BigTech Credit, Small Business, and Monetary Policy Transmission: Theory and Evidence*

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** The views expressed here are solely the authors' and should not be attributed to the BIS or its policies*

Motivation

- FinTech has been a major phenomenon in recent financial market
  - Use of technology in providing financial services FSB (2019)
  - Unprecedentedly prominent in circuiting the economy during COVID-19 Core and De Marco (2021), Kwan et al. (2021), Bao and Huang (2021), Fu and Mishra (2021)
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LendingClub

PROSPER

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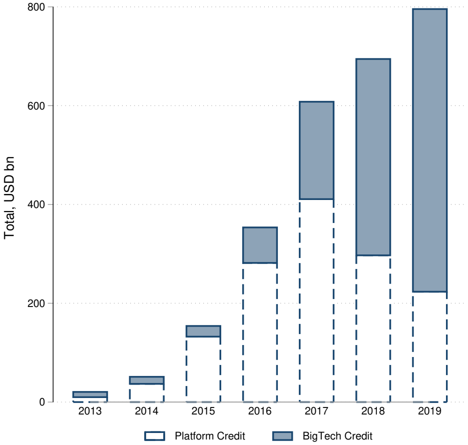

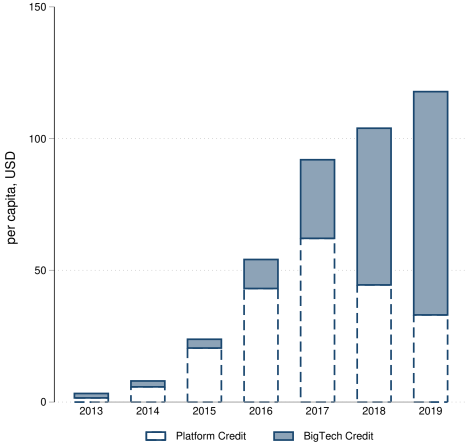

- BigTech credit is overtaking the platform credit Cornelli et al (2020)
- Account for 2%-3% GDP in countries with large BigTech presence

Motivation

- Expansion of BigTech credit
  - BigTech credits are particularly important for MSMEs that are underserved by banks
  - Interaction with incumbent financial institutions is key to the future financial market
  - A top concern for economic policymaking Carstens et al. (2021), Adrian (2021)

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  - Interaction with incumbent financial institutions is key to the future financial market
  - A top concern for economic policymaking Carstens et al. (2021), Adrian (2021)
- Implication for monetary policy transmission
  - "Brave new world" for monetary policymakers Philippon (2016), Lagarde (2018)
  - Little is known, despite the rapidly growing literature on BigTech Allen et al. (2021)

This Paper

- Research Questions
  - What is the difference between BigTech lenders and banks in lending to small businesses?
  - In particular in the context of monetary policy transmission?

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  - Monetary policy: funding costs, as a part of required returns

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- Theory
  - Optimal portfolio selection + lending ambiguity
  - BigTech holds information advantage over banks for smaller firms: higher expected returns
  - Monetary policy: funding costs, as a part of required returns
- Two Key Implications
  - Differences between the two types of lenders are more evident at the extensive margin
    - ★ Extensive margin: decision to enter or exit particular lending markets
    - ★ Intensive margin: methodologies to determine loan amounts are similar
  - Asymmetric: more pronounced effects when monetary policy eases
    - ★ Funding cost $\downarrow$ expands lending to firms where information advantage is smaller

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  - Observations of the same firm borrowing from both BigTech lenders and banks
  - Credit variables: establishment of lending relationship, loan amounts and other terms

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  - Observations of the same firm borrowing from both BigTech lenders and banks
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  $\Rightarrow$ A unique dataset of the borrowing history of sampled MSMEs from Ant Financial and traditional banks in China
- Identification: granular FE
  - Compare the new lending relationship and loan amount by the BigTech lender and incumbent banks in response to MP changes to the same MSMEs at the same time
    - ★ firm-time FE to disentangle estimates of credit supply from credit demand
  - Compare the effects between easing and tightening periods
- Findings consistent with the theoretical predictions

Related Literature

Related Literature

1. Monetary policy transmission
   - Bank lending channel (Bernanke and Blinder, 1988, 1992; Kashyap and Stein, 1995)
   - Cross-sectional heterogeneity: liquidity, size, income gap, leverage, market power, risk-tolerance and exposure (Kashyap and Stein 2000, Brissimis et al. 2014, Drechsler et al. 2017, Gomez et al.2021, Wang et al. 2021, Coimbra et al. 2021, Di Tella and Kurlat, 2021)
   - Lenders' technological characteristics (Hasan et al. 2024, Hasan et al. 2022, De Fiore et al. 2022, Zhou 2022)
2. Portfolio selection under lending ambiguity
   - Knighitan uncertainty (Di Tella 2017, Alfaro et al. 2024, Wu and Suardi 2021, Berger et al. 2022)
   - Ambiguity and diversification strategies (Maenhout 2004, Uppal and Wang 2003)
3. Comparison between BigTech lenders and banks
   - Data abundance, soft information codification (Stulz 2019, Boot et al. 2020, Thakor 2020, Berg et al. 2021)
   - Consequence of loan defaults: reduced profits v.s. collateral loss (De Fiore et al. 2022, Li and Pegoraro 2022)
   - Borrowing constraints: collateral-based v.s. earnings-based (Su 2021)

- Contribution: Bring in BigTech as the new player, model its information advantage over banks for small firms via lending ambiguity, and provide direct micro evidence

Theoretical Model

Model Setup

- Infinite-horizon continuous-time economy with a representative bank ($\mathcal{B}$) and a representative BigTech lender ($\mathcal{F}$)
- Consume a homogeneous good c, same unity function $u(c)$ and time preference

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  - Interest rates on deposits: $r_t = r(X_t)$, X_t: economic fundamentals
  - Monetary policy: changes in r

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  - Monetary policy: changes in r
- Invest in N risky business loans
  - Whether and how much to allocate investments, $n \in \{1, 2, \ldots, N\}$ is increasing in firm size
  - Return process: $dR_t = \mu_R(R_t, X_t)\, dt + \sigma_R(R_t, X_t)\, d\mathcal{Z}_t \leftarrow$ reference model
    - ★ Simplifying assumption: $\mu_{R,i} = \mu_{R,j}$, $\forall i, i = \{\mathcal{B}, \mathcal{F}\}, j \in \{1, 2, \ldots, N\}$
  - Downward perceived return by Δ_R^i, $i = \{\mathcal{B}, \mathcal{F}\} \leftarrow$ Lending ambiguity
  - Profitability criteria: $\mu_R - \Delta_R^i \geq r + \underline{\mu}$

Key Assumption

- BigTech and banks encounter varying levels of lending ambiguity across different firms
  - Γ: degree of model misspecification, a higher number indicating less ambiguity and higher information advantage
  - Λ: relative ratio between $\Gamma_{\mathcal{F}}$ for BigTech firms and $\Gamma_{\mathcal{B}}$ for banks, capturing the comparative information accuracy between the two

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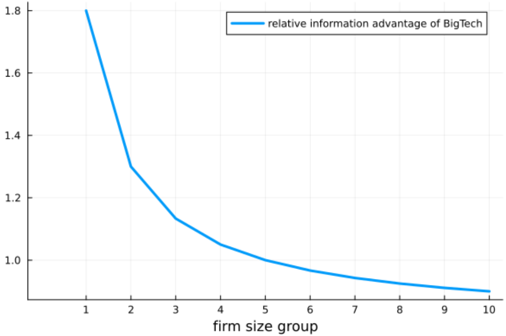
- BigTech, relative to traditional banks, possess an information advantage that decreases and becomes convex as firm size n increases
  - Bank's information advantage is linearly increasing in firm size, i.e., $\frac{\partial \gamma_n^{\mathcal{B}}}{\partial n} > 0, \frac{\partial^2 \gamma_n^{\mathcal{B}}}{\partial n^2} = 0$
  - BigTech's information advantage is decreasing in firm size, i.e., $\frac{\partial \gamma_n^{\mathcal{F}}}{\partial n} < 0$
  - The relative information advantage of BigTech compared to banks is a convex and decreasing function of firm size, i.e., $\frac{\partial \lambda_n}{\partial n} < 0, \frac{\partial^2 \lambda_n}{\partial n^2} < 0$
  - $\gamma_1^{\mathcal{B}} = \gamma_N^{\mathcal{F}}$ and $\gamma_N^{\mathcal{B}} = \gamma_1^{\mathcal{F}}$

Key Assumption

- Illustration: firm sizes and relative information advantage of BigTech to banks



- **Empirical support** (Berg et al. 2020, Di Maggio and Yao 2021, Liu et al. 2022, Beaumont et al. 2022, Huang et al. 2020, Jagtiani and Lemieux 2018, Hughes et al. 2022)

Optimization Problem

- Financial intermediary maximizes lifetime utility, subject to budget constraint
- Dynamics of financial intermediary's wealth:

$$d\omega_t = \omega_t \left[r_t + \pi_t \left(\mu_R - r_t \right) - \frac{c_t}{\omega_t} \right] dt + \omega_t \pi_t \sigma_R d\mathcal{Z}_t \tag{1}$$

  - π_n: the share of the intermediary's wealth invested in the *n*-th risky business loans $\leftarrow$ the intensive margin
- Indirect utility function: $\mathcal{J}\left(t; \omega_t, R_t, X_t\right)$

Equilibrium Characterization

- Optimal portfolio selection

Proposition

- *The optimal investment portfolio for the traditional bank is* $[n_{\mathcal{B}}^*, N]$, *where* $n_{\mathcal{B}}^*$ *satisfies the condition that* $\mu_{R,n_{\mathcal{B}}^*} - r - \Delta_{R,n_{\mathcal{B}}^*}^{\mathcal{B}} = \underline{\mu}$. *Meanwhile, the optimal investment portfolio for the BigTech is* $[1, n_{\mathcal{F}}^*]$, *where* $n_{\mathcal{F}}^*$ *satisfies the condition that* $\mu_{R,n_{\mathcal{F}}^*} - r - \Delta_{R,n_{\mathcal{F}}^*}^{\mathcal{F}} = \underline{\mu}$.
- *Within their optimal portfolio, the weight of wealth invested in each group of firms:*

$$\pi^i = -\frac{1}{\omega \mathcal{J}_{\omega\omega}} \left[\sigma_R \sigma_R^T\right]^{-1} \left[\mathcal{J}_\omega \left(\mu_R - r - \Delta_R^i\right) + \sigma_R \sigma_X^T \mathcal{J}_{\omega X} + \sigma_R \sigma_R^T \mathcal{J}_{\omega R}\right] \tag{2}$$

where $i = \{\mathcal{B}, \mathcal{F}\}$ *and*

$$\begin{bmatrix} \Delta_R^i \\ \Delta_X^i \end{bmatrix} = \frac{1}{\psi(\mathcal{J})} \Gamma_i^{-1} \begin{bmatrix} \mathcal{J}_\omega \omega_\pi + \mathcal{J}_R \\ \mathcal{J}_X \end{bmatrix} \tag{3}$$

where ψ *is a usual penalty normalization term.*

Equilibrium Characterization

- Impact of monetary policy changes

Proposition

- *The difference of the impact of monetary policy shocks on the intensive margin is negligible between banks and BigTech.*

$$\frac{\partial \pi_{\mathcal{B},n_{\mathcal{B}}}}{\partial r} \approx \frac{\partial \pi_{\mathcal{F},n_{\mathcal{F}}}}{\partial r} \text{ for } n_{\mathcal{B}} \in [n^*_{\mathcal{B}}, N] \text{ and } n_{\mathcal{F}} \in [1, n^*_{\mathcal{F}}].$$

- *However, the extensive margin shows significant differences in responses to monetary policy shocks between banks and BigTech, and the differences are asymmetric: BigTech lenders are more sensitive to monetary easing but less so to tightening, compared to banks.*

$$\left|\frac{\partial n^*_{\mathcal{B}}}{\partial r}\right| > \left|\frac{\partial n^*_{\mathcal{F}}}{\partial r}\right| \text{ for } r > r^* \text{ and } \left|\frac{\partial n^*_{\mathcal{B}}}{\partial r}\right| < \left|\frac{\partial n^*_{\mathcal{F}}}{\partial r}\right| \text{ for } r < r^*.$$

Predictions for Empirical Test

Prediction

1. *The primary distinction between how BigTech and traditional banks reacting to monetary policy shocks is observed at the* **extensive margin**, *rather than the intensive margin.*
2. *The difference of responses in the extensive margin are* **asymmetric**. *Specifically, compared to traditional banks, BigTech firms are more responsive to easing monetary policy shocks at the extensive margin but exhibit less sensitivity to tightening monetary policy shocks.*

Empirical Analyses

Empirical Analyses

- Data: micro-level dataset of Chinese small firms' borrowing from both a representative BigTech lender and traditional banks, matched with changes in monetary policy

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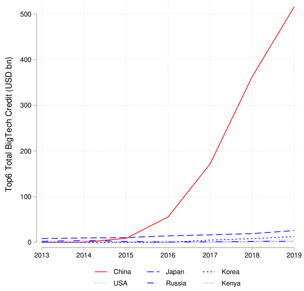
- Data: micro-level dataset of Chinese small firms' borrowing from both a representative BigTech lender and traditional banks, matched with changes in monetary policy
    - Institutional Background
    - Dataset Construction
    - Specification and Results

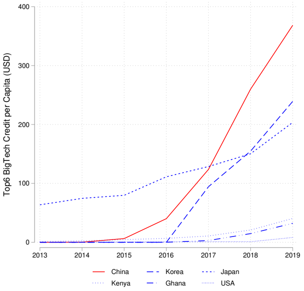
Institutional Background

Institutional Background

BigTech in China

- China is a leading player in BigTech credit market
  - Surpassed other countries in both absolute and per capita terms since 2017
  - BigTech credit is small in U.S.: Amazon USD 1bn in 2018, Apple 7bn in 2019
  - The four Chinese BigTech lent USD 363 bn and 516 bn in 2018 and 2019





Institutional Background

BigTech in China

- China is a leading player of BigTech credit
  - Ability to build and maintain a large user base
  - Regulatory tolerance in the early stage
- Differ from other countries
  - Dominated by business lending rather than mortgage lending

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- The BigTech lender in this paper: MYbank
  - Alibaba: e-commerce as the main business
  - Ant Group: Alibaba's FinTech business
    - Mobile payment: Alipay
    - Wealth management: Yu'E bao
    - Credit rating: Sesame credit
    - Banking: MYbank $\leftarrow$ an online bank without physical branches

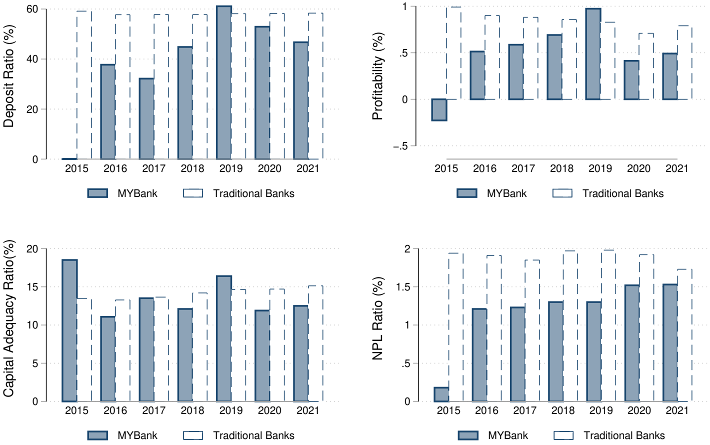
Institutional Background

MYbank

- Founded in 2015, among the first batch of private commercial banks
- Leverage AI, computing, and risk management technologies
- Loan granting: contact-free based on big data and machine learning ("3-1-0" mode)
  - Completion of user registration and loan application within 3 minutes
  - Money transfer to an Alipay account within 1 second
  - 0 human intervention
- MSMEs are its main customer: e-commerce (online) and QRcode merchants (offline)
- Used in recent studies (Huang et al. 2020, Hong et al. 2020, Hau et al. 2021, Gambacorta et al. 2023, Liu et al. 2022)

Institutional Background

MYbank



- Depend less on deposits; better risk management; lower profitability; lower capital adequacy ratio
- Higher volatility, structural shift in 2020

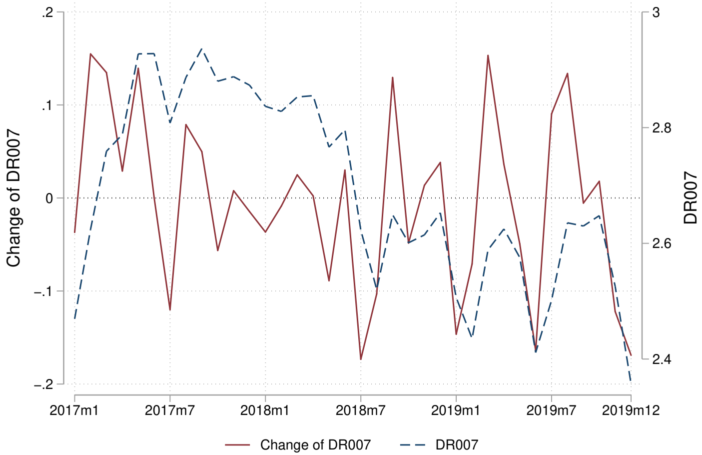
Institutional Background

Monetary Policy in China

- Gradual transition from the quantity-based to price-based monetary policy framework
- 7-day pledged interbank repo rate for deposit institutions (DR007)
  - Quarterly MP Executive Reports: "an active role to cultivate the market base rate"
  - *de facto* intermediate target (McMahon et al. 2018)
- Monthly change ($\Delta DR007$)
  - positive: contractionary; negative: expansionary
- Impulses of MP transmission in China comparable to that in advanced economies (Fernald et al. 2014, Chen et al. 2018, Kamber and Mohanty, 2018, Das and Song 2023) $\rightarrow$ general implications

Institutional Background

Monetary Policy in China



- Large variations, tightening and easing cycles happened in turn

Dataset Construction

Dataset

- Sample Firms
  - Draw 10% random sample of the MSME customers of MYbank
    - Not the full sample due to privacy rules
    - Stratified sampling by province and sector
  - 340,000 firms 2017M1-2019M12; mainly in retail industry Sector Distribution
  - Firm characteristics: location, age and gender of the owner, monthly sales, network score
    - Network score: a measurement of the firm's centrality based on payments history
  - Online and offline

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  - Online and offline
- Credit History
  - Loan issuance from the BigTech lender, MYbank
    - No collateral/non-secured loan
  - Counterparts of traditional bank loans
    - Aggregated bank credits but not the granular composition of specific banks
    - Can distinguish between secured and non-secured bank loans

Dataset

- The Good ☺
  - Simultaneous observation of BigTech credit and traditional bank credit
  - Firm-lender-month level data
    - ★ Two lenders, many firms

Dataset

- The Good ☺
  - Simultaneous observation of BigTech credit and traditional bank credit
  - Firm-lender-month level data
    - ★ Two lenders, many firms
- The Bad ☹
  - No breakdown of banks → no discussion about conventional bank-level characteristics such as capitalisation and bank size, or comparison between stated- and non-stated-owned banks
  - One lender to represent BigTech credit → underestimate the responses of BigTech credits, no interactions within BigTech lenders
  - Other terms not comparable for the two types of lends → additional discussion on interest rate and maturity for BigTech lending

Summary Statistics

Variables	N	Mean	St. Dev.
Panel A: Credit			
Credit use -All	15,139,162	0.034	0.181
Credit use -BigTech	7,569,581	0.055	0.229
Credit use -Bank	7,569,581	0.012	0.110
Loan amount -All	173,484	38,852.85	168,685.82
Loan amount -BigTech	158,795	21,841.59	38,277.23
Loan amount -Bank credit	14,689	216,895.73	525,568.78
Panel B: Firm Characteristics			
Network Centrality	15,139,162	37.50	21.00
Sales	15,139,162	10,414.67	68,203.85
Online	15,138,972	0.015	0.123
Owner Age	15,139,162	38.33	8.87
Owner Gender-Male	15,139,162	0.51	0.50
Panel C: Macroeconomic Condition			
DR007	15,139,162	2.631	0.148
Δ DR007	15,139,162	-0.019	0.095
GDP-city (bn)	15,139,162	189.771	204.226
Bank branch density-city	14,853,908	0.11	0.039

By Type: Loan Char
By Type: Firm Char

Empirical Tests

Empirical Test

Identification Strategy

$$Credit_{ibt} = \alpha + \beta MP_t \times D(BigTech)_b + \delta_b + \theta_{it} + \epsilon_{ibt}$$

- $D(BigTech)_b$: dummy indicating BigTech lender; MP_t: $\Delta DR007 \uparrow$ tightening $\downarrow$ easing
- δ_b: bank FE; θ_{it}: firm-time FE
  - saturate confounding factors that are firm-time variant, including credit demand
  - when firm- and time FE separately, control L.Ln(Sales), L.Centrality, L.Ln(GDP)
- Comparing the behavior by two types of lenders to the same firm at the same time
- $\beta \rightarrow$ differences in responses to MP arising from credit supply

Empirical Analysis

Identification Strategy

$$Credit_{ibt} = \alpha + \beta MP_t \times D(BigTech)_b + \delta_b + \theta_{it} + \epsilon_{ibt}$$

- $Credit_{ibt}$: extensive and intensive Khwaja and Mian (2008), Bittner et al. (2020)
  - $D(New\ Lending\ Relationship)_{ibt}$ firm i starts to obtain credit from bank b at time t
  - $Ln(Loan)_{ibt}$, amount of credit issued
    1. The firm has already established a lending relationship with the lender
    2. The loan amount is positive
    3. The firm obtains credit from both traditional banks and the BigTech lender

    ★ Quasi-loan-level regression
- A significant and negative β indicates that BigTech lenders are more responsive to MP

Baseline Results

DepVar	D(New Lending Relationship)		Ln(Loan)	
	(1)	(2)	(3)	(4)
Δ DR007 $\times$ D(BigTech)	-0.026***	-0.026***	-0.080	-0.020
	(0.0003)	(0.0005)	(0.134)	(2.553)
L.Sales	0.001***		0.012***	
	(0.00005)		(0.003)	
L.Network Centrality	0.001***		-0.001	
	(0.00002)		(0.001)	
L.Regional GDP	0.001***		0.048**	
	(0.0003)		(0.023)	
Obs	15,139,162	15,139,162	173,484	173,484
Adj R-Square	0.405	0.166	0.676	0.490
Bank FE	YES	YES	YES	YES
Firm FE	YES	-	YES	-
Month FE	YES	-	YES	-
Firm $\times$ Month FE	NO	YES	NO	YES

- When MP eases by one SD, the probability of a BigTech lender to build a new lending relationship with the firm is 0.25 percentage points higher (average probability is 3.4%)
- Insignificant difference in the intensive margin

Robustness Checks

- Comparability between bank and BigTech credit Table
- Unsecured nature of BigTech credit v.s. secured bank credit Table
- Relationship between BigTech and traditional banks: complementary or substitute Table
- Other confounding factors from the macroeconomic or firm-specific side Table

Asymmetric Effects

$$Credit_{ibt} = \alpha' + \beta_1'|MP_t| \times D(BigTech)_b + \beta_2' D(BigTech)_b \times D(Tightening)_t \\ + \beta_3' D(BigTech)_b \times |MP_t| \times D(Tightening)_t + \delta_b + \theta_{it} + \epsilon_{ibt} \tag{4}$$

DepVar	D(New Lending Relationship)		Ln(Loan Amount)	
	(1)	(2)	(3)	(4)
$\mid \Delta$ DR007 $\mid \times$ D(BigTech)	0.102***	0.102***	0.323	0.310
	(0.001)	(0.002)	(0.296)	(5.761)
D(BigTech) $\times$ D(Tightening)	-0.001***	-0.001***	-0.094**	-0.136
	(0.0001)	(0.0001)	(0.041)	(0.870)
$\mid \Delta$ DR007 $\mid \times$ D(BigTech) $\times$ D(Tightening)	-0.009***	-0.009***	-0.651	1.199
	(0.001)	(0.002)	(0.451)	(9.037)
Obs	15,139,162	15,139,162	173,484	173,484
Adj R-Square	0.167	0.405	0.490	0.676
Lender FE	YES	YES	YES	YES
Firm FE	YES	-	YES	-
Month FE	YES	-	YES	-
Firm $\times$ Month FE	NO	YES	NO	YES

- The transmission-enhancing role of BigTech lender is stronger when MP is loosening
  - When MP eases by one SD, the probability of a BigTech lender to build a new lending relationship with a firm is 0.97 pp higher than that of a bank
  - When MP tightens by one SD, the credit contraction in the extensive margin is smaller for the BigTech lender than banks by 0.88 pp

Heterogeneity in Firm Size

- Stronger impact for larger firms, where BigTech's relative information advantage is smaller

DepVar	D(New Lending Relationship)				Ln(Loan Amount)			
Quartile	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Δ DR007 $\times$ D(BigTech)	-0.013 ***	-0.024***	-0.031***	-0.039***	0.819	0.438	0.060	-0.195
	(0.001)	(0.001)	(0.001)	(0.001)	(13.562)	(12.949)	(5.848)	(2.576)
Obs	3,355,370	3,698,164	3,908,142	41,778,128	14,029	32,695	49,905	76,844
Adj R-Square	0.092	0.117	0.117	0.202	0.623	0.199	0.199	0.489
Lender FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm $\times$ Time FE	YES	YES	YES	YES	YES	YES	YES	YES

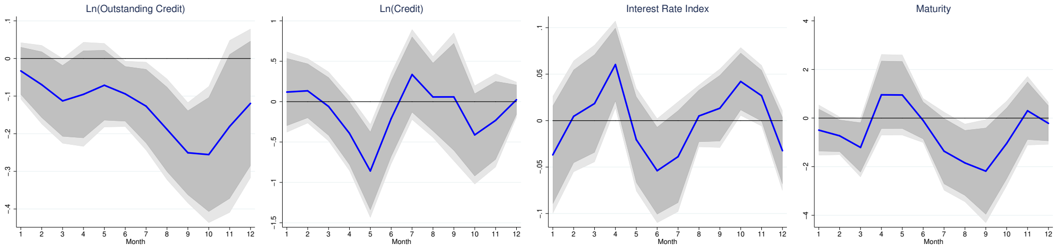
Further Discussion

Further Discussions Skip

- Extended dataset covering until 2021 for BigTech loans
  - Other terms: outstanding amount, interest rate, maturity
  - Regulatory policies, which became prominent in 2021
- Methodology: local projection (Jorda 2005)

$$Term_i^{t+h} - Term_i^t = \alpha_0^h + \Sigma_{k=0}^{k=2}(\beta_k^h MP_{t-k} + \zeta_k^h Macro_{t-k}) + \gamma^h \Gamma_{i,t-1} + \delta_i^h + \epsilon_{i,t}^h \quad (5)$$

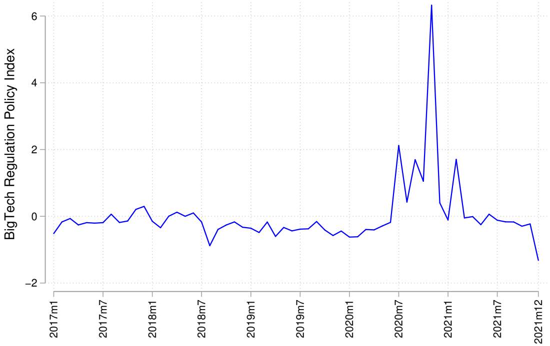
Further Discussions



- MP rate ↑, both outstanding and newly issued loans by BigTech ↓
- MP MP rate ↑, interest rate ↑ and loan maturity ↓ in the short term
- Opposite findings on the quantity and price help distinguish between credit demand and supply effects

Further Discussions

- A measurement of BigTech regulation policy stringency
  - Announcement dates of regulation policy in 2017-2021 $\rightarrow$ 27 specific regulatory polcies
  - Abnormal returns of Alibaba and Tencent within three days following annoucement
  - Search index of "Ant Financial" and "FinTech"
  - Principle component analysis



Further Discussions

$$Term_i^{t+h} - Term_i^t = {\alpha'_0}^h + D(Before)_t \Sigma_{k=0}^{k=2} ({\beta'_{mp,k}}^{h,before} MP_{t-k} + {\beta'_{reg,k}}^{h,before} Reg_{t-k})$$
$$+ D(After)_t \Sigma_{k=0}^{k=2} ({\beta'_k}^{h,after} MP_{t-k} + {\beta'_k}^{h,after} Reg_{t-k}) + \Sigma_{k=0}^{k=2} {\zeta'_k}^h Macro_{t-k} + {\gamma'}^h \Gamma_{i,t-1} + {\delta'_i}^h + {\epsilon'}_{i,t}^h \quad (6)$$

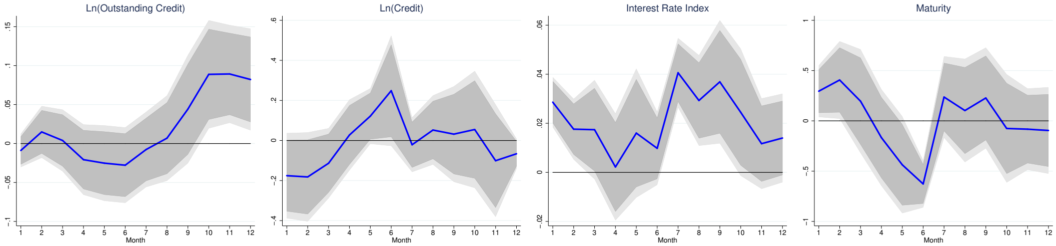


Figure: Impact of Regulation Before COVID

- Same changes in quantity and price $\rightarrow$ likely driven by credit demand
- Firms opt for more BigTech loans with longer maturities when regulation tightens

Further Discussions

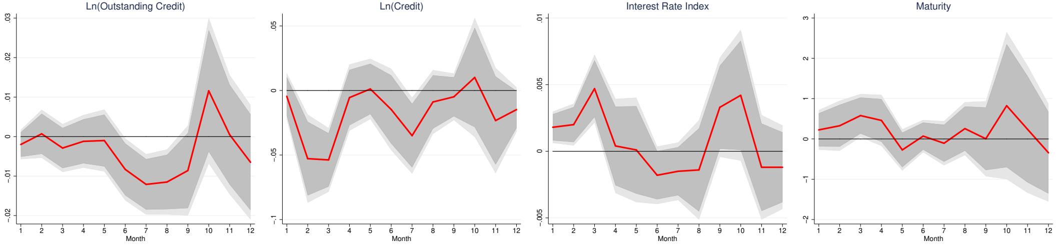


Figure: Impact of Regulation After COVID

- Regulatory tightening is associated with a significant decrease in loan amounts and a significant increase in interest rates, while changes in loan maturity remain insignificant

Conclusion

Conclusion

- Theoretically
  - Portfolio selection under Knightian uncertainty
  - BigTech has stronger information advantage for smaller firms compared to traditional banks
    - Difference mainly at extensive margin
    - Asymmetric effects between easing and tightening
- Empirically
  - Micro-level data of MSMEs' borrowing history from a BigTech lender and traditional banks
  - BigTech more responsive to MP at the extensive but not the intensive margin
  - More pronounced during periods of monetary easing than tightening
- Policy Implications
  - Monetary policy needs to account for the growing role of BigTech lenders
  - Coordination between macroeconomic policies and BigTech regulation policies is necessary

Thank You

An illustration of the key assumption

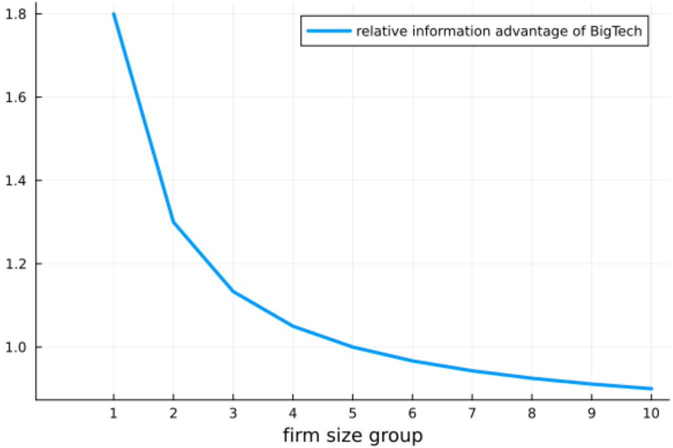


Figure: Firm Sizes and Relative Information Advantage of BigTech to Banks

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Sector Distribution

Sectors	Proportion
Catering services	35%
Grain, oil, food, drink, alcohol and tobacco	11.40%
Clothing, shoes and hats, needles and textiles	10.90%
Local life services	7.90%
Furniture	4.50%
Cultural and entertainment services	3.80%
Healthcare services	3.70%
Motor vehicles	3.60%
Drug	3.10%

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Summary Statistics

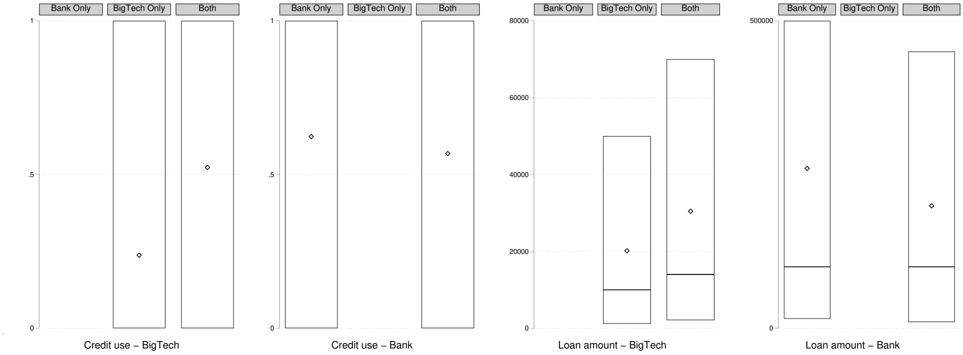

Figure: Loan Characteristics

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Summary Statistics

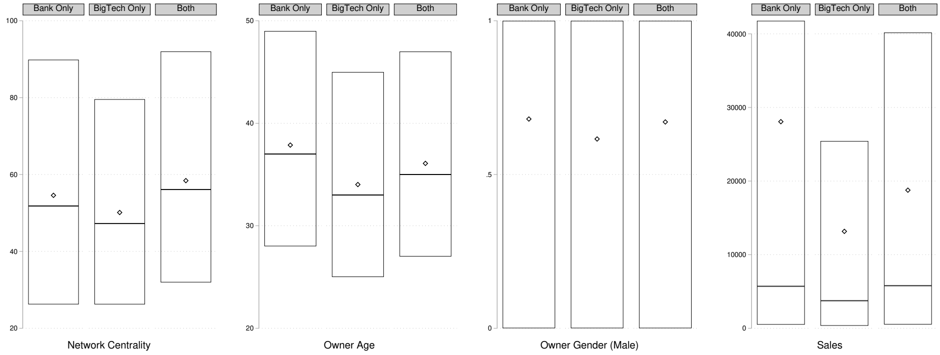

Figure: Firm Characteristics

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Robustness Checks

- Comparability between bank and BigTech credit
- Small bank credits ($\leq$ 75th BigTech credit)

DepVar	D(New Lending Relationship)		Ln(Loan)	
	(1)	(2)	(3)	(4)
Δ DR007 $\times$ D(BigTech)	-0.028***	-0.028***	-0.281	-0.098
	(0.0004)	(0.0003)	(8.069)	(0.254)
Obs	15,139,162	15,139,162	173,484	173,484
Adj R-Square	0.405	0.166	0.676	0.490
Bank FE	YES	YES	YES	YES
Firm FE	YES	-	YES	-
Month FE	YES	-	YES	-
Firm $\times$ Month FE	NO	YES	NO	YES

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Robustness Checks

- Unsecured nature of BigTech credit v.s. secured bank credit

DepVar:	D(New Lending Relationship)		Ln(Loan Amount)	
Bank Loan Type:	Secured	Unsecured	Secured	Unsecured
	(1)	(2)	(3)	(4)
$\Delta DR007 \times$ D(BigTech)	-0.028***	-0.026***	-2.226	0.121
	(0.0004)	(0.0005)	(20.161)	(2.803)
Obs	15,139,162	15,139,162	161,184	171,233
Adj R-Square	0.058	0.154	0.492	0.488
Lender FE	YES	YES	YES	YES
Firm $\times$ Month FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

- The key distinction in response to MP between BigTech and traditional banks does not stem from differences between earnings- and collateral-based lending models.

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Robustness Checks

- Relationship between BigTech and traditional banks: complementary or substitute

DepVar:	D(New Lending Relationship)		Ln(Loan Amount)	
Bank Branch Density:	High	Low	High	Low
	(1)	(2)	(3)	(4)
$\Delta DR007 \times$ D(BigTech)	-0.026***	-0.026***	-0.227	0.028
	(0.001)	(0.001)	(4.154)	(3.196)
Obs	7,257,970	7,595,938	78,858	91,988
Adj R-Square	0.155	0.175	0.480	0.500
Lender FE	YES	YES	YES	YES
Firm $\times$ Month FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

- Small businesses are likely unserved or underserved by traditional banks due to information asymmetries

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Robustness Checks

- Other confounding factors from the macroeconomic or firm-specific side

DepVar	D(New Lending Relationship)			Ln(Loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta DR007\times$ D(BigTech)	-0.017^{***}	-0.026^{***}	-0.022^{***}	0.142	-0.079	0.057
	(0.0004)	(0.0003)	(0.0005)	(0.376)	(0.328)	(0.376)
Real GDP Growth $\times$ D(BigTech)	-0.002^{***}		-0.003^{***}	-0.104^{*}		-0.108^{*}
	(0.0001)		(0.0001)	(0.061)		(0.061)
Inflation $\times$ D(BigTech)	0.019^{***}		0.019^{***}	0.186^{***}		0.191^{***}
	(0.0002)		(0.0002)	(0.053)		(0.052)
SOE VA Growth $\times$ D(BigTech)	-0.004^{***}		-0.005^{***}	-0.053^{*}		-0.059^{*}
	(0.0001)		(0.0001)	(0.031)		(0.031)
NSOE VA Growth $\times$ D(BigTech)	0.001^{***}		0.001^{***}	-0.022		-0.023
	(0.00002)		(0.00002)	(0.017)		(0.017)
L.Network Centrality $\times$ D(BigTech)		0.001^{***}	0.001^{***}		0.003	0.004^{*}
		(0.00002)	(0.00002)		(0.002)	(0.002)
L.Ln(Sales) $\times$ D(BigTech)		0.002^{***}	0.001^{***}		-0.019	-0.025
		(0.0001)	(0.0001)		(0.026)	(0.026)
L.Ln(Regional GDP) $\times$ D(BigTech)		-0.002^{***}	-0.002^{***}		0.028	0.030
		(0.0004)	(0.0004)		(0.050)	(0.049)
D(Male) $\times$ D(BigTech)		0.014^{***}	0.014^{***}		0.139	0.163^{*}
		(0.001)	(0.001)		(0.098)	(0.096)
Owner Age $\times$ D(BigTech)		-0.002^{***}	-0.002^{***}		-0.021^{***}	-0.021^{***}
		(0.00004)	(0.00004)		(0.007)	(0.007)
Obs	15,139,162	15,139,162	15,139,162	173,484	173,484	173,484
Adj R-Square	0.171	0.189	0.195	0.497	0.494	0.503
Bank FE	YES	YES	YES	YES	YES	YES
Firm $\times$ Month FE	YES	YES	YES	YES	YES	YES

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