

BigTech Credit and Monetary Policy Transmission: Micro-level Evidence from China*

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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)
 - ▶ What's new? players outside the financial market e.g., decentralized platforms, BigTech firms

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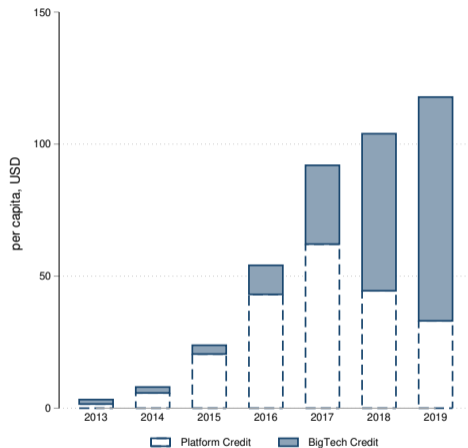
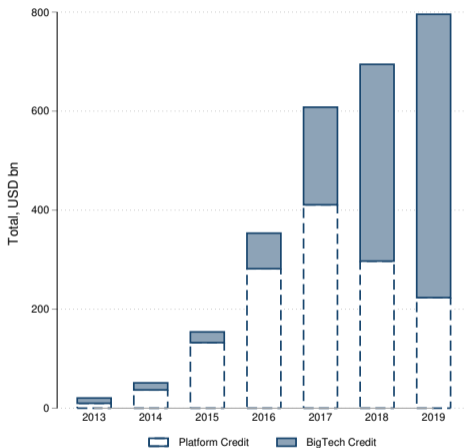
The logo for LendingClub, featuring a red grid icon to the left of the text "LendingClub" in a dark blue, sans-serif font.The logo for PROSPER, with the word "PROSPER" in a grey, sans-serif font. The letter "O" is replaced by a stylized icon consisting of two overlapping shapes, one orange and one pink.

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Motivation



- BigTech credit is overtaking the platform credit [Cornelli \(2020\)](#)
- 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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- Implication for **monetary policy transmission**
 - ▶ “Brave new world” for monetary policymakers Philippon (2016), Lagarde (2018)
 - ▶ Little is known, despite the rapidly growing literature on FinTech Allen et al. (2021)

This Paper

- Research Questions

- ▶ Whether and how BigTech works differently from banks in monetary policy transmission?
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- ▶ Observations of the same firm borrowing from both BigTech lenders and banks
- ▶ Credit and performance variables

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- ▶ Credit and performance variables

⇒ A unique dataset tackling the challenge from both extensive and intensive margin:
borrowing history of sampled MSMEs from Ant Financial and traditional banks in China

This Paper

- Identification

- ▶ 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 sales in response to MP changes for firms use BigTech credit and those do not

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- Main Findings

- ▶ BigTech lender is more responsive to MP changes, but only in extensive margin
- ▶ Stronger impact for online MSMEs, and when compared with secured bank loans
- ▶ BigTech credit is associated with a larger real effects of monetary policy

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 (Kashyap and Stein 2000, Brissimis et al. 2014, Drechsler et al. 2017, Gomez et al.2021, Wang et al. 2021)
- ▶ Risk-tolerance and exposure (Coimbra et al. 2021, Di Tella and Kurlat, 2021)
- ▶ Lenders' technological characteristics: blank until recently (Hasan et al. 2020, Hasan and Li 2021, De Fiore et al. 2022)
- ▶ Bring in BigTech as the new player, direct micro evidence

Related Literature

② Relationship between FinTech lenders and banks

- ▶ Data abundance, codification of soft information (Stulz 2019, Boot et al. 2020, Thakor 2020, Berg et al. 2021)
- ▶ Substitute or complement bank lending in mortgage and personal credit (Buchak et al. 2018, Di Maggio and Yao 2021, Jagtiani 2021, Jagtiani and Lemieux 2018, Hughes et al. 2022, Bharadwaj et al. 2019, Tang 2019) or in small business during COVID (Erel and Liebersohn 2020)
- ▶ Technology adoption by banks and its impact on lending (Pierri and Timmer 2021, Lin et al. 2021, Kwan et al. 2021, He et al. 2021, Hasan and Li 2021)
- ▶ Corporate lending between BigTech lenders and banks

Related Literature

③ Financial innovation and economic growth

- ▶ Banking innovation relates to higher growth (Beck et al. 2016, Gorton and He 2021)
- ▶ FinTech credit reduces sales volatility, increases sales level, spurs firm investment and entrepreneurship (Chen et al. 2019, Eca et al. 2021, Ahnert et al. 2021, Beck et al. 2022)
- ▶ BigTech credit enhances MSMEs' responses in sale growth, real impact of monetary policy

Institutional Background

Institutional Background

BigTech in China

- China is a leading player of BigTech credit
 - ▶ 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



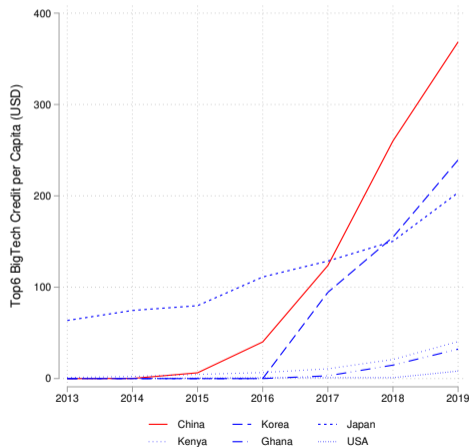
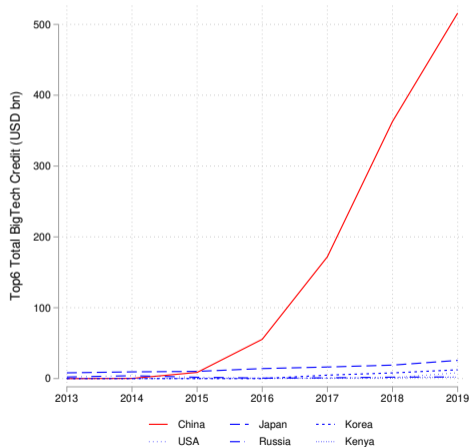
Tencent 腾讯



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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](#) ← an online bank without physical branches

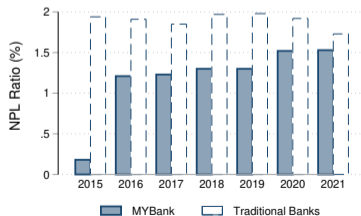
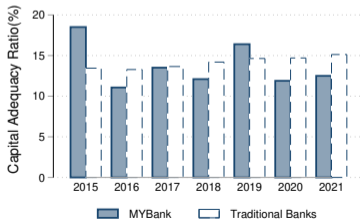
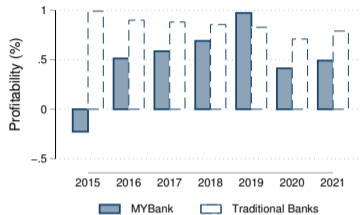
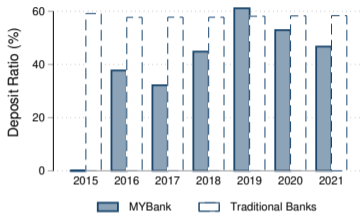
Institutional Background

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 Frost et al.(2019), Huang et al. (2020), Hau et al. (2021), Gambacorta et al. (2022), Beck et al. (2022)

Institutional Background

MYbank



- Depend less on deposits; better risk management; lower profitability; lower capital adequacy ratio

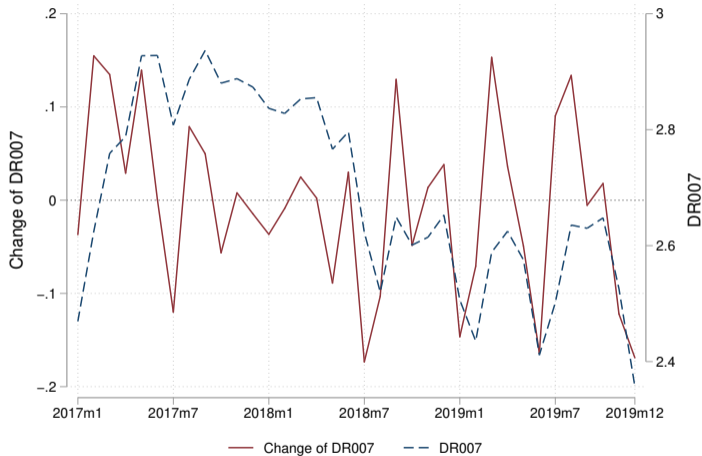
Institutional Background

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
- Quantity-based quarterly M2 shock used as robustness check (Chen et al. 2018)
- Impulses of MP transmission in China is similar to that in advanced economies (Chen et al. 2018, Kamber and Mohanty, 2018)
→ general implications

Institutional Background

Monetary Policy in China



- Large variations, tightening and easing cycles happened in turn

Dataset

Dataset

- Sample Firms

- ▶ Draw 10% random sample of the customers of MYbank
 - ★ Not the full sample due to privacy rules
- ▶ 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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- 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

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- ▶ Simultaneous observation of BigTech credit and traditional bank credit
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 - ★ Two lenders, many firms

- The Bad 😞

- ▶ No breakdown of banks → no discussion about conventional bank-level characteristics such as capitalisation and bank size
- ▶ One lender to represent BigTech credit → underestimate the responses of BigTech credits, no interactions within BigTech lenders
- ▶ No info of interest rates and default history due to data privacy → no discussions of the riskiness of loans

Summary Statistics

Variables	N	Mean	St. Dev.
<i>Panel A: Credit</i>			
Credit use -All	16,281,080	0.034	0.181
Credit use -Bigtech	8,140,540	0.055	0.229
Credit use -Bank	8,140,540	0.012	0.110
Loan amount -All	178,838	38,852.850	168,685.800
Loan amount -Bigtech	163,241	21,841.590	38,277.230
Loan amount -Bank credit	15,597	216,895.700	525,568.800
<i>Panel B: Firm Characteristics</i>			
Network Centrality	16,153,432	37.501	20.997
Sales	16,281,080	10,414.670	68,203.850
Online	16,280,882	0.015	0.123
Owner Age	16,276,528	38.328	8.866
Owner Gender-Male	16,281,080	0.511	0.500
<i>Panel C: Macroeconomic Condition</i>			
DR007	16,281,080	2.637	0.150
Δ DR007	16,281,080	-0.017	0.095
GDP-city (bn)	15,918,248	195.182	210.853
Bank branch density-city	15,731,950	0.110	0.039

Empirical Analysis

Empirical Analysis

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 Age, L.Ln(Sales), L.Centrality, L.Ln(GDP)
- Comparing the behavior by two types of lenders to the same firm at the same time
- β \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

<i>DepVar</i>	D(New Lending Relationship)		Ln(Loan)	
	(1)	(2)	(3)	(4)
Δ DR007 \times D(BigTech)	-0.026*** (0.0003)	-0.026*** (0.0005)	-0.080 (0.134)	-0.020 (2.553)
Owner Age	0.002*** (0.0001)		0.002 (0.011)	
L.Sales	0.001*** (0.00005)		0.012*** (0.003)	
L.Network Centrality	0.001*** (0.00002)		-0.001 (0.001)	
L.Regional GDP	0.001*** (0.0003)		0.048** (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

Baseline Results

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

<i>DepVar</i>	D(New Lending Relationship)		Ln(Loan)	
	(1)	(2)	(3)	(4)
Δ DR007 \times D(BigTech)	-0.028*** (0.0004)	-0.028*** (0.0003)	-0.281 (8.069)	-0.098 (0.254)
Owner Age	0.002*** (0.0001)		0.003 (0.011)	
L.Sales	0.001*** (0.00004)		0.013*** (0.003)	
L.Network Centrality	0.0001*** (0.00002)		-0.0005 (0.001)	
L.Regional GDP	0.001*** (0.0002)		0.049** (0.024)	
Obs	15,139,162	15,139,162	173,484	173,484
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Baseline Results

- Aggregate effect combining extensive and intensive margin
- Also to further mitigate the concern that we cannot detect individual banks
⇒ BigTech and bank credits at the **city-level**

	(1)	(2)
MP \times D(BigTech)	-4.487***	-4.487***
	(0.515)	(0.722)
L.Regional GDP	-0.004	
	(0.178)	
Obs	19,392	19,392
Adj R-Square	0.555	0.491
Lender FE	YES	YES
City FE	YES	-
Time FE	YES	-
City \times Time FE	NO	YES

- When MP eases by one SD, the BigTech lender issues more credits than banks by 41.73%
- Interpretation: the stronger role of BigTech mainly comes from expanding financial access to MSMEs, which are under-served by banks

Mechanisms

Mechanism Investigation

- 1 Data abundance → mitigate information asymmetry
Boot et al. (2020), Stulz (2019), Di Maggio and Yao (2021)
 - 2 Credit assessment → better predict default risk
Berg et al. (2020), Di Maggio et al. (2021)
- Financial intermediaries that are stronger in these aspects can be more responsive to the change in MP Coimbra and Rey (2017), Coimbra et al. (2021)

Mechanism Investigation

Data Abundance

- ① Data abundance → mitigate information asymmetry
- Split the full sample into online and offline subsamples
- The effect will be stronger for **online sellers**

DepVar:	D(New Lending Relationship)		Ln(Loan Amount)	
	Offline	Online	Offline	Online
Firm Type:	(1)	(2)	(3)	(4)
$\Delta DR007 \times D(\text{BigTech})$	-0.026*** (0.0004)	-0.053*** (0.0005)	-2.232 (19.639)	-2.208 (16.531)
Obs	14,902,838	236,134	156,138	5,273
Adj R-Square	0.165	0.187	0.507	0.462
Lender FE	YES	YES	YES	YES
Firm \times Time FE	YES	YES	YES	YES

Mechanism Investigation

Risk Assessment

- ② Credit assessment → better predict default risk
- Split the full sample into BigTech credit v.s. secured bank credit and BigTech credit v.s. unsecured bank credit
- The effect will be stronger for **BigTech credit v.s. secured bank credit**

DepVar:	D(New Lending Relationship)		Ln(Loan Amount)	
	Secured	Unsecured	Secured	Unsecured
Bank Loan Type:	(1)	(2)	(3)	(4)
$\Delta DR_{007} \times D(\text{BigTech})$	-0.028*** (0.0004)	-0.026*** (0.0005)	-2.226 (20.161)	0.121 (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 Time FE	YES	YES	YES	YES

Discussions

Discussion

Competition Between Banks and BigTech Lenders

- Unsettled debate whether banks and FinTech lenders are complements or substitutes (Buchak et al. 2018, Tang 2019, Jagtiani and Lemieux 2018, Erel and Liebersohn 2020)
- Bank branch density at city-level i.e., # branches per 1K, below and above median

DepVar:	D(New Lending Relationship)		Ln(Loan Amount)	
	High	Low	High	Low
Bank Branch Density:	(1)	(2)	(3)	(4)
$\Delta DR007 \times D(\text{BigTech})$	-0.026*** (0.001)	-0.026*** (0.001)	-0.227 (4.154)	0.028 (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 Time FE	YES	YES	YES	YES

- Our findings do not necessarily rely on the competition relationship
- These MSMEs are likely unbanked or underbanked

Discussion

Asymmetric Effects of Monetary Policy

- $D(\text{Tightening})_t$, indicate when the change in monetary policy rate is positive
- 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**

<i>DepVar</i>	D(New Lending Relationship)		Ln(Loan Amount)	
	(1)	(2)	(3)	(4)
Δ DR007 \times D(BigTech)	0.102*** (0.001)	0.102*** (0.002)	0.323 (0.296)	0.310 (5.761)
D(BigTech) \times D(Tightening)	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.094** (0.041)	-0.136 (0.870)
Δ DR007 \times D(BigTech) \times D(Tightening)	-0.009*** (0.001)	-0.009*** (0.002)	-0.651 (0.451)	1.199 (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

Discussion

Firm Heterogeneity: Size

- Stronger impact for larger firms

<i>DepVar</i> <i>Quartile</i>	D(New Lending Relationship)				Ln(Loan Amount)			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Δ DR007 \times D(BigTech)	-0.013 *** (0.001)	-0.024 *** (0.001)	-0.031 *** (0.001)	-0.039 *** (0.001)	0.819 (13.562)	0.438 (12.949)	0.060 (5.848)	-0.195 (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

Discussion

Firm Heterogeneity: Network Centrality

- Stronger impact for firms with higher network centrality

<i>DepVar</i>	D(New Lending Relationship)		Ln(Loan)	
	(1)	(2)	(3)	(4)
Δ DR007 \times D(BigTech)	0.010*** (0.001)	0.010*** (0.001)	-0.025 (0.363)	-0.204 (8.942)
Δ DR007 \times Network Centrality	-0.0001*** (0.000)		0.003 (0.005)	
D(BigTech) \times Network Centrality	0.002*** (0.000)	0.002*** (0.000)	0.008*** (0.001)	0.003 (0.018)
D(BigTech) \times Network Centrality \times DR007	-0.001*** (0.000)	-0.001*** (0.000)	-0.001 (0.006)	-0.004 (0.129)
Obs	15,759,926	15,759,926	174,531	174,531
Adj R-Square	0.405	0.184	0.676	0.491
Bank FE	YES	YES	YES	YES
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Firm \times Month FE	NO	YES	NO	YES

Discussion

Real Effects

- Role of BigTech credit in MP transmission to the real economy
- Firm-level instead of quasi-loan-level

$$\ln(\text{Sale})_{it} = \alpha_0 + \gamma_1 \text{BigTech}_{it-1} + \gamma_2 \text{BigTech}_{it-1} \times \text{MP}_t + \Gamma' X_{it-1} + \theta_i + \eta_t + \epsilon_{it}$$

<i>BigTech</i>	Dummy of Usage	Amount of Usage
DepVar: $\ln(\text{Sale})$	(1)	(2)
$\Delta \text{DR007} \times \text{L.BigTech}$	-0.107*** (0.037)	-0.011*** (0.004)
L.BigTech	0.114*** (0.007)	0.012*** (0.001)
Obs	8,140,540	8,140,540
Adj R-Square	0.511	0.531
Controls	YES	YES
Firm FE	YES	YES
Month FE	YES	YES

- Firms that accessed BigTech credit are more responsive in sales growth by 10.7%
- Firms using BigTech credit by one SD more show a stronger response by 5%

Conclusion

Conclusion

- Main Findings

- ▶ BigTech is more responsive to MP in the extensive but not the intensive margin
- ▶ Data abundance and risk assessment techniques are the possible mechanisms
- ▶ Financial access to BigTech credit also shows a more pronounced real effect of MP

- Policy Implications

- ▶ Monetary policy needs to account for the increasing role of FinTech, BigTech in particular
- ▶ A coordination between macroeconomic policies and BigTech regulation policies is necessary

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%