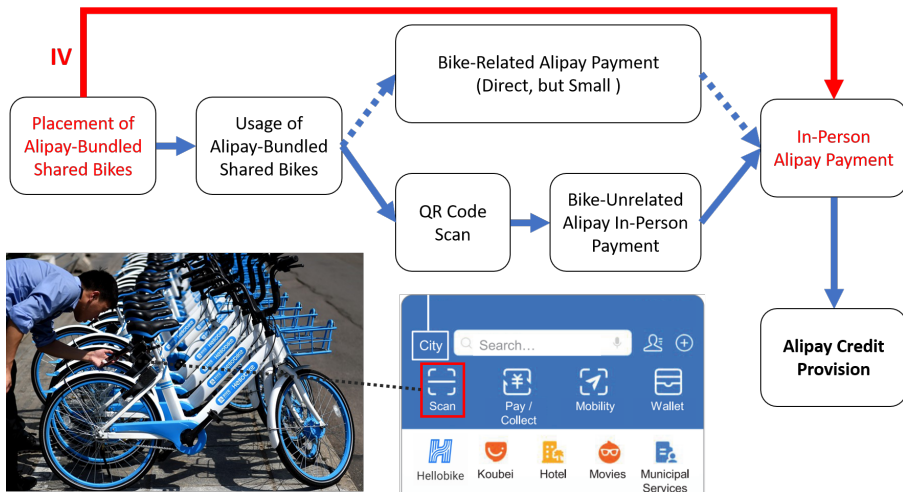
# Data

- Representative Random Sample from Population
  - 41,485 Alipay users with in-person cashless payment activities
  - Individual-level monthly panel data with detailed information
    - Personal characteristics
    - Payment, credit, investment, and other digital footprints
- Sample Period
  - From May 2017 to September 2020
  - Both mobile payment and bike-sharing industries develop fast

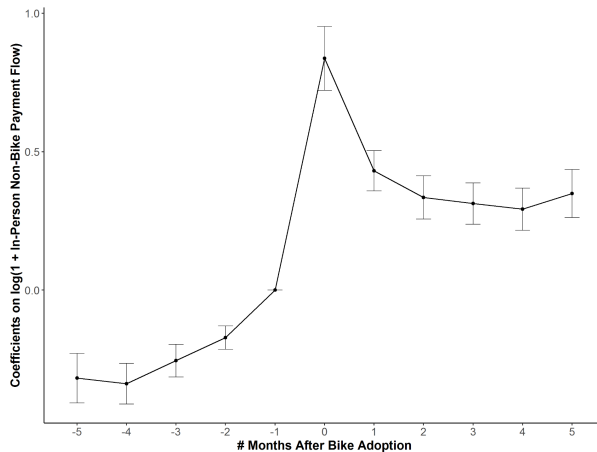
Summary Statistics

Alipay and Bike-Sharing Industry

# My Solution for the Identification Challenge



# The Nudge: Bike Adoption and Non-Bike Payment Flow



$$\log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t} = \alpha_0 + \sum_{\tau=-5}^4 \beta_{\tau} \cdot \mathbb{1}(t = \tau) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t}$$

# The Relevance Condition

	$\log(1 + \text{In-Person Payment Flow})_{i,t}$		
	(1)	(2)	(3)
$\log(\text{Bike Placement})_{c,t}$	0.041*** (0.010)	0.011 (0.009)	
$\text{Bike User}_i \times \log(\text{Bike Placement})_{c,t}$		0.103*** (0.017)	
After First Bike Usage $_{i,t}$			-0.123 (0.161)
After First Bike Usage $_{i,t} \times \log(\text{Bike Placement})_{c,t}$			0.049*** (0.014)
Individual FE	YES	YES	YES
Year-Month FE	YES	YES	-
City $\times$ Year-Month FE	NO	NO	YES
Clustered by City and Year-Month	YES	YES	YES
Sample	Full Sample	Full Sample	Bike Users
Observations	1,238,309	1,238,309	435,872
Adjusted $R^2$	0.551	0.552	0.490
Note:	* $p < 0.1$ ; ** $p < 0.05$ ; *** $p < 0.01$		



# The Exclusion Restriction

	$\log(1 + \text{Credit Line})_{i,t}$		
	(1)	(2)	(3)
$\log(\text{Bike Placement})_{c,t}$	0.027*** (0.008)	0.009 (0.010)	
$\text{Bike User}_i \times \log(\text{Bike Placement})_{c,t}$		0.060** (0.023)	
After First Bike Usage $_{i,t}$			-0.231 (0.157)
After First Bike Usage $_{i,t} \times \log(\text{Bike Placement})_{c,t}$			0.070*** (0.013)
Individual FE	YES	YES	YES
Year-Month FE	YES	YES	-
City $\times$ Year-Month FE	NO	NO	YES
Clustered by City and Year-Month	YES	YES	YES
Sample	Full Sample	Full Sample	Bike Users
Observations	1,238,309	1,238,309	435,872
Adjusted $R^2$	0.800	0.800	0.774
Note: $*p < 0.1$ ; $**p < 0.05$ ; $***p < 0.01$			

Bike-Related Characteristics

Characteristics and Exclusion Restriction

Bike Usage and Exclusion Restriction

Bike Placement and Local Economy

Staggered Bike Placement

Distribution of Bike-Placement Shock

# IV Analysis

# In-Person Payment Facilitates Credit Provision

	Credit Access <sub><i>i,t</i></sub>			$\log(\text{Credit Line})_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Two-Stage Least Squares						
Measure of In-Person Payment Flow <sub><i>i,t</i></sub>	0.086*** (0.024)	0.563*** (0.175)	0.087** (0.043)	0.281*** (0.085)	2.033** (0.766)	0.409*** (0.132)
Panel B. First Stage for Measure of In-Person Payment Flow <sub><i>i,t</i></sub>						
$\log(\text{Bike Placement})_{c,t}$	0.041*** (0.010)	0.006*** (0.002)	0.030*** (0.009)	0.043*** (0.012)	0.006*** (0.002)	0.024*** (0.008)
F-Statistic	15.5	10.8	11.2	13.9	10.6	9.1
Adjusted $R^2$	0.551	0.465	0.432	0.527	0.439	0.401
Panel C. Ordinary Least Squares						
Measure of In-Person Payment Flow <sub><i>i,t</i></sub>	0.010*** (0.001)	0.062*** (0.007)	0.007*** (0.001)	0.022*** (0.003)	0.072*** (0.023)	0.029*** (0.002)
Adjusted $R^2$	0.740	0.741	0.700	0.836	0.835	0.841
Form of the IPF Measure	$\log(1+x)$	$\mathbb{1}(x > 0)$	$\log(x)$	$\log(1+x)$	$\mathbb{1}(x > 0)$	$\log(x)$
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Full Sample	Has Credit	Has Credit	Has Credit
Observations	1,238,309	1,238,309	662,010	779,283	779,283	516,570

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

# Information Channel vs. Enforcement Channel

	Credit Access $_{i,t}$		$\log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares - <b>Information</b> Channel				
$\log(1 + \text{In-Person Noncredit Payment Flow})_{i,t}$	0.094*** (0.024)	0.095*** (0.026)	0.329*** (0.103)	0.358*** (0.124)
$\log(1 + \text{In-Person Credit Payment Flow})_{i,t}$		-0.005 (0.006)		-0.044 (0.029)
Panel B. Two-Stage Least Squares - <b>Enforcement</b> Channel				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.097*** (0.025)	0.098*** (0.026)	0.280*** (0.085)	0.282*** (0.086)
$\log(1 + \text{Assets under Management})_{i,t}$	-0.005 (0.004)	-0.008 (0.005)	-0.015 (0.011)	-0.026* (0.013)
Whether AUM Include Account Balance	NO	YES	NO	YES
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit	Has Credit
Observations	1,238,309	1,238,309	779,283	779,283

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

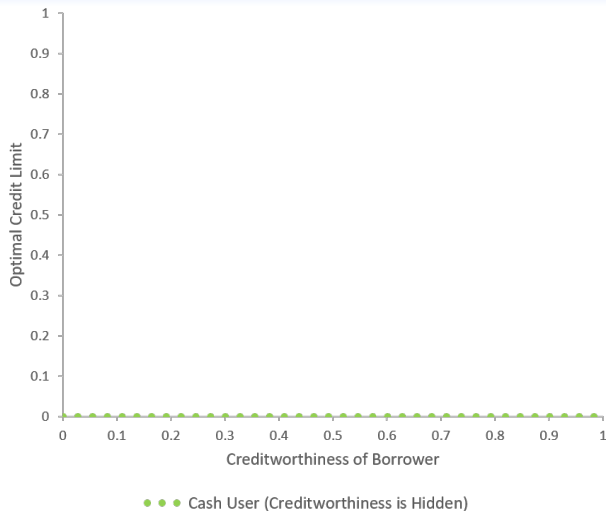
# In-Person Payment Increases Credit Take-Up

	Virtual Credit Card Share $_{i,t}$		Compulsive Spending Share $_{i,t}$	
	In-Person Payment (1)	Online Payment (2)	In-Person Payment (3)	Online Payment (4)
Panel A. Two-Stage Least Squares				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.094*** (0.034)	0.030*** (0.011)	0.004 (0.010)	0.002 (0.002)
Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$				
$\log(\text{Bike Placement})_{c,t}$	0.028*** (0.009)	0.064*** (0.014)	0.028*** (0.009)	0.064*** (0.014)
F-Statistic	11.0	22.7	11.0	22.7
Adjusted $R^2$	0.434	0.505	0.434	0.505
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Observations	662,010	806,938	662,010	806,938

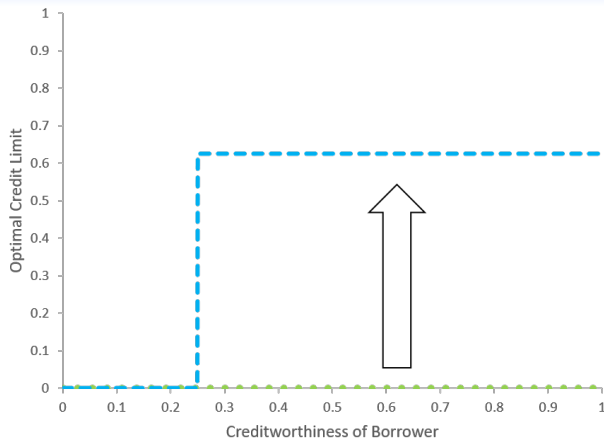
Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

# More Precise Information, More Credit to the Less Creditworthy?



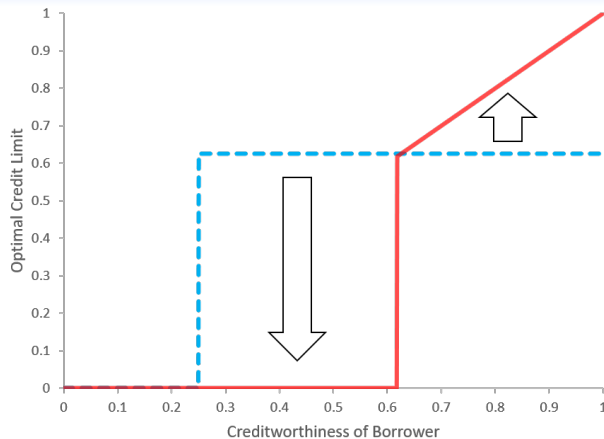
# More Precise Information, More Credit to the Less Creditworthy?



● ● ● Cash User (Creditworthiness is Hidden)

— • — New Digital Money Adopter (Knows if Creditworthiness  $\geq 0.25$ )

# More Precise Information, More Credit to the Less Creditworthy?

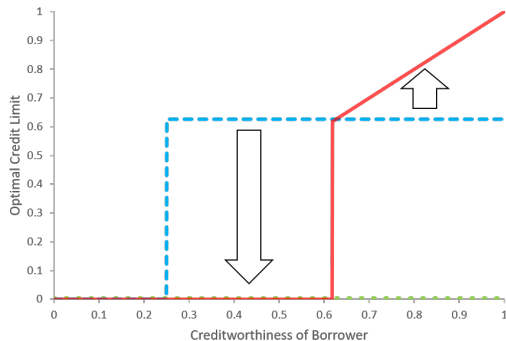


—•— New Digital Money Adopter (Knows if Creditworthiness  $\geq 0.25$ )

— Digital Money User (Knows Exact Creditworthiness)



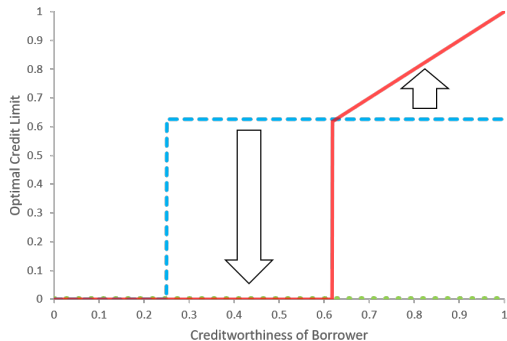
# More Precise Information, More Credit to the Less Creditworthy?



- ● ● Cash User (Creditworthiness is Hidden)
- • — New Digital Money Adopter (Knows if Creditworthiness  $\geq 0.25$ )
- Digital Money User (Knows Exact Creditworthiness)

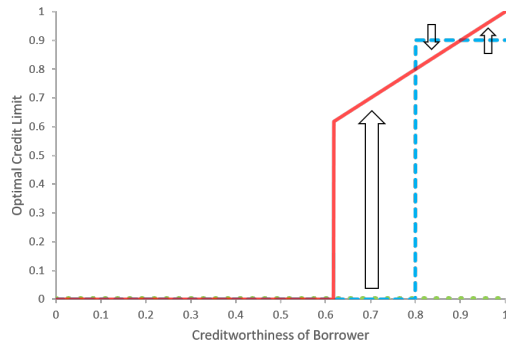
(a) Scenario of **Financial Divide**

# More Precise Information, More Credit to the Less Creditworthy?



- ● ● Cash User (Creditworthiness is Hidden)
- ● — New Digital Money Adopter (Knows if Creditworthiness  $\geq 0.25$ )
- Digital Money User (Knows Exact Creditworthiness)

(a) Scenario of **Financial Divide**



- ● ● Cash User (Creditworthiness is Hidden)
- ● — New Digital Money Adopter (Knows if Creditworthiness  $\geq 0.8$ )
- Digital Money User (Knows Exact Creditworthiness)

(b) Scenario of **Financial Inclusion**

# The Financially Underserved Segments

	Financial Service Usage			Financial Literacy		
	# Debit Cards; (1)	$\log(1 + \text{Max. AUM})_i$ (2)	# Investment Months; (3)	Pay with Real Name; (4)	Use Own Account; (5)	Complete Profile; (6)
Low Education; Older than Median;	-0.694*** (0.046)	-1.078*** (0.075)	-3.076*** (0.282)	-0.119*** (0.006)	-0.087*** (0.008)	-0.122*** (0.008)
	-0.863*** (0.025)	-0.671*** (0.045)	-2.512*** (0.141)	-0.191*** (0.006)	-0.223*** (0.009)	-0.089*** (0.005)
Gender FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City	YES	YES	YES	YES	YES	YES
Observations	39,459	39,459	39,459	39,459	39,459	39,459
Adjusted $R^2$	0.081	0.052	0.036	0.081	0.101	0.046

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

# Financial Inclusion: The Less Educated Get More Credit

	Credit Access $_{i,t}$		$\log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.093*** (0.027)	0.024 (0.044)	0.334*** (0.109)	0.038 (0.073)
Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$				
$\log(\text{Bike Placement})_{c,t}$	0.039*** (0.010)	0.043*** (0.013)	0.039*** (0.011)	0.053*** (0.014)
F-Statistic	13.7	10.9	11.6	14.2
Adjusted $R^2$	0.554	0.563	0.528	0.483
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit	Has Credit
Subsample	Low Education	High Education	Low Education	High Education
Observations	1,065,769	171,938	657,878	121,194

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

# Model-Based Analysis

# Why Do We Need a Model?

- What we have learned
  - Exogenous payment adoption shock leads to more credit provision
  - Positive credit provision effects are stronger for the underserved

# Why Do We Need a Model?

- What we have learned
  - Exogenous payment adoption shock leads to more credit provision
  - Positive credit provision effects are stronger for the underserved
- What we do not know yet
  - Real effects: consumer surplus, lender profit, default rate
  - Mechanism: why payment data play an important role
  - Quantification: the information value of payment data

# Why Do We Need a Model?

- What we have learned
  - Exogenous payment adoption shock leads to more credit provision
  - Positive credit provision effects are stronger for the underserved
- What we do not know yet
  - Real effects: consumer surplus, lender profit, default rate
  - Mechanism: why payment data play an important role
  - Quantification: the information value of payment data
- I try to achieve these goals with a simple structural model



# Economy of the Model

- The cashless payment company as the only lender
  - Offers a personalized credit line to each borrower
    - Not rely on credit history or collateral information
    - Same interest rate for everyone
    - Different credit limits for different borrowers
  - Sufficient funds

# Economy of the Model

- The cashless payment company as the only lender
  - Offers a personalized credit line to each borrower
    - Not rely on credit history or collateral information
    - Same interest rate for everyone
    - Different credit limits for different borrowers
  - Sufficient funds
- Borrowers' consumption gradually shifts from cash to digital money
  - Cash user: lender does not know any information
  - New digital money adopter: lender knows only the personal characteristics
  - Digital money user: lender knows both personal characteristics and consumption

# Overview of the Model

- There are two periods in the model [Timeline: Details](#)

# Overview of the Model

- There are two periods in the model [Timeline: Details](#)
  - First period: credit line provision, first income, credit usage, and consumption
  - Second period: second income, credit payoff or default

# Overview of the Model

- There are two periods in the model [Timeline: Details](#)
  - First period: credit line provision, first income, credit usage, and consumption
  - Second period: second income, credit payoff or default

- Random income flow:  $e_{it} = \underbrace{X_i}_{\text{Characteristics}} \beta + \underbrace{y_i}_{\text{Hidden Type}} + \underbrace{\epsilon_{it}}_{\text{Shock}}$  [Random Income Flow: Details](#)

# Overview of the Model

- There are two periods in the model Timeline: Details
  - First period: credit line provision, first income, credit usage, and consumption
  - Second period: second income, credit payoff or default

- Random income flow:  $e_{it} = \underbrace{X_i}_{\text{Characteristics}} \beta + \underbrace{y_i}_{\text{Hidden Type}} + \underbrace{\epsilon_{it}}_{\text{Shock}}$  Random Income Flow: Details

- Lender's problem:  $\max_{l_i} R \cdot \underbrace{b_i}_{\text{Used Credit}} - \underbrace{E[\mathbb{1}_i^D | X_i, b_i, c_i; \beta, R, A]}_{\text{Expected Default Rate}} \cdot \underbrace{l_i}_{\text{Credit Line}}$

Lender's Problem: Details

# Overview of the Model

- There are two periods in the model Timeline: Details
  - First period: credit line provision, first income, credit usage, and consumption
  - Second period: second income, credit payoff or default

- Random income flow:  $e_{it} = \underbrace{X_i}_{\text{Characteristics}} \beta + \underbrace{y_i}_{\text{Hidden Type}} + \underbrace{\epsilon_{it}}_{\text{Shock}}$  Random Income Flow: Details

- Lender's problem:  $\max_{l_i} R \cdot \underbrace{b_i}_{\text{Used Credit}} - \underbrace{E[\mathbb{1}_i^D | X_i, b_i, c_i; \beta, R, A]}_{\text{Expected Default Rate}} \cdot \underbrace{l_i}_{\text{Credit Line}}$

Lender's Problem: Details

- Borrower  $i$ 's problem:

$$\max_{b_i} \underbrace{c_i}_{\text{Consumption}} - \rho \cdot E[\mathbb{1}_i^D | X_i, b_i, c_i; \beta, R, A] \cdot \underbrace{D}_{\text{Default Cost}} - \rho \cdot (1 - E[\mathbb{1}_i^D | X_i, b_i, c_i; \beta, R, A]) \cdot b_i$$

where  $c_i = e_{i1} + (1 - R) \cdot b_i$  and  $0 \leq b_i \leq l_i$

Borrower  $i$ 's Problem: Details

FOCs: Details

# Estimation Results

- Estimated Parameter Values

Estimation Procedure and Identification

Specifications

Summary Statistics

Parameter	Value	Description
$\sigma_{\epsilon}$	864.8	Standard deviation of the unobservant idiosyncratic income shocks
$\sigma_y$	1,344.0	Standard deviation of the unobservant type of borrowers
$A$	4,692.0	External funding that can be used to pay off the credit balance
$D$	57,039.7	Utility cost to a borrower if she defaults in the second period
$R^2_{ols}$	0.0807	R squared of the OLS regression that predicts income



# Estimation Results

- Estimated Parameter Values

Estimation Procedure and Identification

Specifications

Summary Statistics

Parameter	Value	Description
$\sigma_\epsilon$	864.8	Standard deviation of the unobservant idiosyncratic income shocks
$\sigma_y$	1,344.0	Standard deviation of the unobservant type of borrowers
$A$	4,692.0	External funding that can be used to pay off the credit balance
$D$	57,039.7	Utility cost to a borrower if she defaults in the second period
$R^2_{ols}$	0.0807	R squared of the OLS regression that predicts income

- Fitness of the model
  - The model yields a prediction for the equilibrium credit line offered to each borrower
  - Predicted credit lines explain 12% of cross-sectional variation in the data

$$\text{Credit Line}_i^{\text{observed}} = 1777.70 + 0.94 \cdot \text{Credit Line}_i^{\text{cashless}}$$

(89.81)    (0.01)

# Counterfactuals

- We are interested in the information value of payment data

# Counterfactuals

- We are interested in the information value of payment data
- The key counterfactual: new digital money adopter
  - Borrowers still borrow from the lender, but consume with cash
  - Lender knows borrowers' personal characteristics, but not their consumption

# Counterfactuals

- We are interested in the information value of payment data
- The key counterfactual: new digital money adopter
  - Borrowers still borrow from the lender, but consume with cash
  - Lender knows borrowers' personal characteristics, but not their consumption
- Steady State Comparison: New Digital Money Adopter vs. Digital Money User

	Mean New DM Adopter	DM User	Mean Difference	Relative Change
Credit Line <sub>i</sub>	3,619.9	5,707.5	2,087.6	57.7%
Used Credit <sub>i</sub>	1,562.6	1,780.4	217.7	13.9%
Consumer Welfare <sub>i</sub>	1,209.9	1,222.5	12.6	1.0%
Lender Profit <sub>i</sub>	45.3	50.6	5.2	11.6%
Total Welfare <sub>i</sub>	1,255.2	1,273.0	17.8	1.4%
Annualized Default Rate <sub>i</sub>	0.51%	0.58%	0.07%	13.3%

# Conclusion

# Conclusion

- Open questions (Berg, Fuster and Puri, 2021)
  - Is information from payment flows a causal factor behind credit expansion?
  - Does it benefit customers previously underserved by traditional financial institutions?

# Conclusion

- Open questions (Berg, Fuster and Puri, 2021)
  - Is information from payment flows a causal factor behind credit expansion?
  - Does it benefit customers previously underserved by traditional financial institutions?
- This paper argue that answer to both questions is **YES**
  - With unique data and a new identification strategy
  - The first paper showing that payment information fuels BigTech credit to households

# Conclusion

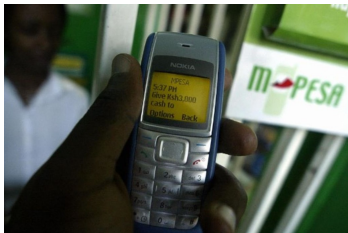
- Open questions (Berg, Fuster and Puri, 2021)
  - Is information from payment flows a causal factor behind credit expansion?
  - Does it benefit customers previously underserved by traditional financial institutions?
- This paper argue that answer to both questions is **YES**
  - With unique data and a new identification strategy
  - The first paper showing that payment information fuels BigTech credit to households
- Policy implications
  - Service bundling in payment systems brings new opportunities
  - Mobile payment can facilitate sustainable and inclusive finance



## Strands of Related Literature (See the paper for a complete list of papers)

- **Digital Payment and Credit:** Parlour et al. (2022), ?
  - **This paper:** Direct causal evidence in the consumer credit market
- **Payment Adoption on Consumers:** Mbiti and Weil (2015), Bachas et al. (2021), Riley (2018), Hong et al. (2020), Suri and Jack (2016), Brunnermeier and Payne (2022), Agarwal et al. (2021)
  - **This paper:** Value of payment data and power of service bundling
- **Consequences of Consumer Credit:** Zinman (2015), Karlan and Zinman (2010), Morse (2011), Melzer (2011), Ausubel (1991), Di Maggio and Yao (2020), Di Maggio et al. (2022)
  - **This paper:** Effects of BigTech consumer credit
- **Determinants of Consumer Credit:** Rampini and Viswanathan (2020), Chatterjee et al. (2020), Liberti and Petersen (2019), Berg et al. (2020), Rishabh (2022), Fuster et al. (2022)
  - **This paper:** Information channel vs. enforcement channel

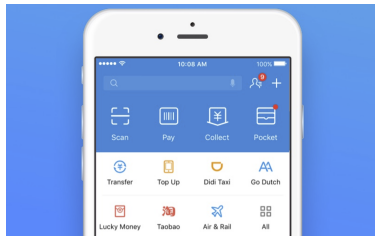
## Different Types of Mobile Payments



(a) *M-Pesa* and Mobile Phone



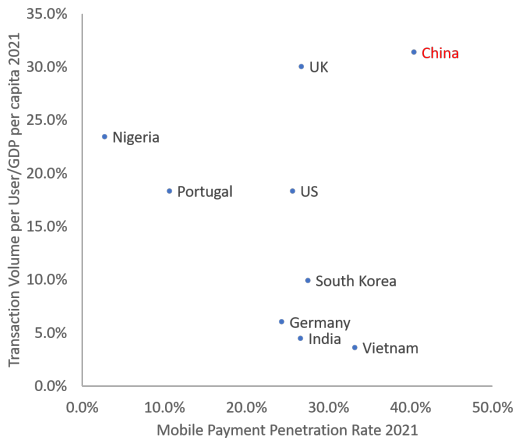
(b) *Apple Pay*, Card, and Phone



(c) *Alipay* and Smart Phone

[Go Back](#)

# Mobile Payment Penetration across Countries

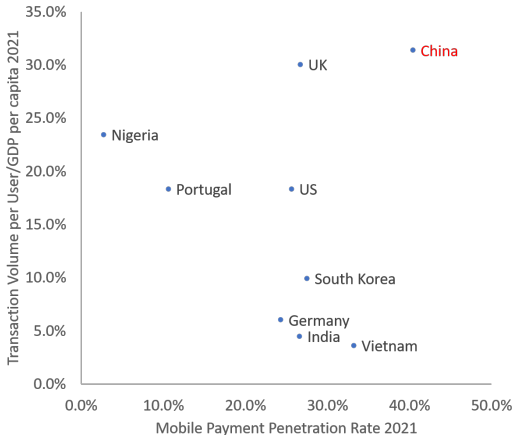


(a) 2021

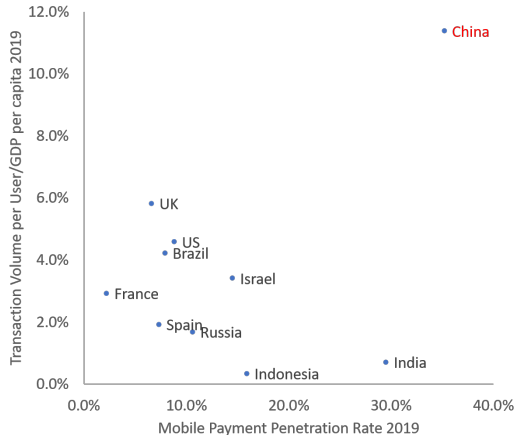
Source: Statista Digital Market Outlook, World Bank

[Go Back](#)

# Mobile Payment Penetration across Countries



(a) 2021



(b) 2019

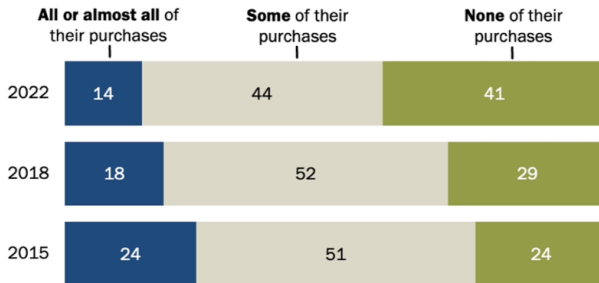
Source: Statista Digital Market Outlook, World Bank

[Go Back](#)

## Declining Use of Cash in the US

## Americans have become more likely to say they don't use cash for purchases in a typical week

% of U.S. adults who say they make \_\_ (including things like groceries, gas, services or meals) in a typical week using cash

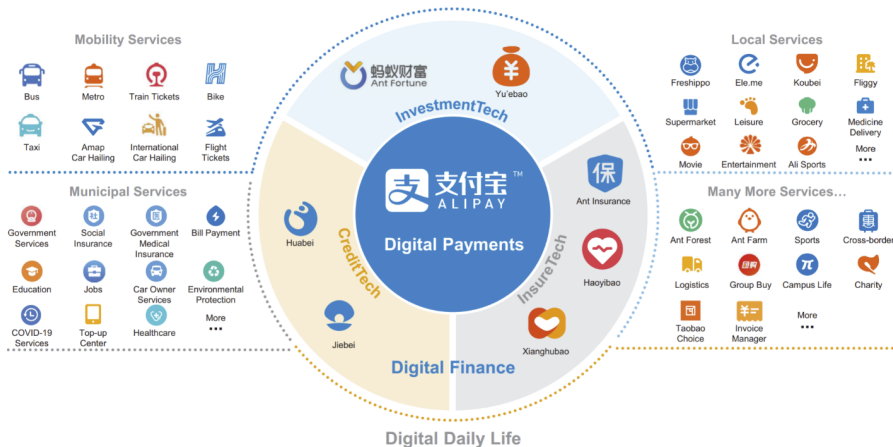


Note: Respondents who did not give an answer are not shown.

Source: Survey of U.S. adults conducted July 5-17, 2022.

PEW RESEARCH CENTER

## Alipay: the “All-in-One” Approach to Mobile Payment



Source: IPO Prospectus of Ant Group, 2020

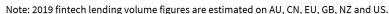
## Features of Alipay's Huabei Credit Line

- No active application required
  - Qualification status and credit line instantly available
- No price discrimination
  - 0.05% daily rate (18.25% annually)
  - Interest-free period of up to 40 days
- Excellent risk management
  - Delinquency rate as of June 2019
    - Huabei: 1.16%
    - Credit cards issued by public banks in China: 1.21% to 2.49%



## BigTech Credit is Booming Globally

## Big Tech Credit Is Overtaking Fintech Credit

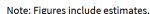


### (a) BigTech and Fintech Credit

Source: Cornelli et al. (2020), CESifo Forum

[Go Back](#)

## Big Tech Credit Is Booming in Asia, the United States and Africa



### (b) Global Boom in BigTech Credit



# Summary Statistics

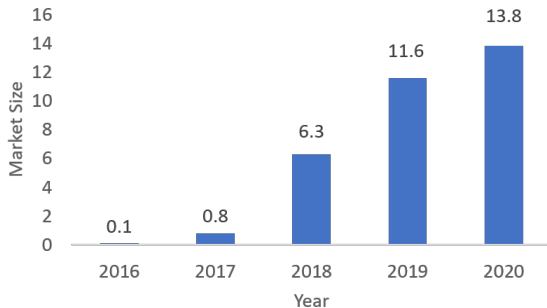
	N	Mean	Std	Min	p25	Median	p75	Max
Individual Level								
# Active months <sub>i</sub>	41,485	31.86	11.38	1.00	24.00	37.00	41.00	41.00
Is Male <sub>i</sub>	41,214	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Low Education <sub>i</sub>	41,459	0.88	0.33	0.00	1.00	1.00	1.00	1.00
Birth Year <sub>i</sub>	41,214	1,983.38	12.75	1,930.00	1,974.00	1,985.00	1,993.00	2,014.00
Bike User <sub>i</sub>	41,485	0.29	0.45	0.00	0.00	0.00	1.00	1.00
City-Month Level								
log(Bike Placement) <sub>c,t</sub>	12,665	7.08	3.39	0.00	4.11	7.85	9.91	13.91
Individual-Month Level								
Credit Access <sub>i,t</sub>	1,321,837	0.62	0.49	0.00	0.00	1.00	1.00	1.00
log(Credit Line) <sub>i,t</sub>	819,812	7.88	1.58	3.00	6.91	8.13	9.13	11.02
log(In-Person Payment Flow) <sub>i,t</sub>	688,428	5.70	2.29	-4.61	4.31	6.04	7.27	15.88
log(Online Payment Flow) <sub>i,t</sub>	843,993	5.76	1.80	-4.61	4.70	5.88	6.93	15.74
Virtual Credit Card Share in In-Person Payment <sub>i,t</sub>	688,428	0.34	0.42	0.00	0.00	0.04	0.82	1.00
Virtual Credit Card Share in Online Payment <sub>i,t</sub>	843,993	0.33	0.41	0.00	0.00	0.01	0.80	1.00
Compulsive Spending Share in In-Person Payment <sub>i,t</sub>	688,428	0.03	0.14	0.00	0.00	0.00	0.00	1.00
Compulsive Spending Share in Online Payment <sub>i,t</sub>	843,993	0.01	0.10	0.00	0.00	0.00	0.00	1.00

[Go Back](#)

# Alipay and Dockless Bike-Sharing Service

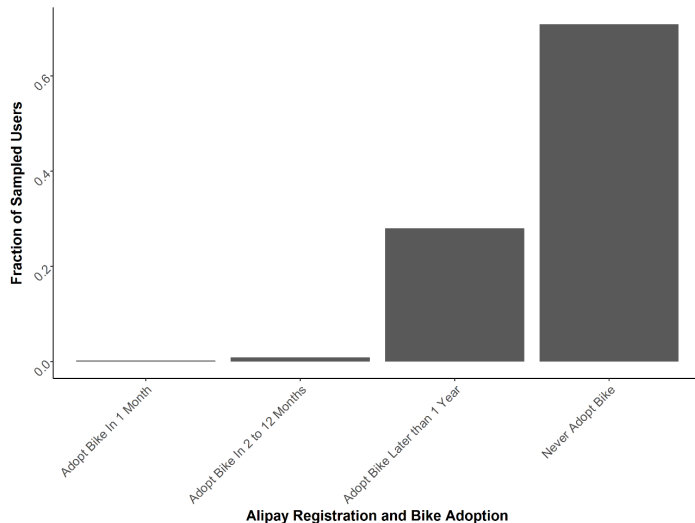
- Fast growing bike-sharing industry
- Alipay-bundled shared bikes
  - Investment  $\geq$  3.5 billion dollars
  - Strategic partnership
  - Unlock bike directly with Alipay

Size of China's Shared Two-Wheeler Market  
(GTV, Billion CNY)



Source: IPO Prospectus of Hello Inc, 2021; iResearch Report

# Alipay Registration and Shared-Bike Adoption



# Bike-Related Personal Characteristics

	Bike User <sub>i</sub>		
	(1)	(2)	(3)
Low Education <sub>i</sub>	-0.173*** (0.009)	-0.109*** (0.010)	-0.065*** (0.009)
Older than Median <sub>i</sub>	-0.095*** (0.005)	-0.110*** (0.005)	-0.096*** (0.004)
Early Alipay User <sub>i</sub>	-0.129*** (0.007)	-0.113*** (0.006)	-0.030*** (0.005)
Male <sub>i</sub>	0.049*** (0.004)	0.059*** (0.004)	0.045*** (0.004)
Pay with Real Name <sub>i</sub>	0.088*** (0.006)	0.081*** (0.005)	0.012** (0.005)
Use Own Account <sub>i</sub>	0.076*** (0.006)	0.071*** (0.005)	0.033*** (0.005)
Complete Profile <sub>i</sub>	0.012* (0.007)	0.001 (0.006)	-0.012* (0.006)
Constant	0.421*** (0.013)		
City FE	NO	YES	YES
Occupation FE	NO	YES	YES
Controls Financial Activity Measures	NO	NO	YES
Clustered by City	YES	YES	YES
Observations	39,459	39,459	39,459
Adjusted R <sup>2</sup>	0.123	0.178	0.260

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

# Bike Usage, Personal Characteristics, and Exclusion Restriction

	Dependent Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Ordinary Least Squares with Dependent Variable: $\log(1 + \text{In-Person Payment Flow})_{i,t}$						
$\log(\text{Bike Placement})_{c,t}$	-0.022 (0.014)	0.008 (0.010)	0.029** (0.011)	0.021** (0.009)	-0.013 (0.015)	-0.010 (0.010)
$\text{Bike User}_i \times \log(\text{Bike Placement})_{c,t}$	0.139*** (0.029)	0.110*** (0.018)	0.092*** (0.017)	0.099*** (0.021)	0.057** (0.025)	0.139*** (0.029)
$\text{Characteristic Measure}_i \times \log(\text{Bike Placement})_{c,t}$	0.036** (0.017)	0.004 (0.013)	-0.038*** (0.012)	-0.023** (0.008)	0.033* (0.019)	0.036** (0.017)
$\text{Bike User}_i \times \text{Characteristic Measure}_i \times \log(\text{Bike Placement})_{c,t}$	-0.040 (0.031)	-0.017 (0.018)	0.009 (0.025)	0.009 (0.020)	0.046** (0.023)	-0.045 (0.031)
Adjusted $R^2$	0.552	0.552	0.552	0.552	0.552	0.552
Panel B. Ordinary Least Squares with Dependent Variable: $\log(1 + \text{Credit Line})_{i,t}$						
$\log(\text{Bike Placement})_{c,t}$	0.009 (0.021)	0.014 (0.010)	0.020 (0.013)	0.004 (0.014)	-0.008 (0.013)	0.003 (0.015)
$\text{Bike User}_i \times \log(\text{Bike Placement})_{c,t}$	0.051* (0.030)	0.053* (0.026)	0.057* (0.029)	0.056** (0.025)	0.049* (0.029)	0.042** (0.020)
$\text{Characteristic Measure}_i \times \log(\text{Bike Placement})_{c,t}$	0.0001 (0.026)	-0.011 (0.018)	-0.023 (0.025)	0.008 (0.012)	0.024* (0.014)	0.012 (0.014)
$\text{Bike User}_i \times \text{Characteristic Measure}_i \times \log(\text{Bike Placement})_{c,t}$	0.012 (0.025)	0.016 (0.028)	-0.008 (0.046)	0.007 (0.019)	0.007 (0.037)	0.022 (0.034)
Adjusted $R^2$	0.800	0.799	0.800	0.799	0.800	0.800
Personal Characteristic Measure	Low Education; YES	Older than Median; YES	Early Alipay User; YES	Male; YES	Pay with Real Name; YES	Use Own Account; YES
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Observations	1,237,707	1,237,707	1,237,707	1,237,707	1,237,707	1,237,707

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ 

Go Back

# Background of Bike Sharing Service



## Low Cost of Usage

- 0.23 USD/first 15 min
- After the first 15min, 0.08 USD/15min
- Unlimited plan: About 3 USD/month

[Go Back](#)

## Large User Base

- The size of the user base of shared bikes in China is 260 million as of late 2019
- Over 400 million Hellobike users in 2021

## Direct Effects of Bike Usage

	$\log(1 + \text{In-Person Payment Flow})_{i,t}$ (1)	$\log(1 + \text{Credit Line})_{i,t}$ (2)	$\log(1 + \text{Credit Line})_{i,t}$ (3)	$\log(1 + \text{Credit Line})_{i,t}$ (4)
$\log(\text{Bike Placement})_{c,t}$	0.011 (0.009)		0.009 (0.010)	
One-Time Bike User <sub><i>i</i></sub> $\times$ $\log(\text{Bike Placement})_{c,t}$	0.088*** (0.020)	0.072*** (0.019)	0.048** (0.023)	0.035 (0.025)
Repeat Bike User <sub><i>i</i></sub> $\times$ $\log(\text{Bike Placement})_{c,t}$	0.106*** (0.018)	0.078*** (0.017)	0.062** (0.025)	0.040 (0.029)
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	-	YES	-
City $\times$ Year-Month FE	NO	YES	NO	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Observations	1,238,309	1,238,309	1,238,309	1,238,309
Adjusted $R^2$	0.552	0.555	0.800	0.801

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

[Go Back](#)

# Bike Placement and Local Economy

	$\log(\text{GDP})_{c,t}$ (1)	$\log(\text{GDP per capita})_{c,t}$ (2)	Fiscal Spending/ $\text{GDP}_{c,t}$ (3)	Fiscal Income/ $\text{GDP}_{c,t}$ (4)
$\log(\text{Bike Placement})_{c,t}$	0.002 (0.002)	0.000 (0.002)	-0.001 (0.001)	0.000 (0.000)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Clustered by City and Year	YES	YES	YES	YES
Observations	895	775	886	891
Adjusted $R^2$	0.992	0.979	0.957	0.903

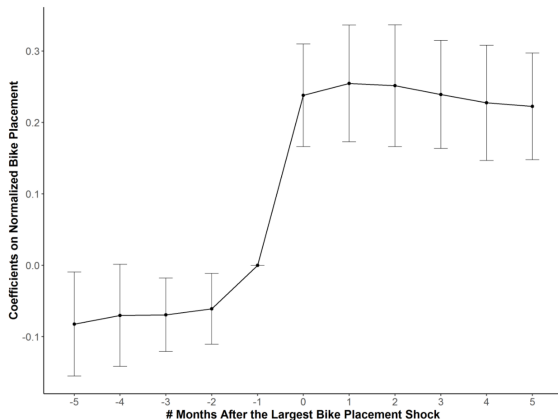
Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ 

Go Back

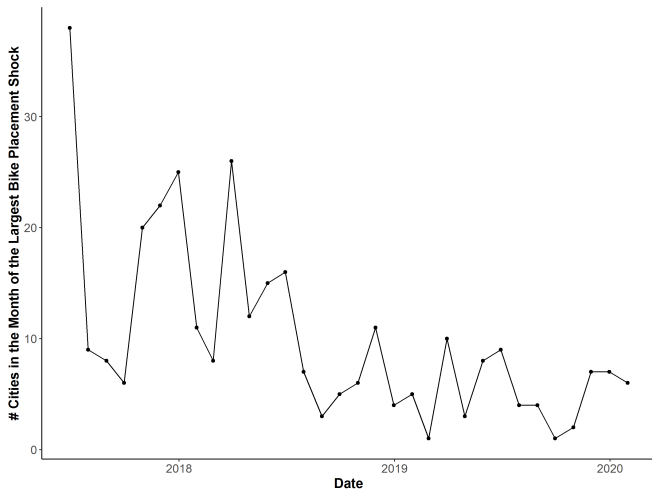


# Staggered Placement of Shared Bikes



$$\text{Normalized Bike Placement}_{c,t} = \alpha_0 + \sum_{\tau=-5}^4 \beta_{\tau} \cdot \mathbb{1}(t = \tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_c + \mu_t + \varepsilon_{c,t}$$

# Broad Distribution of Bike-Placement Shock



# Why IV Estimate $\gg$ OLS Estimate

- Reason 1: Omitted variables
  - OLS can have a downward bias due to omitted variables
  - Example: A negative health shock

Explanation with an Econometric Framework

- Reason 2: Non-monotone payment-credit relationship
  - Below a threshold, payment flow  $\rightarrow$  information  $\rightarrow$  credit provision
  - Above a threshold, payment flow  $\rightarrow$  over-spending  $\rightarrow$  risky  $\rightarrow$  less credit provision

Evidence of Non-Monotone Payment-Credit Relationship

Go Back

# OLS and IV Estimates

- An econometric framework with endogeneity Econometric Framework Setup

- OLS Estimate

- Assume  $0 < \alpha_1 < 1$ ,  $0 < \beta_1 < 1$ , and  $\varepsilon_{i,t}^{EE} \perp \varphi_{i,t}$ , then

$$\begin{aligned}\hat{\alpha}_1^{OLS} &= \frac{\text{Cov}(cl_{i,t}, ipf_{i,t})}{\text{Var}(ipf_{i,t})} \\ &= \underbrace{\alpha_1}_{+} + \underbrace{\frac{1}{1 - \alpha_1 \cdot \beta_1}}_{+} \cdot \underbrace{\left[ \frac{\text{Var}(\delta_i + \theta_t + \varepsilon_{i,t}^{OV} + \varepsilon_{i,t}^{EE})}{\text{Var}(ipf_{i,t})} \cdot \beta_1 + \frac{\text{Cov}(\varepsilon_{i,t}^{OV}, \varphi_{i,t})}{\text{Var}(ipf_{i,t})} \right]}_{+ \text{ or } -}\end{aligned}$$

- IV Estimate

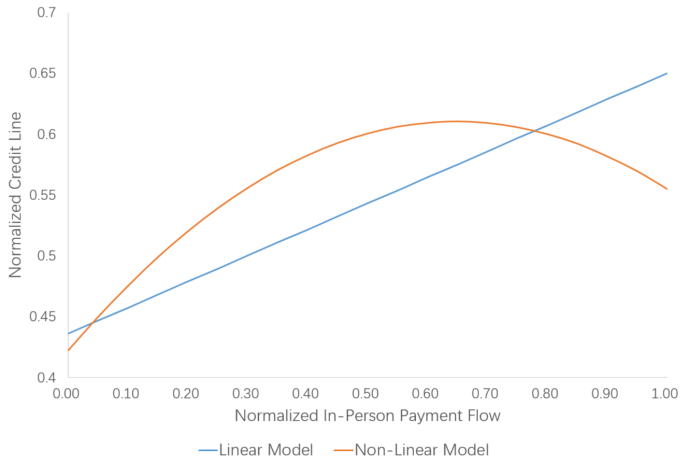
- Given  $\text{Cov}(ipf_{i,t}, bp_{c,t}) = \frac{1}{1 - \alpha_1 \cdot \beta_1} \cdot \text{Cov}(\varphi_{i,t}, bp_{c,t}) \neq 0$

$$\hat{\alpha}_1^{IV} = \frac{\text{Cov}(cl_{i,t}, bp_{c,t})}{\text{Cov}(ipf_{i,t}, bp_{c,t})} = \alpha_1$$

# Econometric Framework Setup

- Three Parties: Lender, Borrower  $i$ , Bike-Sharing Company
  - Credit Supply:  $cl_{i,t} = \alpha_0 + \alpha_1 \cdot ipf_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t}^{OV} + \varepsilon_{i,t}^{EE}$
  - In-Person Payment Decision:  $ipf_{i,t} = \beta_0 + \beta_1 \cdot cl_{i,t} + \mu_i + \omega_t + \varphi_{i,t}$
  - Exogenous Bike Placement Decision:  $bp_{c,t}$
  
- Identifying Assumptions
  - Both  $\varepsilon_{i,t} = \varepsilon_{i,t}^{OV} + \varepsilon_{i,t}^{EE}$  and  $\varphi_{i,t}$  are orthogonal to 1,  $\delta_i$ ,  $\theta_t$ ,  $\mu_i$ ,  $\omega_t$
  - $bp_{c,t}$  is a valid instrument for  $ipf_{i,t}$ :
    - $E[(\varepsilon_{i,t}^{OV} + \varepsilon_{i,t}^{EE}) \cdot bp_{c,t}] = 0$
    - $E[\varphi_{i,t} \cdot bp_{c,t}] \neq 0$

# Non-Monotone Payment-Credit Relationship

[Evidence in Regressions](#)[Go Back](#)

# Non-Monotone Payment-Credit Relationship: Regression

	Normalized Credit Line <sub><i>i,t</i></sub>			
	(1)	(2)	(3)	(4)
Normalized In-Person Payment Flow <sub><i>i,t</i></sub>	0.214*** (0.033)	0.581*** (0.076)	0.040*** (0.006)	0.105*** (0.013)
(Normalized In-Person Payment Flow <sub><i>i,t</i></sub> ) <sup>2</sup>		-0.448*** (0.064)		-0.075*** (0.009)
Constant	0.436*** (0.042)	0.422*** (0.043)		
Individual FE	NO	NO	YES	YES
Year-Month FE	NO	NO	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Observations	1,030,678	1,030,678	1,030,678	1,030,678
Adjusted <i>R</i> <sup>2</sup>	0.016	0.022	0.767	0.767

Note:

\**p* < 0.1; \*\**p* < 0.05; \*\*\**p* < 0.01

# Control for City $\times$ Year-Month Fixed Effects

	Credit Access $_{i,t}$		$\log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.115*** (0.004)	0.108*** (0.004)	0.398*** (0.016)	0.418*** (0.019)
Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$				
Bike User $_i \times \log(\text{Bike Placement})_{c,t}$	0.209*** (0.008)	0.178*** (0.008)	0.166*** (0.007)	0.134*** (0.007)
F-Statistic	772.9	476.0	503.2	343.0
Adjusted $R^2$	0.168	0.190	0.147	0.173
Panel C. Ordinary Least Squares				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.054*** (0.001)	0.047*** (0.001)	0.147*** (0.004)	0.121*** (0.004)
Adjusted $R^2$	0.193	0.245	0.181	0.363
City $\times$ Year-Month FE	YES	YES	YES	YES
Controls Individual Characteristics	NO	YES	NO	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit	Has Credit
Observations	1,238,309	664,727	779,283	440,418

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$



# In-Person Payment Flow and Future Credit Provision

	Credit Access $_{i,T}$			$\log(\text{Credit Line})_{i,T}$		
	$t + 1$	$t + 2$	$t + 3$	$t + 1$	$t + 2$	$t + 3$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Two-Stage Least Squares						
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.088*** (0.023)	0.085*** (0.024)	0.083*** (0.024)	0.250*** (0.071)	0.242*** (0.069)	0.235*** (0.064)
Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$						
$\log(\text{Bike Placement})_{c,t}$	0.041*** (0.011)	0.042*** (0.011)	0.042*** (0.011)	0.048*** (0.012)	0.048*** (0.013)	0.049*** (0.013)
F-Statistic	15.4	15.1	15.4	15.0	14.6	15.0
Adjusted $R^2$	0.552	0.553	0.554	0.523	0.522	0.521
Panel C. Ordinary Least Squares						
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.008*** (0.001)	0.007*** (0.001)	0.006*** (0.001)	0.025*** (0.003)	0.026*** (0.003)	0.027*** (0.003)
Adjusted $R^2$	0.743	0.750	0.757	0.837	0.839	0.841
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Full Sample	Has Credit	Has Credit	Has Credit
Observations	1,199,746	1,161,435	1,123,295	775,512	763,560	750,694

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

# Control for Past In-Person Payment Flow

	Credit Access $_{i,t}$			$\log(\text{Credit Line})_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Two-Stage Least Squares						
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.139*** (0.038)	0.154*** (0.048)	0.157*** (0.056)	0.388*** (0.129)	0.457*** (0.167)	0.531** (0.204)
Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$						
$\log(\text{Bike Placement})_{c,t}$	0.024*** (0.006)	0.019*** (0.005)	0.016*** (0.005)	0.027*** (0.007)	0.022*** (0.006)	0.018*** (0.005)
F-Statistic	16.7	14.0	11.0	16.4	14.5	12.3
Adjusted $R^2$	0.636	0.647	0.651	0.596	0.605	0.608
Panel C. Ordinary Least Squares						
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.007*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.015*** (0.002)	0.012*** (0.002)	0.010*** (0.002)
Adjusted $R^2$	0.743	0.751	0.759	0.837	0.840	0.842
Controls $\log(1 + \text{In-Person Payment Flow})_{i,t-1}$	YES	YES	YES	YES	YES	YES
Controls $\log(1 + \text{In-Person Payment Flow})_{i,t-2}$	NO	YES	YES	NO	YES	YES
Controls $\log(1 + \text{In-Person Payment Flow})_{i,t-3}$	NO	NO	YES	NO	NO	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Full Sample	Has Credit	Has Credit	Has Credit
Observations	1,199,825	1,161,573	1,123,548	775,601	763,711	750,940

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

# Control for Bike Usage

	Credit Access <sub><i>i,t</i></sub>		$\log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.098*** (0.030)	0.097*** (0.030)	0.329*** (0.112)	0.329*** (0.112)
$\log(1 + \text{Measure of Bike Usage})_{i,t}$	-0.034** (0.015)	-0.028** (0.012)	-0.112** (0.048)	-0.094** (0.041)
Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$				
$\log(\text{Bike Placement})_{c,t}$	0.034*** (0.010)	0.034*** (0.010)	0.036*** (0.011)	0.036*** (0.011)
$\log(1 + \text{Measure of Bike Usage})_{i,t}$	0.497*** (0.022)	0.391*** (0.030)	0.408*** (0.021)	0.324*** (0.027)
F-Statistic	11.2	11.2	10.2	10.2
Adjusted $R^2$	0.554	0.554	0.530	0.529
Panel C. Ordinary Least Squares				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.010*** (0.001)	0.010*** (0.001)	0.021*** (0.003)	0.022*** (0.003)
$\log(1 + \text{Measure of Bike Usage})_{i,t}$	0.010*** (0.002)	0.007*** (0.001)	0.015*** (0.005)	0.007* (0.004)
Adjusted $R^2$	0.740	0.740	0.836	0.836
Measure of Bike Usage	# Bike Rides	Riding Distance	# Bike Rides	Riding Distance
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit	Has Credit
Observations	1,238,309	1,238,309	779,283	779,283

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

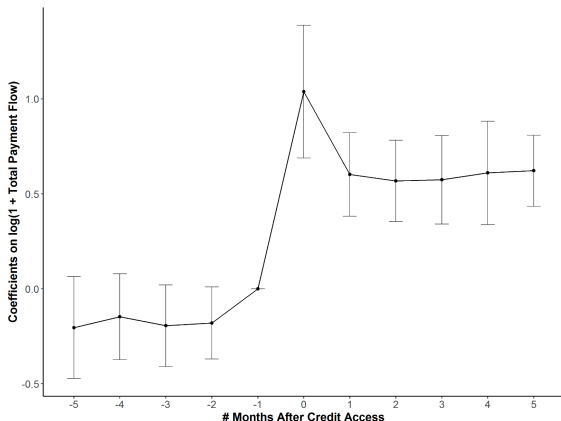
# Control for Online Payments

	Credit Access <sub>i,t</sub>		$\log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.086*** (0.023)	0.085*** (0.023)	0.280*** (0.085)	0.277*** (0.082)
$\log(1 + \text{Measure of Online Payment})_{i,t}$	-0.009 (0.006)	-0.028 (0.017)	-0.037* (0.021)	-0.107* (0.054)
Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$				
$\log(\text{Bike Placement})_{c,t}$	0.041*** (0.010)	0.042*** (0.010)	0.043*** (0.012)	0.044*** (0.012)
$\log(1 + \text{Measure of Online Payment})_{i,t}$	0.260*** (0.007)	0.716*** (0.015)	0.246*** (0.008)	0.649*** (0.018)
F-Statistic	16.0	16.2	14.0	14.3
Adjusted $R^2$	0.572	0.574	0.544	0.545
Panel C. Ordinary Least Squares				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.008*** (0.001)	0.008*** (0.001)	0.018*** (0.002)	0.018*** (0.002)
$\log(1 + \text{Measure of Online Payment})_{i,t}$	0.011*** (0.001)	0.027*** (0.002)	0.027*** (0.003)	0.061*** (0.007)
Adjusted $R^2$	0.742	0.742	0.837	0.836
Measure of Online Payment	Online Payment Flow	# Online Transactions	Online Payment Flow	# Online Transactions
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit	Has Credit
Observations	1,238,309	1,238,309	779,283	779,283

Note:

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

# Credit Access and Payment Changes



$$\log(1 + \text{Total Payment Flow})_{i,t} = \alpha_0 + \sum_{\tau=-5}^4 \beta_{\tau} \cdot \mathbb{1}(t = \tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t}$$

## Setup of the Illustrative Example

- There are a monopolistic lender and a continuum of borrowers
- Type of borrower  $i$ :  $\theta_i \sim U[0, 1]$
- Lender's expected profit of lending  $l_i$  to borrower  $i$ , given  $\theta_i$

$$\pi_i(\theta_i, l_i) = \begin{cases} \theta_i + 2 \cdot \theta_i \cdot l_i - l_i^2 - 1 & , \text{ if } l_i > 0 \\ 0 & , \text{ if } l_i = 0 \end{cases}$$

- Properties of the expected profit function
  - Fix credit line  $l_i$ ,  $\pi_i(\theta_i, l_i)$  increases with borrower type  $\theta_i$
  - Fix  $\theta_i$ ,  $\exists$  optimal credit line  $l^*(\theta_i)$  that maximizes  $\pi_i(\theta_i, l_i)$
  - If optimal credit line  $l^*(\theta_i)$  is non-zero,  $l^*(\theta_i)$  increases with  $\theta_i$
- When the lender only knows the type distribution of a group, it will lend the same to everyone if expected profit is positive

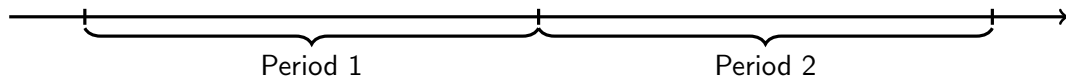
## Age and Payment-Credit Relationship

	Credit Access <sub><i>i,t</i></sub>		$\log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$\log(1 + \text{In-Person Payment Flow})_{i,t}$	0.124*** (0.041)	0.047** (0.020)	0.440*** (0.177)	0.176** (0.065)
Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$				
$\log(\text{Bike Placement})_{c,t}$	0.032*** (0.010)	0.049*** (0.012)	0.030*** (0.011)	0.054*** (0.013)
F-Statistic	9.7	17.8	7.0	16.6
Adjusted $R^2$	0.552	0.539	0.559	0.483
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit	Has Credit
Subsample	Older than Median	Younger than Median	Older than Median	Younger than Median
Observations	577,711	654,823	335,670	443,402

*Note:*

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

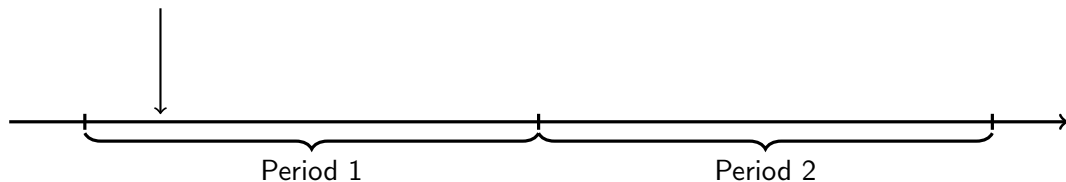
# Timeline

[Go Back](#)



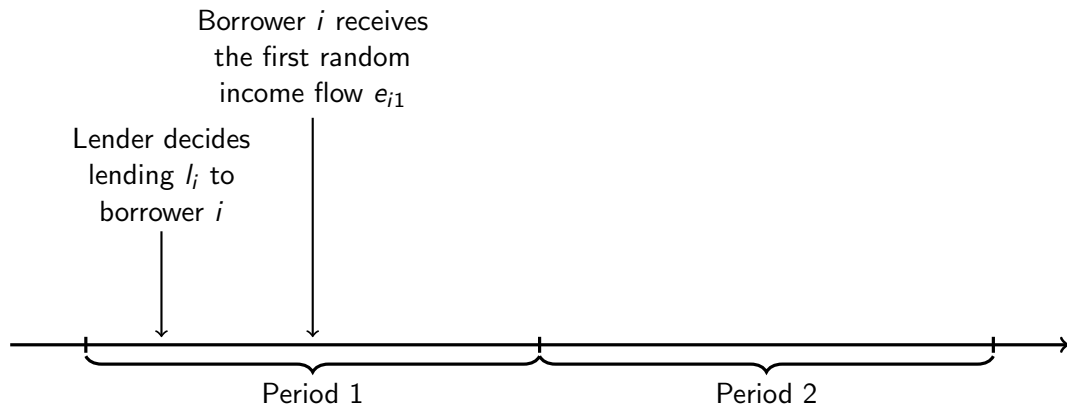
# Timeline

Lender decides  
lending  $l_i$  to  
borrower  $i$

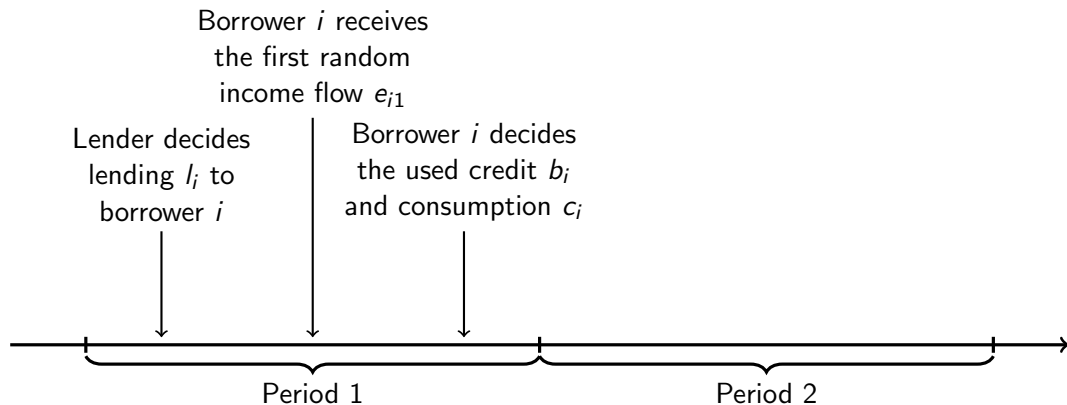


Go Back

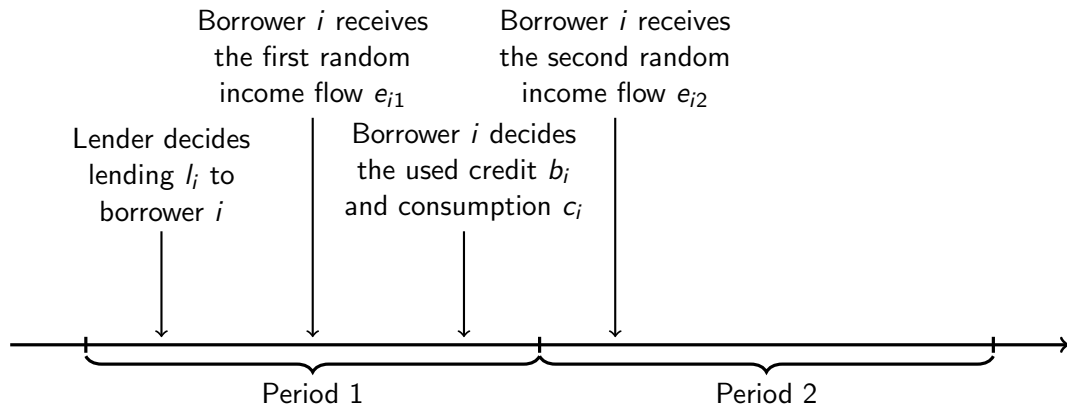
# Timeline



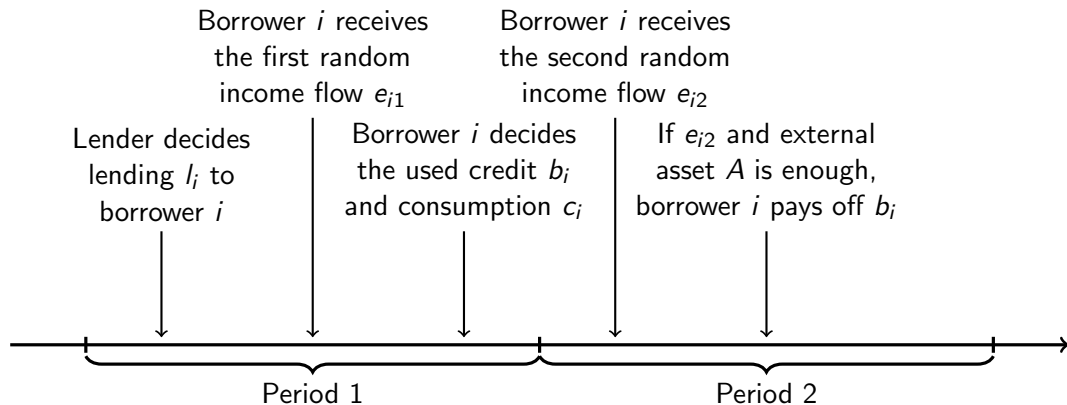
# Timeline



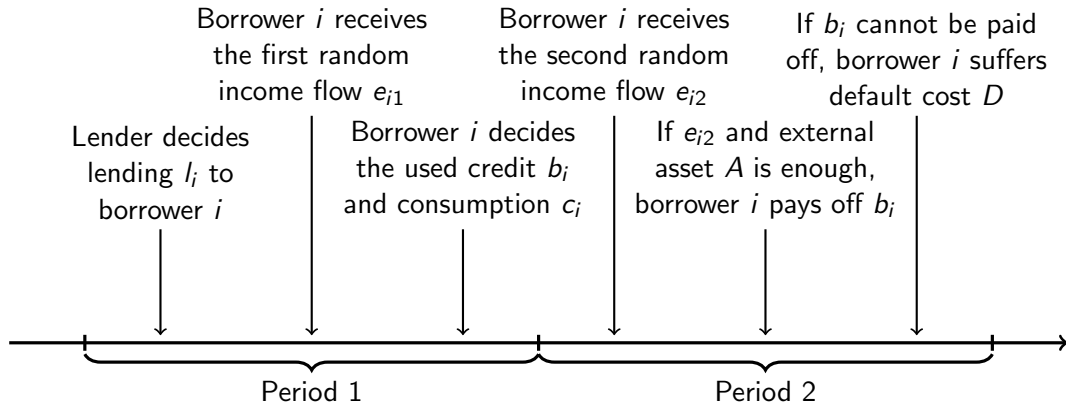
# Timeline



## Timeline



## Timeline



[Go Back](#)

## Random Income Flow

- Income flow of borrow  $i$  in period  $t = 1, 2$  is determined by:

$$e_{it} = X_i\beta + y_i + \epsilon_{it}$$

where

- $X_i$  is a vector of observable characteristics of borrower  $i$
- $y_i$  is an unobservable type of borrower  $i$ 
  - We assume  $y_i \in \mathcal{N}(0, \sigma_y^2)$
  - The density function is  $g(y) = \frac{1}{\sigma_y \sqrt{2\pi}} e^{-y^2/2\sigma_y^2}$
- $\epsilon_{it}$  is an unobservable shock to borrower  $i$  in period  $t$ 
  - We assume idiosyncratic shock  $\epsilon_{it} \in \mathcal{N}(0, \sigma_\epsilon^2)$  and  $\epsilon_{it} \perp\!\!\!\perp y_i$
  - The density function is  $f(\epsilon) = \frac{1}{\sigma_\epsilon \sqrt{2\pi}} e^{-\epsilon^2/2\sigma_\epsilon^2}$

[Go Back](#)

## Lender's Problem

- In period  $t = 1$ , the lender decides to offer a credit line of  $l_i$  to borrower  $i$ , and charges a unit fee of  $R$  for used credit  $b_i$ . In the digital payment era, we assume all the consumption are paid with digital money, and the lender observes borrower  $i$ 's consumption  $c_i$
- In period  $t = 2$ , the lender suffers a loss of the credit line amount  $l_i$  if the borrower  $i$  defaults
- The lender choose optimal credit line  $l_i$  to maximize its profit

$$\max_{l_i} R \cdot b_i - \mathbb{E}[\mathbb{1}_i^D | X_i, b_i, c_i; \beta, R, A] \cdot l_i$$

where  $\mathbb{1}_i^D$  is a dummy variable indicating whether borrower  $i$  defaults in period  $t = 2$



## Borrower $i$ 's Problem

- In period  $t = 1$ , the borrower  $i$  receives the random income flow  $e_{i1}$ , knows about the credit line available to her  $l_i$ , decides the amount of credit she would like to use  $b_i$ , and make the consumption  $c_i$ 
  - We assume the borrower is hand to mouth in period  $t = 1$ , and the consumption is  $c_i = e_{i1} + (1 - R) \cdot b_i$
- In period  $t = 2$ , borrower  $i$  receives the random income flow  $e_{i2}$ , and tries to pay off the credit balance  $b_i$  with the income and an external illiquid asset  $A$ . If the balance cannot be paid off, borrower  $i$  defaults and suffers a default cost  $D$
- Borrower  $i$  is risk-neutral and discounts future cash flows, she chooses optimal used credit  $b_i$  to maximize the utility

$$\max_{b_i} c_i - \rho \cdot \mathbb{E}[\mathbb{1}_i^D | X_i, b_i, c_i; \beta, R, A] \cdot D - \rho \cdot (1 - \mathbb{E}[\mathbb{1}_i^D | X_i, b_i, c_i; \beta, R, A]) \cdot b_i$$

such that

$$0 \leq b_i \leq l_i$$

## First Order Conditions

- FOC of the lender's problem

$$R \cdot \frac{\partial b_i}{\partial l_i} - \Phi\left(\frac{b_i - A - e_{i1}}{\sqrt{2}\sigma_\epsilon}\right) - \phi\left(\frac{b_i - A - e_{i1}}{\sqrt{2}\sigma_\epsilon}\right) \cdot \frac{l_i}{\sqrt{2}\sigma_\epsilon} \cdot \frac{\partial b_i}{\partial l_i} = 0$$

- FOC of the borrower  $i$ 's problem

$$(1 - R) - \phi\left(\frac{b_i - A - e_{i1}}{\sqrt{2}\sigma_\epsilon}\right) \cdot \frac{\rho \cdot (D - b_i)}{\sqrt{2}\sigma_\epsilon} - \rho \cdot [1 - \Phi\left(\frac{b_i - A - e_{i1}}{\sqrt{2}\sigma_\epsilon}\right)] = 0$$

[Go Back](#)

## Estimation Steps and Identification

- Calibrate credit usage fee  $R = 0.03$  and discounting parameter  $\rho = 0.9$
- Assume borrower  $i$  has fully shifted from cash to digital money for consumption when her credit line stops increasing
  - Assume borrowers are hand-to-mouth in these months, thus  $c_i = e_{i1} + (1 - R) \cdot b_i$
  - The observed consumption  $c_i$  and used credit  $b_i$  imply monthly income  $e_{i1}$
  - Monthly income is determined by  $e_{i1} = X_i\beta + y_i + \epsilon_{i1}$
  - The variations in monthly income help us to estimate  $\sigma_\epsilon$
  - Use the average monthly values as the observed  $c_i$ ,  $b_i$  and  $e_{i1}$  respectively
- Estimate the parameters  $\beta$  and  $\sigma_y$  with a cross-sectional regression
  - Run the OLS regression:  $e_{i1} = X_i\beta + y_i + \epsilon_{i1}$
  - Let observables  $X_i$  include gender, education, age, and city
- Estimate external funding  $A$  by using lender's FOC as the moment condition
  - Assume lender uses heuristics to predict used credit:  $b_i = \lambda \cdot l_i$
- Estimate default cost  $D$  by using borrower's FOC as the moment condition

## Expectation of Default

- When lender knows borrower  $i$ 's consumption  $c_i$  (Digital Money User) Derivation

$$\begin{aligned}
 E[\mathbb{1}_i^D | X_i, b_i, c_i; \beta, R, A] &= \Phi\left(\frac{b_i - A - e_{i1}}{\sqrt{2}\sigma_\epsilon}\right) \\
 &= E[\mathbb{1}(X_i\beta + y_i + \epsilon_{i1} - \epsilon_{i1} + \epsilon_{i2} + A - b_i < 0) | X_i, b_i, c_i; \beta, R, A] \\
 &= \int_{-\infty}^{+\infty} \mathbb{1}(\epsilon_{i2} - \epsilon_{i1} < b_i - A - e_{i1} | b_i, e_{i1}) f(\epsilon_{i1}) f(\epsilon_{i2}) d\epsilon_{i1} d\epsilon_{i2}
 \end{aligned}$$

- When lender doesn't know consumption  $c_i$  (New Digital Money Adopter) Derivation

$$\begin{aligned}
 E[\mathbb{1}_i^D | X_i, b_i; \beta, R, A] &= \Phi\left(\frac{b_i - A - X_i\beta}{\sqrt{\sigma_\epsilon^2 + \sigma_y^2}}\right) \\
 &= E[\mathbb{1}(X_i\beta + y_i + \epsilon_{i2} + A - b_i < 0) | X_i, b_i; \beta, R, A] \\
 &= \int_{-\infty}^{+\infty} \mathbb{1}(y_i + \epsilon_{i2} < b_i - A - X_i\beta | X_i, b_i; \beta) g(y) f(\epsilon_{i2}) dy d\epsilon_{i2}
 \end{aligned}$$

## Expectation of Borrower $i$ 's Default

- When the agent knows borrower  $i$ 's consumption  $c_i$

$$\begin{aligned}
 & E[\mathbb{1}_i^D | X_i, b_i, c_i; \beta, R, A] \\
 &= E[\mathbb{1}(e_{i2} + A - b_i < 0) | X_i, b_i, c_i; \beta, R, A] \\
 &= E[\mathbb{1}(X_i\beta + y_i + \epsilon_{i2} + A - b_i < 0) | X_i, b_i, c_i; \beta, R, A] \\
 &= E[\mathbb{1}(X_i\beta + y_i + \epsilon_{i1} - \epsilon_{i1} + \epsilon_{i2} + A - b_i < 0) | X_i, b_i, c_i; \beta, R, A] \\
 &= E[\mathbb{1}(\epsilon_{i1} - \epsilon_{i1} + \epsilon_{i2} + A - b_i < 0) | X_i, b_i, c_i; \beta, R, A] \\
 &= E[\mathbb{1}(\epsilon_{i2} - \epsilon_{i1} < b_i - A - e_{i1}) | b_i, e_{i1}] \\
 &= \int_{-\infty}^{+\infty} \mathbb{1}(\epsilon_{i2} - \epsilon_{i1} < b_i - A - e_{i1} | b_i, e_{i1}) f(\epsilon_{i1}) f(\epsilon_{i2}) d\epsilon_{i1} d\epsilon_{i2} \\
 &= \Phi\left(\frac{b_i - A - e_{i1}}{\sqrt{2}\sigma_\epsilon}\right)
 \end{aligned}$$

## Expectation of Borrower $i$ 's Default

- When the agent doesn't know borrower  $i$ 's consumption  $c_i$ 
  - E.g. when the borrower makes consumption with cash instead of digital money, the lender does not know this information

$$\begin{aligned}
 & E[\mathbb{1}_i^D | X_i, b_i; \beta, R, A] \\
 &= E[\mathbb{1}(e_{i2} + A - b_i < 0) | X_i, b_i; \beta, R, A] \\
 &= E[\mathbb{1}(X_i\beta + y_i + \epsilon_{i2} + A - b_i < 0) | X_i, b_i; \beta, R, A] \\
 &= E[\mathbb{1}(y_i + \epsilon_{i2} < b_i - A - X_i\beta) | X_i, b_i; \beta] \\
 &= \int_{-\infty}^{+\infty} \mathbb{1}(y_i + \epsilon_{i2} < b_i - A - X_i\beta | X_i, b_i; \beta) g(y) f(\epsilon_{i2}) dy d\epsilon_{i2} \\
 &= \Phi\left(\frac{b_i - A - X_i\beta}{\sqrt{\sigma_\epsilon^2 + \sigma_y^2}}\right)
 \end{aligned}$$

# Estimation Specifications

- Data cleaning
  - Consumption and used credit are winsorized at 5% and 95%
  - The months with zero consumption are dropped
- OLS regression specification

$$e_{i1} = \beta_0 + \beta_{male} \cdot \mathbb{1}_i^{male} + \sum_{edu \in U} \beta_{edu} \cdot \mathbb{1}_i^{edu} + \sum_{k \in K} \beta_k \cdot \mathbb{1}_i^{k-5 < age \leq k} + \sum_{city \in C} \beta_{city} \cdot \mathbb{1}_i^{city} + u_i$$

where  $U = \{\text{Below College, Undergraduate, Graduate}\}$ ,  
 $K = \{1930, 1935, \dots, 2010\}$ ,  $C$  include 340 unique cities in China, and error term  $u_i = y_i + \epsilon_{i1}$ , thus  $u_i \in \mathcal{N}(0, \sigma_y^2 + \sigma_\epsilon^2)$

## Distribution of Observed Variables

	N	Mean	Std	Min	p25	Median	p75	Max
$c_i$	38,276	1,595.1	2,049.9	0.0	134.4	715.5	2,210.5	7,606.7
$b_i$	38,276	487.7	732.9	0.0	0.0	56.3	731.0	2,377.8
$e_{i1}$	38,276	1,122.0	1,665.8	0.0	48.8	344.2	1,431.9	7,606.7
$l_i$	38,276	7,145.5	10,256.8	0.0	0.0	3,000.0	10,000.0	61,000.0

[Go Back](#)



