Cashless Payment and Financial Inclusion

Shumiao Ouyang

Department of Economics and Bendheim Center for Finance,
Princeton University

CB&DC Job Market Candidate Virtual Workshop
October 2022

A Solution to the Financial Inclusion Challenge?

- Hard to extend credit access to the underprivileged

A Solution to the Financial Inclusion Challenge?

- Hard to extend credit access to the underprivileged
- BigTech credit is booming globally and overtaking FinTech credit (Cornelli et al., 2021)

A Solution to the Financial Inclusion Challenge?

- Hard to extend credit access to the underprivileged
- BigTech credit is booming globally and overtaking FinTech credit (Cornelli et al., 2021)
- Mobile cashless payment provided by BigTech firms
  - Naturally combines important technological advancements
  - Has accelerated the shift from cash to cashless economy

A Solution to the Financial Inclusion Challenge?

- Hard to extend credit access to the underprivileged
- BigTech credit is booming globally and overtaking FinTech credit (Cornelli et al., 2021)
- Mobile cashless payment provided by BigTech firms
  - Naturally combines important technological advancements
  - Has accelerated the shift from cash to cashless economy

Research Question

Has cashless payment facilitated lending to the traditionally underserved? If so, how?

Hard to Estimate Effects of Cashless Payment on Credit

Hard to Estimate Effects of Cashless Payment on Credit

- Requires an exogenous shock on the cashless payment activity

Hard to Estimate Effects of Cashless Payment on Credit

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

Hard to Estimate Effects of Cashless Payment on Credit

- Requires an exogenous shock on 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 $\rightarrow$ likelihood of credit access $\uparrow$ 56.3%
  - In-person payment amount $\uparrow$ 1% $\rightarrow$ credit line $\uparrow$ 0.41%

The Main Findings

- Cashless payment flow facilitates credit provision and take-up
  - Use in-person payment in a month $\rightarrow$ likelihood of credit access $\uparrow$ 56.3%
  - In-person payment amount $\uparrow$ 1% $\rightarrow$ credit line $\uparrow$ 0.41%
- BigTech takes advantage of information in the payment flow
  - Beyond what is in credit usage, repayment, and assets under management (AUM)

The Main Findings

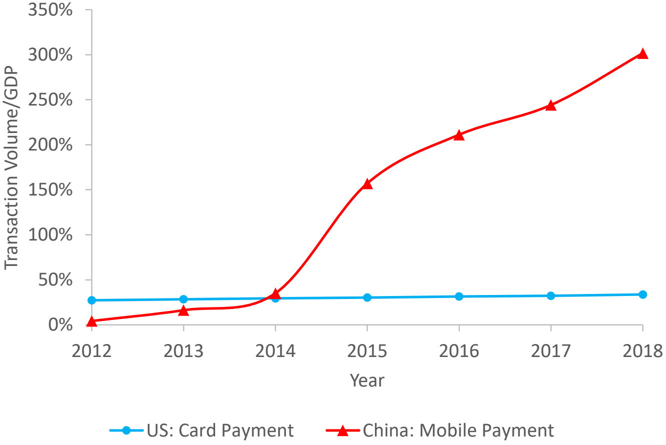
- Cashless payment flow facilitates credit provision and take-up
  - Use in-person payment in a month $\rightarrow$ likelihood of credit access $\uparrow$ 56.3%
  - In-person payment amount $\uparrow$ 1% $\rightarrow$ credit line $\uparrow$ 0.41%
- BigTech takes advantage of information in the payment flow
  - Beyond what is in credit usage, repayment, and assets under management (AUM)
  - Information value of payment data
    - Credit line $\uparrow$ 57.7% (2,088 CNY)
    - Annual consumer welfare $\uparrow$ 151.2 CNY per capita
    - Annual lender profit $\uparrow$ 62.4 CNY per capita

The Main Findings

- Cashless payment flow facilitates credit provision and take-up
  - Use in-person payment in a month $\rightarrow$ likelihood of credit access $\uparrow$ 56.3%
  - In-person payment amount $\uparrow$ 1% $\rightarrow$ credit line $\uparrow$ 0.41%
- BigTech takes advantage of information in the payment flow
  - Beyond what is in credit usage, repayment, and assets under management (AUM)
  - Information value of payment data
    - Credit line $\uparrow$ 57.7% (2,088 CNY)
    - Annual consumer welfare $\uparrow$ 151.2 CNY per capita
    - Annual lender profit $\uparrow$ 62.4 CNY per capita
- The financially underserved benefit more from it
  - Stronger credit provision effects on the less educated and older
  - More credit provision also leads to higher consumer welfare

Data and Identification

Observation 1: Rise of Cashless Payments



Source: US Federal Reserve, PBOC, World Bank

Types of Mobie Payments
Mobie Payments Penetration across Countries

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

Global Boom of BigTech Credit

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

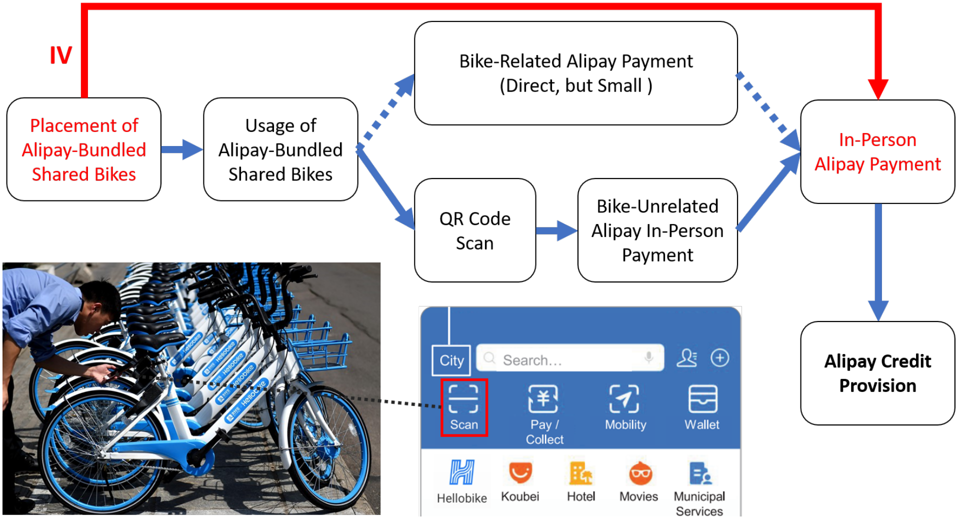
Data

- 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

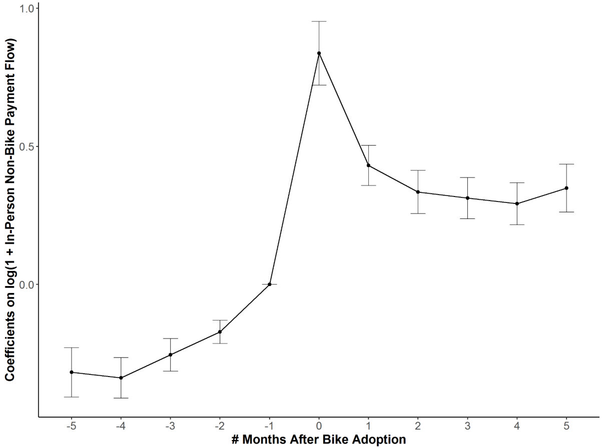
- Sample Period
  - From May 2017 to September 2020
  - Both mobile payment and bike-sharing industries develop fast

Alipay and Bike-Sharing Industry Alipay Registration and Bike Adoption

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***	0.011	
	(0.010)	(0.009)	
$\text{Bike User}_i \times log(\text{Bike Placement})_{c,t}$		0.103***	
		(0.017)	
$\text{After First Bike Usage}_{i,t}$			-0.123
			(0.161)
$\text{After First Bike Usage}_{i,t} \times log(\text{Bike Placement})_{c,t}$			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***	0.009	
	(0.008)	(0.010)	
Bike $\text{User}_i \times log(\text{Bike Placement})_{c,t}$		0.060**	
		(0.023)	
After First Bike $\text{Usage}_{i,t}$			-0.231
			(0.157)
After First Bike $\text{Usage}_{i,t} \times log(\text{Bike Placement})_{c,t}$			0.070***
			(0.013)
Individual FE	YES	YES	YES
Year-Month FE	YES	YES	-
City × 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 Sharing Background | 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$_{i,t}$			log(Credit Line)$_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Two-Stage Least Squares						
Measure of In-Person Payment Flow$_{i,t}$	0.086***	0.563***	0.087**	0.281***	2.033**	0.409***
	(0.024)	(0.175)	(0.043)	(0.085)	(0.766)	(0.132)
Panel B. First Stage for Measure of In-Person Payment Flow$_{i,t}$						
log(Bike Placement)$_{c,t}$	0.041***	0.006***	0.030***	0.043***	0.006***	0.024***
	(0.010)	(0.002)	(0.009)	(0.012)	(0.002)	(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$_{i,t}$	0.010***	0.062***	0.007***	0.022***	0.072***	0.029***
	(0.001)	(0.007)	(0.001)	(0.003)	(0.023)	(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: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

IV-OLS Comparison | City-Time FEs | Effect Persistence | Past Payments | Bike Usage | Online Payments

Information Channel vs. Enforcement Channel

	Credit Access$_{i,t}$		log(Credit Line)$_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares - Information Channel				
$log(1 +$ In-Person Noncredit Payment Flow$)_{i,t}$	0.094***	0.095***	0.329***	0.358***
	(0.024)	(0.026)	(0.103)	(0.124)
$log(1 +$ In-Person Credit Payment Flow$)_{i,t}$		-0.005		-0.044
		(0.006)		(0.029)
Panel B. Two-Stage Least Squares - Enforcement Channel				
$log(1 +$ In-Person Payment Flow$)_{i,t}$	0.097***	0.098***	0.280***	0.282***
	(0.025)	(0.026)	(0.085)	(0.086)
$log(1 +$ Assets under Management$)_{i,t}$	-0.005	-0.008	-0.015	-0.026*
	(0.004)	(0.005)	(0.011)	(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

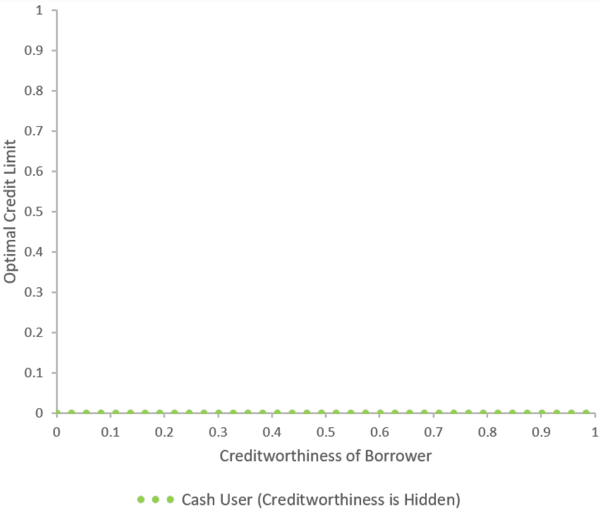
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

In-Person Payment Increases Credit Take-Up

	Virtual Credit Card Share$_{i,t}$		Compulsive Spending Share$_{i,t}$	
	In-Person Payment	Online Payment	In-Person Payment	Online Payment
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	0.094***	0.030***	0.004	0.002
	(0.034)	(0.011)	(0.010)	(0.002)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$				
$log(\text{Bike Placement})_{c,t}$	0.028***	0.064***	0.028***	0.064***
	(0.009)	(0.014)	(0.009)	(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:			$*p < 0.1$; $**p < 0.05$; $***p < 0.01$	

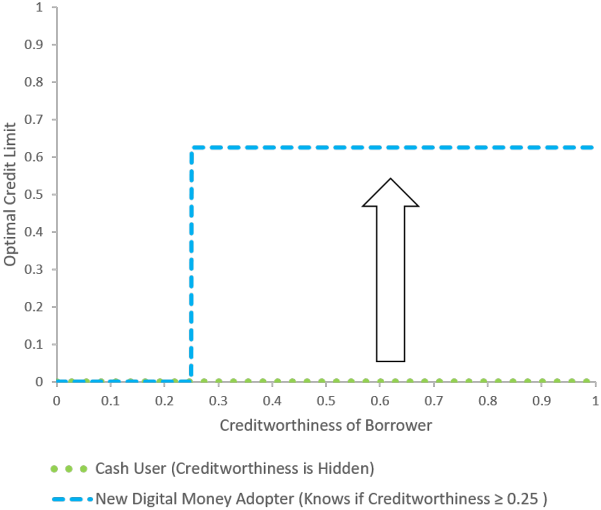
Credit Access and Payment Changes

More Precise Information, More Credit to the Less Creditworthy?



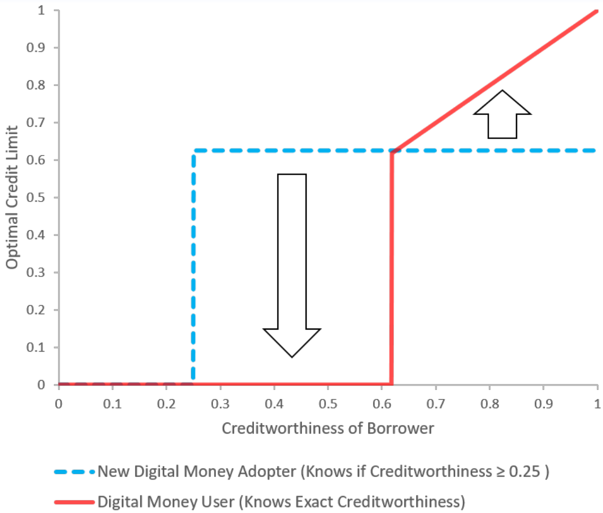
Setup of the Illustrative Example

More Precise Information, More Credit to the Less Creditworthy?



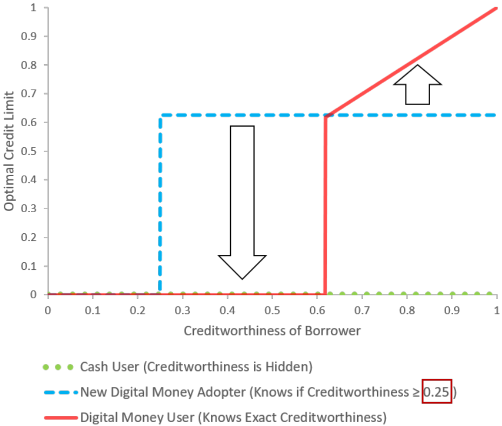
Setup of the Illustrative Example

More Precise Information, More Credit to the Less Creditworthy?



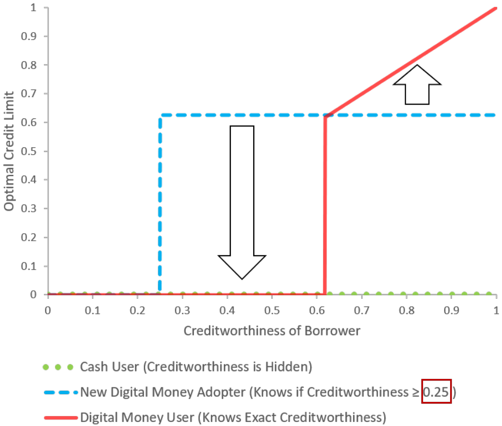
Setup of the Illustrative Example

More Precise Information, More Credit to the Less Creditworthy?

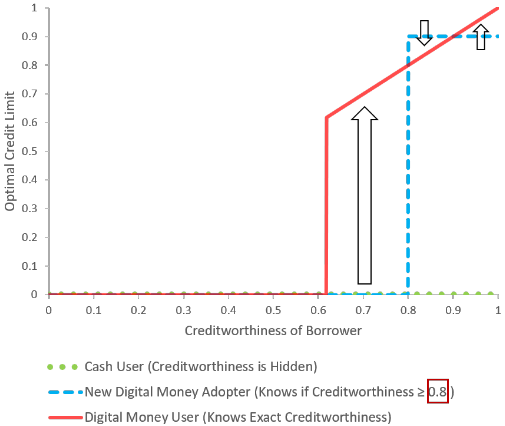


(a) Scenario of **Financial Divide**

More Precise Information, More Credit to the Less Creditworthy?



(a) Scenario of **Financial Divide**



(b) Scenario of **Financial Inclusion**

The Financially Underserved Segments

	Financial Service Usage			Financial Literacy		
	# Debit Cards$_i$	$log(1 + \text{Max. AUM})_i$	# Investment Months$_i$	Pay with Real Name$_i$	Use Own Account$_i$	Complete Profile$_i$
	(1)	(2)	(3)	(4)	(5)	(6)
Low Education$_i$	-0.694***	-1.078***	-3.076***	-0.119***	-0.087***	-0.122***
	(0.046)	(0.075)	(0.282)	(0.006)	(0.008)	(0.008)
Older than Median$_i$	-0.863***	-0.671***	-2.512***	-0.191***	-0.223***	-0.089***
	(0.025)	(0.045)	(0.141)	(0.006)	(0.009)	(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(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***	0.024	0.334***	0.038
	(0.027)	(0.044)	(0.109)	(0.073)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$				
$log(\text{Bike Placement})_{c,t}$	0.039***	0.043***	0.039***	0.053***
	(0.010)	(0.013)	(0.011)	(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:				$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Age and Payment-Credit Relationship

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

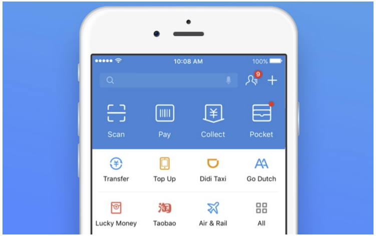
Conclusion

- 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
  - Mobile payment provides opportunities for sustainable and inclusive finance

Different Types of Mobile Payments

(a) *M-Pesa* and Mobile Phone

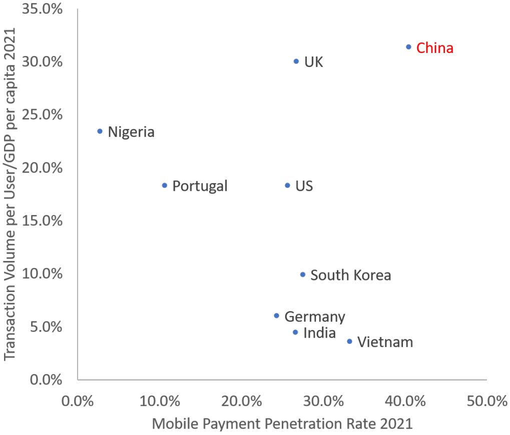
(b) *Apple Pay*, Card, and Phone



(c) *Alipay* and Smart Phone

Go Back

Mobile Payment Penetration across Countries

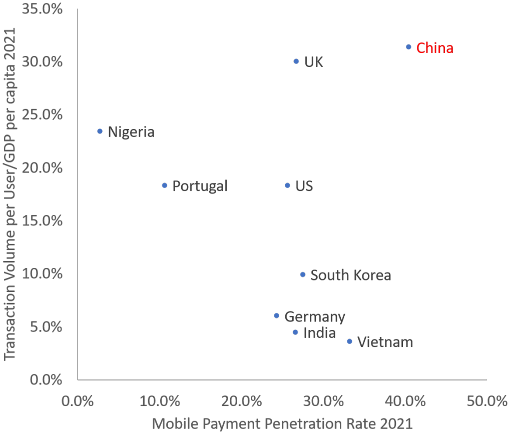


(a) 2021

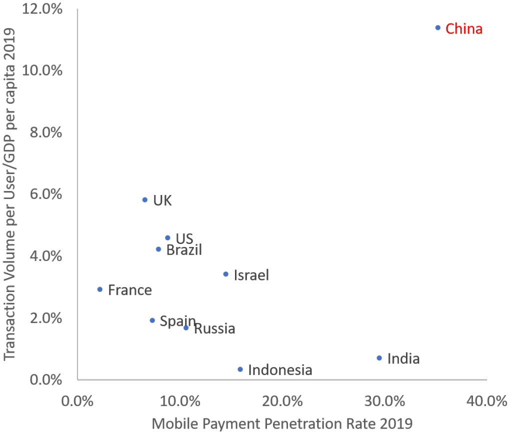
Source: Statista Digital Market Outlook, World Bank

Go Back

Mobile Payment Penetration across Countries



(a) 2021

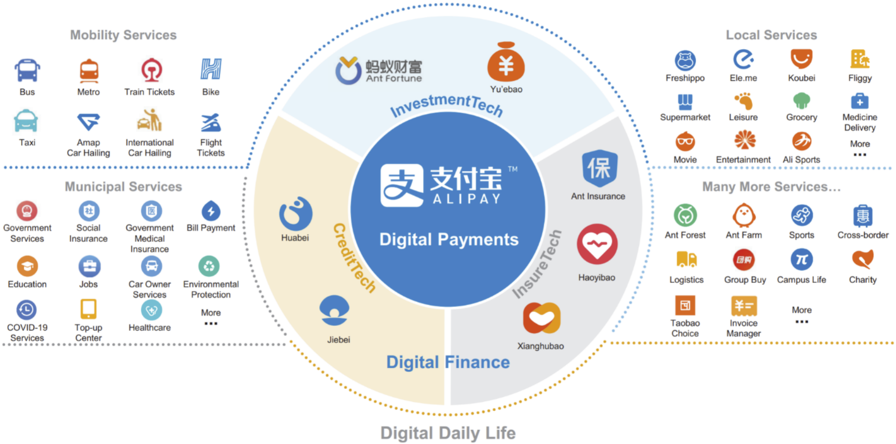


(b) 2019

Source: Statista Digital Market Outlook, World Bank

Go Back

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



Source: IPO Prospectus of Ant Group, 2020

Go Back

Features of Alipay's Huabei Credit Line

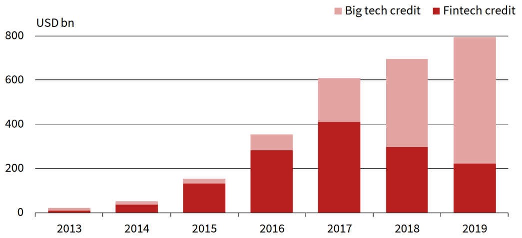
- No active application required
  - Qualification status and credit line instantly available
- No price discrimination
  - 0.05% daily rate (18.25% annually)
  - Interest-free period of up to 40 days
- Excellent risk management
  - Delinquency rate as of June 2019
    - Huabei: 1.16%
    - Credit cards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

Go Back

BigTech Credit is Booming Globally

Figure 1

Big Tech Credit Is Overtaking Fintech Credit

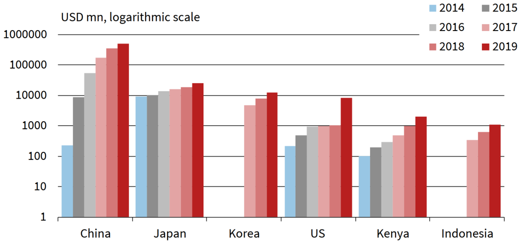


Note: 2019 fintech lending volume figures are estimated on AU, CN, EU, GB, NZ and US.

(a) BigTech and Fintech Credit

Figure 2

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



Note: Figures include estimates.

(b) Global Boom in BigTech Credit

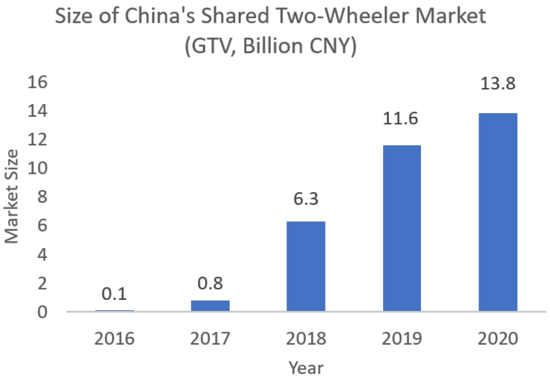
Source: Cornelli et al. (2020), CESifo Forum

Go Back

Alipay and Dockless Bike-Sharing Service

- Fast growing bike-sharing industry

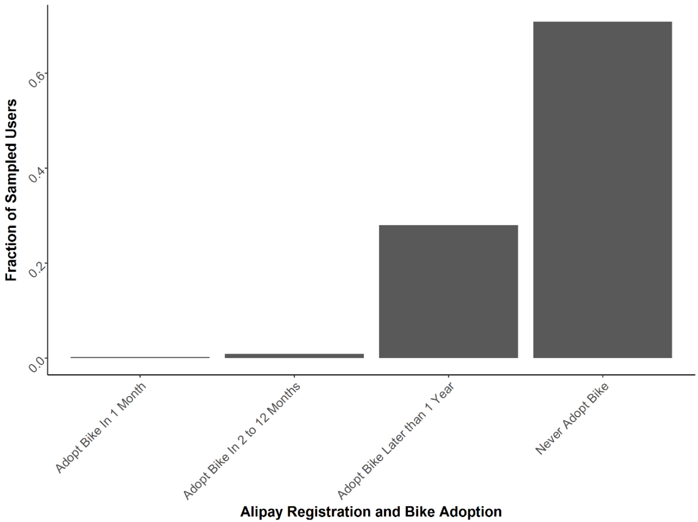
- Alipay-bundled shared bikes
  - Investment $\geq$ 3.5 billion dollars
  - Strategic partnership
  - Unlock bike directly with Alipay



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

Go Back

Alipay Registration and Shared-Bike Adoption



Go Back

Bike-Related Personal Characteristics

	Bike User$_i$		
	(1)	(2)	(3)
Low Education$_i$	-0.173***	-0.109***	-0.065***
	(0.009)	(0.010)	(0.009)
Older than Median$_i$	-0.095***	-0.110***	-0.096***
	(0.005)	(0.005)	(0.004)
Early Alipay User$_i$	-0.129***	-0.113***	-0.030***
	(0.007)	(0.006)	(0.005)
Male$_i$	0.049***	0.059***	0.045***
	(0.004)	(0.004)	(0.004)
Pay with Real Name$_i$	0.088***	0.081***	0.012**
	(0.006)	(0.005)	(0.005)
Use Own Account$_i$	0.076***	0.071***	0.033***
	(0.006)	(0.005)	(0.005)
Complete Profile$_i$	0.012*	0.001	-0.012*
	(0.007)	(0.006)	(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^2	0.123	0.178	0.260
Note:	*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$		

Go Back

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	0.008	0.029**	0.021**	-0.013	-0.010
	(0.014)	(0.010)	(0.011)	(0.009)	(0.015)	(0.010)
Bike $\text{User}_i \times log(\text{Bike Placement})_{c,t}$	0.139***	0.110***	0.092***	0.099***	0.057**	0.139***
	(0.029)	(0.018)	(0.017)	(0.021)	(0.025)	(0.029)
Characteristic $\text{Measure}_i \times log(\text{Bike Placement})_{c,t}$	0.036**	0.004	-0.038***	-0.023**	0.033*	0.036**
	(0.017)	(0.013)	(0.012)	(0.008)	(0.019)	(0.017)
Bike $\text{User}_i \times$ Characteristic $\text{Measure}_i \times log(\text{Bike Placement})_{c,t}$	-0.040	-0.017	0.009	0.009	0.046**	-0.045
	(0.031)	(0.018)	(0.025)	(0.020)	(0.023)	(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	0.014	0.020	0.004	-0.008	0.003
	(0.021)	(0.010)	(0.013)	(0.014)	(0.013)	(0.015)
Bike $\text{User}_i \times log(\text{Bike Placement})_{c,t}$	0.051*	0.053*	0.057*	0.056**	0.049*	0.042**
	(0.030)	(0.026)	(0.029)	(0.025)	(0.029)	(0.020)
Characteristic $\text{Measure}_i \times log(\text{Bike Placement})_{c,t}$	0.0001	-0.011	-0.023	0.008	0.024*	0.012
	(0.026)	(0.018)	(0.025)	(0.012)	(0.014)	(0.014)
Bike $\text{User}_i \times$ Characteristic $\text{Measure}_i \times log(\text{Bike Placement})_{c,t}$	0.012	0.016	-0.008	0.007	0.007	0.022
	(0.025)	(0.028)	(0.046)	(0.019)	(0.037)	(0.034)
Adjusted R^2	0.800	0.799	0.800	0.799	0.800	0.800
Personal Characteristic Measure	Low Education_i	Older than Median_i	Early Alipay User_i	Male_i	Pay with Real Name_i	Use Own Account_i
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

	$log(1 + \text{In-Person Payment Flow})_{i,t}$		$log(1 + \text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
$log(\text{Bike Placement})_{c,t}$	0.011		0.009	
	(0.009)		(0.010)	
One-Time Bike User$_i$ $\times$ $log(\text{Bike Placement})_{c,t}$	0.088***	0.072***	0.048**	0.035
	(0.020)	(0.019)	(0.023)	(0.025)
Repeat Bike User$_i$ $\times$ $log(\text{Bike Placement})_{c,t}$	0.106***	0.078***	0.062**	0.040
	(0.018)	(0.017)	(0.025)	(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: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

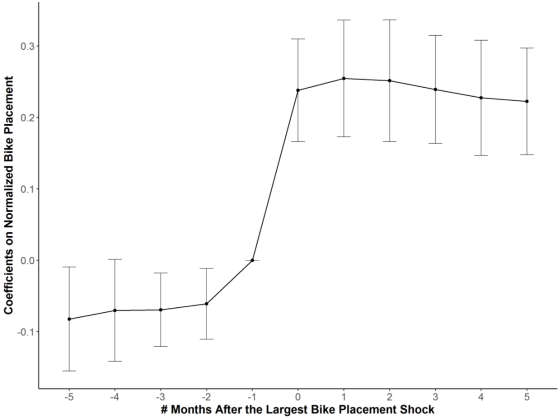
Go Back

Bike Placement and Local Economy

	$log(\text{GDP})_{c,t}$ (1)	$log(\text{GDP per capita})_{c,t}$ (2)	Fiscal Spending/GDP$_{c,t}$ (3)	Fiscal Income/GDP$_{c,t}$ (4)
$log(\text{Bike Placement})_{c,t}$	0.002	0.000	-0.001	0.000
	(0.002)	(0.002)	(0.001)	(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

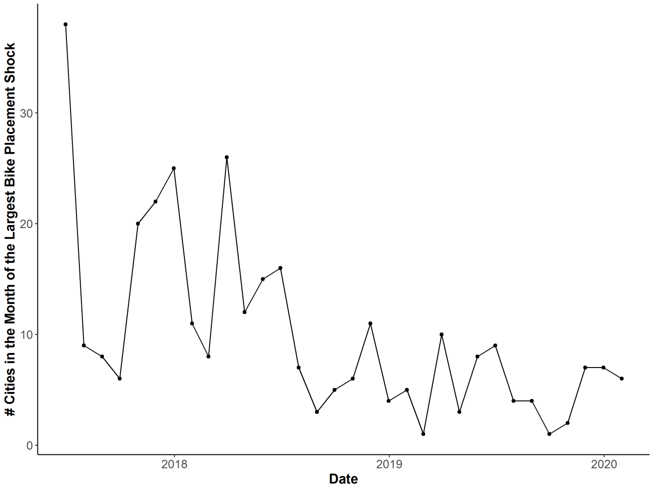
Staggered Placement of Shared Bikes



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

Go Back

Broad Distribution of Bike-Placement Shock



Go Back

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 $\varepsilon^{EE}_{i,t} \perp \varphi_{i,t}$, then

$$\hat{\alpha}_1^{OLS} = \frac{Cov(cl_{i,t}, ipf_{i,t})}{Var(ipf_{i,t})}$$

$$= \alpha_1 + \underbrace{\frac{1}{1-\alpha_1 \cdot \beta_1}}_{+} \cdot [\underbrace{\frac{Var(\delta_i + \theta_t + \varepsilon^{OV}_{i,t} + \varepsilon^{EE}_{i,t})}{Var(ipf_{i,t})} \cdot \beta_1}_{+} + \underbrace{\frac{Cov(\varepsilon^{OV}_{i,t}, \varphi_{i,t})}{Var(ipf_{i,t})}}_{+ \text{ or } -}]$$

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

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

Go Back

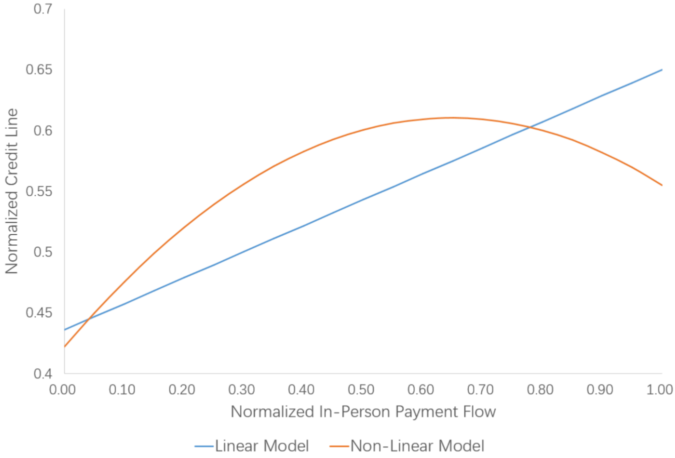
Econometric Framework Setup

- 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, δ_i, θ_t, μ_i, ω_t
  - $bp_{c,t}$ is a valid instrument for $ipf_{i,t}$:
    - $\mathrm{E}[(\varepsilon_{i,t}^{OV} + \varepsilon_{i,t}^{EE}) \cdot bp_{c,t}] = 0$
    - $\mathrm{E}[\varphi_{i,t} \cdot bp_{c,t}] \neq 0$

Go Back

Non-Monotone Payment-Credit Relationship



Evidence in Regressions

Go Back

Non-Monotone Payment-Credit Relationship: Regression

	Normalized Credit Line$_{i,t}$			
	(1)	(2)	(3)	(4)
Normalized In-Person Payment Flow$_{i,t}$	0.214***	0.581***	0.040***	0.105***
	(0.033)	(0.076)	(0.006)	(0.013)
(Normalized In-Person Payment Flow$_{i,t}$)^2		-0.448***		-0.075***
		(0.064)		(0.009)
Constant	0.436***	0.422***		
	(0.042)	(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 R^2	0.016	0.022	0.767	0.767
Note:	$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$			

Go Back

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

	Credit Access$_{i,t}$		log(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***	0.108***	0.398***	0.418***
	(0.004)	(0.004)	(0.016)	(0.019)
	Panel B. First Stage for $log(1+\text{In-Person Payment Flow})_{i,t}$			
Bike User$_i$ $\times$ log(Bike Placement)$_{c,t}$	0.209***	0.178***	0.166***	0.134***
	(0.008)	(0.008)	(0.007)	(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***	0.047***	0.147***	0.121***
	(0.001)	(0.001)	(0.004)	(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:		*$p<0.1$; **$p<0.05$; ***$p<0.01$		

Go Back

In-Person Payment Flow and Future Credit Provision

	Credit Access$_{i,T}$			log(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***	0.085***	0.083***	0.250***	0.242***	0.235***
	(0.023)	(0.024)	(0.024)	(0.071)	(0.069)	(0.064)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$						
$log(\text{Bike Placement})_{c,t}$	0.041***	0.042***	0.042***	0.048***	0.048***	0.049***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)	(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***	0.007***	0.006***	0.025***	0.026***	0.027***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(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: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Go Back

Control for Past In-Person Payment Flow

	Credit Access$_{i,t}$			log(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***	0.154***	0.157***	0.388***	0.457***	0.531**
	(0.038)	(0.048)	(0.056)	(0.129)	(0.167)	(0.204)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$						
$log(\text{Bike Placement})_{c,t}$	0.024***	0.019***	0.016***	0.027***	0.022***	0.018***
	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)	(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***	0.006***	0.006***	0.015***	0.012***	0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(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: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Go Back

Control for Bike Usage

	Credit Access$_{i,t}$		log(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***	0.097***	0.329***	0.329***
	(0.030)	(0.030)	(0.112)	(0.112)
$log(1 + \text{Measure of Bike Usage})_{i,t}$	-0.034**	-0.028**	-0.112**	-0.094**
	(0.015)	(0.012)	(0.048)	(0.041)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$				
$log(\text{Bike Placement})_{c,t}$	0.034***	0.034***	0.036***	0.036***
	(0.010)	(0.010)	(0.011)	(0.011)
$log(1 + \text{Measure of Bike Usage})_{i,t}$	0.497***	0.391***	0.408***	0.324***
	(0.022)	(0.030)	(0.021)	(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***	0.010***	0.021***	0.022***
	(0.001)	(0.001)	(0.003)	(0.003)
$log(1 + \text{Measure of Bike Usage})_{i,t}$	0.010***	0.007***	0.015***	0.007*
	(0.002)	(0.001)	(0.005)	(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:				$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Go Back

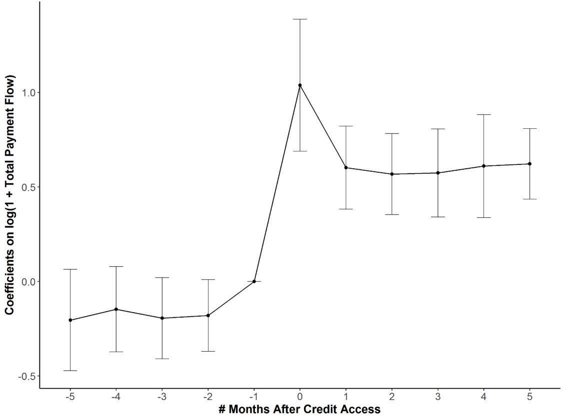
Control for Online Payments

	Credit Access$_{i,t}$		log(Credit Line)$_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$log(1 +$ In-Person Payment Flow$)_{i,t}$	0.086***	0.085***	0.280***	0.277***
	(0.023)	(0.023)	(0.085)	(0.082)
$log(1 +$ Measure of Online Payment$)_{i,t}$	-0.009	-0.028	-0.037*	-0.107*
	(0.006)	(0.017)	(0.021)	(0.054)
Panel B. First Stage for $log(1 +$ In-Person Payment Flow$)_{i,t}$				
log(Bike Placement)$_{c,t}$	0.041***	0.042***	0.043***	0.044***
	(0.010)	(0.010)	(0.012)	(0.012)
$log(1 +$ Measure of Online Payment$)_{i,t}$	0.260***	0.716***	0.246***	0.649***
	(0.007)	(0.015)	(0.008)	(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				
$log(1 +$ In-Person Payment Flow$)_{i,t}$	0.008***	0.008***	0.018***	0.018***
	(0.001)	(0.001)	(0.002)	(0.002)
$log(1 +$ Measure of Online Payment$)_{i,t}$	0.011***	0.027***	0.027***	0.061***
	(0.001)	(0.002)	(0.003)	(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: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Go Back

Credit Access and Payment Changes



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

Go Back

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 θ_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 θ_i
  - Fix θ_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 θ_i
- When the lender only knows the type distribution of a group, it will lend the same to everyone if expected profit is positive

Go Back

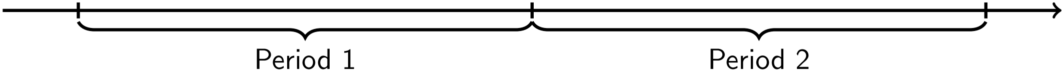
Age and Payment-Credit Relationship

	Credit Access$_{i,t}$		log(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***	0.047**	0.440***	0.176**
	(0.041)	(0.020)	(0.177)	(0.065)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$				
$log(\text{Bike Placement})_{c,t}$	0.032***	0.049***	0.030***	0.054***
	(0.010)	(0.012)	(0.011)	(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: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

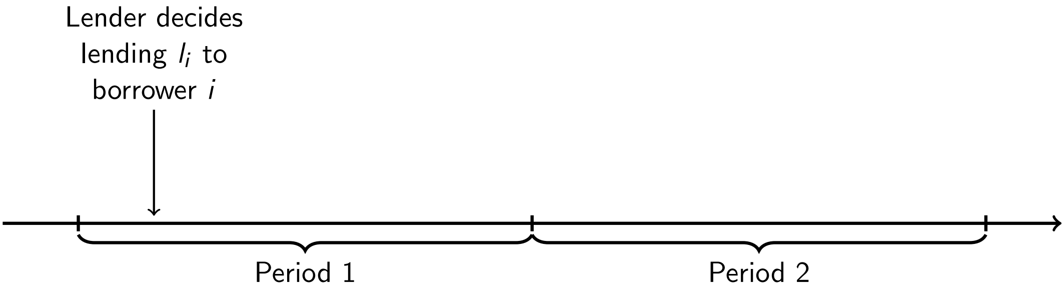
Go Back

Timeline



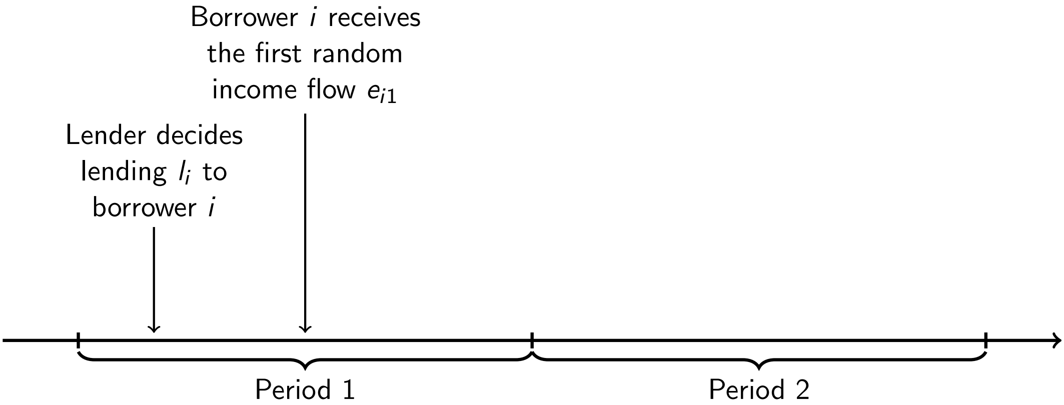
Go Back

Timeline



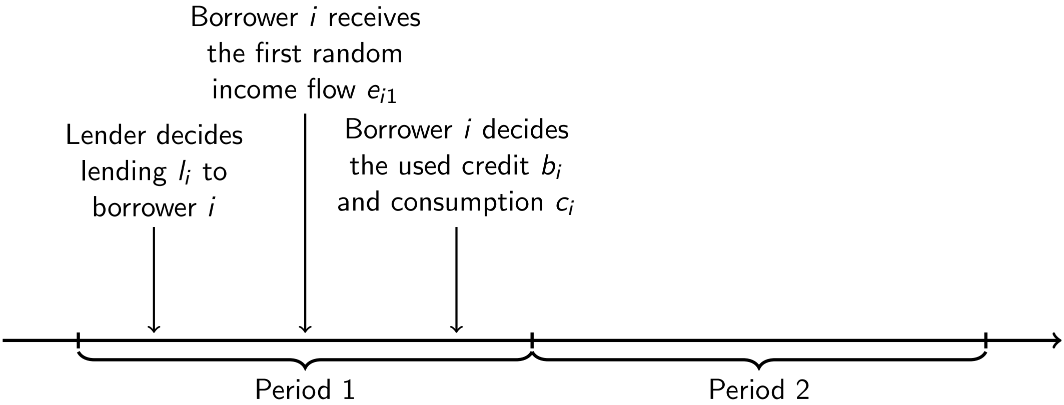
Go Back

Timeline



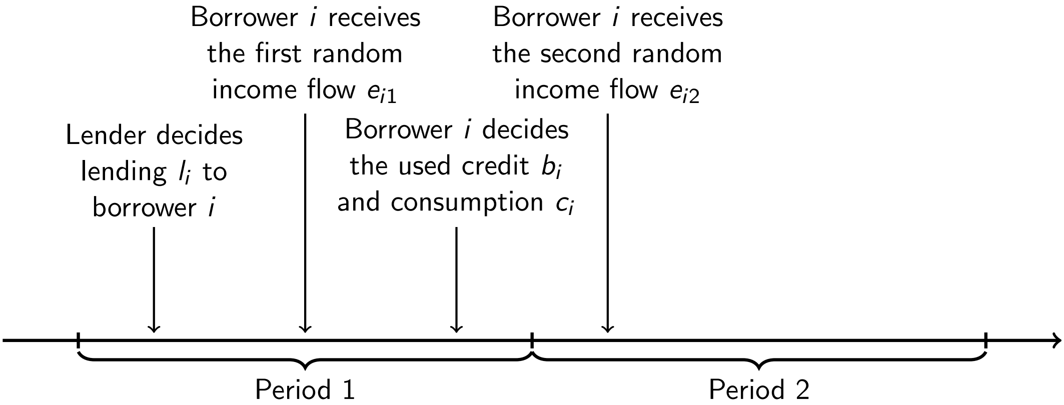
Go Back

Timeline



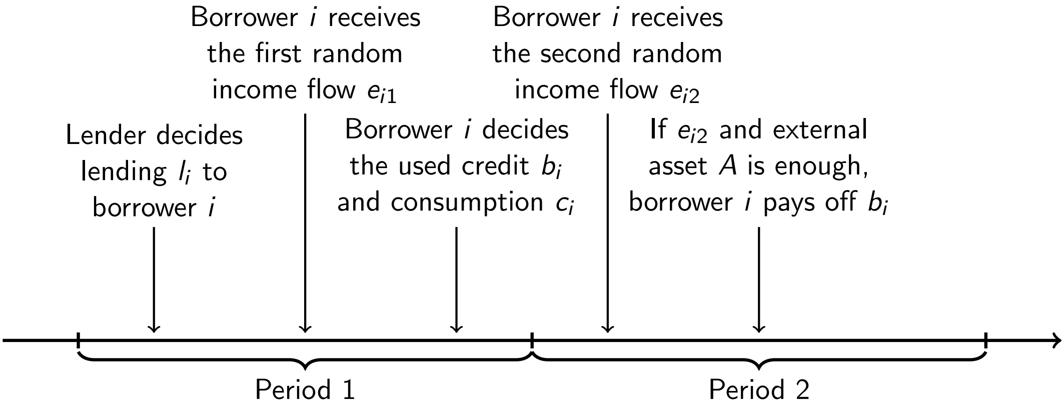
Go Back

Timeline



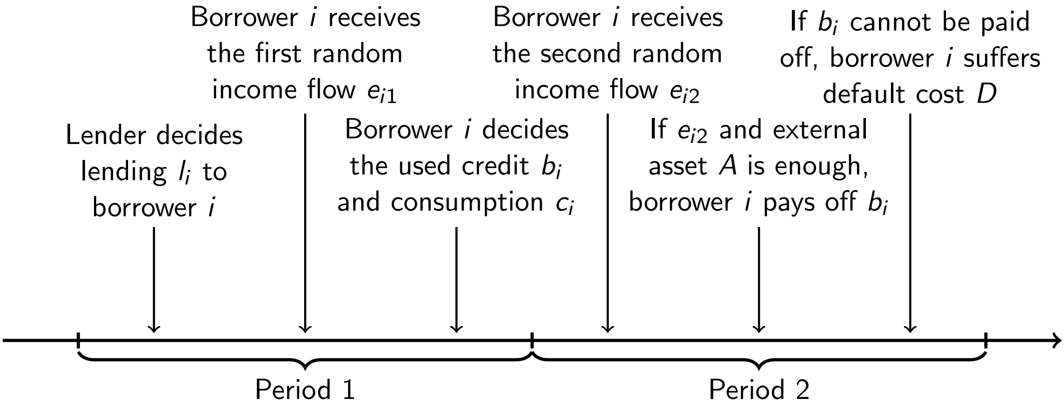
Go Back

Timeline



Go Back

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 observant characteristics of borrower i
- y_i is an unobservant type of borrower i
  - We assume $y_i \in \mathcal{N}(0, \sigma_y^2)$
  - The density function is $g(y) = \frac{1}{\sigma_y\sqrt{2\pi}} e^{-y^2/2\sigma_y^2}$
- ϵ_{it} is an unobservant 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

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

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

Go Back

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 iliquid 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

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

such that

$$0 \leq b_i \leq l_i$$

Go Back

First Order Conditions

- FOC of the lender's problem

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

- FOC of the borrower i's problem

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

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 that in these months, $c_i = e_{i1} + (1 - R) \cdot b_i$ holds
  - Back up monthly income with the consumption and used credit
  - Assume monthly income is determined by $e_{i1} = X_i\beta + y_i + \epsilon_{i1}$
  - The variations in monthly income help us to estimate σ_ϵ
  - Use the average monthly values as the observed c_i, b_i and e_{i1} respectively
- Estimate the parameters β and σ_y with a 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 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 D by using borrower's FOC as the moment condition

Go Back

Expectation of Default

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

$$E[\mathbb{1}_i^D|X_i, b_i, c_i; \beta, R, A] = \Phi(\frac{b_i - A - e_{i1}}{\sqrt{2}\sigma_\epsilon})$$

$$= E[\mathbb{1}(X_i\beta + y_i + \epsilon_{i1} - \epsilon_{i1} + \epsilon_{i2} + A - b_i < 0)|X_i, b_i, c_i; \beta, R, A]$$

$$= \int_{-\infty}^{+\infty} \mathbb{1}(\epsilon_{i2} - \epsilon_{i1} < b_i - A - e_{i1}|b_i, e_{i1})f(\epsilon_{i1})f(\epsilon_{i2})d\epsilon_{i1}d\epsilon_{i2}$$

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

$$E[\mathbb{1}_i^D|X_i, b_i; \beta, R, A] = \Phi(\frac{b_i - A - X_i\beta}{\sqrt{\sigma_\epsilon^2 + \sigma_y^2}})$$

$$= E[\mathbb{1}(X_i\beta + y_i + \epsilon_{i2} + A - b_i < 0)|X_i, b_i; \beta, R, A]$$

$$= \int_{-\infty}^{+\infty} \mathbb{1}(y_i + \epsilon_{i2} < b_i - A - X_i\beta|X_i, b_i; \beta)g(y)f(\epsilon_{i2})dyd\epsilon_{i2}$$

Go Back

Expectation of Borrower i's Default

- When the agent knows borrower i's consumption c_i

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

Go Back

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

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

Go Back

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

Go Back

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

Distributional Effects

- The payment information leads to better financial inclusion

	$\Delta log(\hat{\text{Credit Line}_i}), \%$	$\Delta log(\hat{\text{Consumer Welfare}_i}), \%$	$\Delta log(\hat{\text{Lender Profit}_i}), \%$	$\Delta log(\hat{\text{Annualized Default Rate}_i}), \%$
	(1)	(2)	(3)	(4)
Low Education$_i$	1.558**	0.036***	0.708***	0.007**
	(0.786)	(0.011)	(0.222)	(0.003)
Older than Median$_i$	1.164**	0.027***	0.392***	-0.001
	(0.530)	(0.007)	(0.150)	(0.002)
Male$_i$	1.326***	0.009	0.128	-0.0003
	(0.493)	(0.007)	(0.139)	(0.002)
City FE	YES	YES	YES	YES
Observations	38,008	38,008	38,008	38,008
R^2	0.031	0.006	0.009	0.007
Note:				$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Go Back