北京大学中国经济研究中心
China Center for Economic Research
讨论稿系列
Working Paper Series

E2022011 2022-07-28

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

Yiping Huang, Xiang Li, Han Qiu, Changhua Yu

Abstract

This paper studies monetary policy transmission through BigTech and traditional banks. By comparing business loans made by a BigTech bank with those made by traditional banks, it finds that BigTech loans tend to be smaller, and the BigTech bank grants credit to more new borrowers compared with conventional banks in response to expansionary monetary policy. The BigTech bank's advantages in information, monitoring, and risk management are the potential mechanisms. The analysis also finds that BigTech and traditional bank credits to firms that have already borrowed from these banks respond similarly to changes in monetary policy. Overall, BigTech credit amplifies monetary policy transmission mainly through the extensive margin. In addition, monetary policy has a stronger impact on the real economy through BigTech lending than traditional bank loans.

Keywords: Financial Technology; Bank Lending, Monetary Policy Transmission
JEL Codes: E52; G21; G23

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

Yiping Huang † Xiang Li ‡ Han Qiu § Changhua Yu ¶

July 28, 2022

Abstract

This paper studies monetary policy transmission through BigTech and traditional banks. By comparing business loans made by a BigTech bank with those made by traditional banks, it finds that BigTech loans tend to be smaller, and the BigTech bank grants credit to more new borrowers compared with conventional banks in response to expansionary monetary policy. The BigTech bank's advantages in information, monitoring, and risk management are the potential mechanisms. The analysis also finds that BigTech and traditional bank credits to firms that have already borrowed from these banks respond similarly to changes in monetary policy. Overall, BigTech credit amplifies monetary policy transmission mainly through the extensive margin. In addition, monetary policy has a stronger impact on the real economy through BigTech lending than traditional bank loans.

Keywords: Financial Technology; Bank Lending, Monetary Policy Transmission
JEL Codes: E52; G21; G23

*For comments, discussion, and suggestions, we thank Gene Ambrocio, Christoph Basten, Christiane Baumeister, Jonathan Benchimol (discussant), Thomas Drechsel, Zuzana Fungáčová, Leonardo Gambacorta, Emilia Garcia-Appendini, Alexandra Gutsch, Jiayin Hu (discussant), Yi Huang, Boreum Kwak, Wei Li (discussant), Chang Ma, Aakriti Mathur, Mrinal Mishra, Steven Ongena, Melina Papoutsi, Malte Rieth, Matthias Rottner, Alessandro Sardone, Christoph Schult, Laura Solanko, Ruben Staffa, Gregor von Schweinitz, and other scholars at the China Financial Research Conference; the AsianFA Conference; the workshop on Advanced Analytics: New Methods and Applications for Macroeconomic Policy; and seminars at the University of Zurich, Bank of Finland, and Halle Institute for Economic Research. Any remaining errors are ours alone.

†China Center for Economic Research, National School of Development, and Institute of Digital Finance, Peking University. Yiheyuan Road 5, Beijing, 100871, China. Email: `yhuang@nsd.pku.edu.cn`

‡Halle Institute for Economic Research. Kleine Maekerstrasse 8, Halle(Saale), 06108, Germany. Email: `xiang.li@iwh-halle.de`

§Bank for International Settlements. 78th floor, Two International Finance Centre, 8 Finance Street, Central, Hong Kong. Email: `han.qiu@bis.org`

¶China Center for Economic Research, National School of Development, and Institute of Digital Finance, Peking University. Yiheyuan Road 5, Beijing, 100871, China. Email: `changhuayu@nsd.pku.edu.cn`

1 Introduction

Financial technology (FinTech) has been a major phenomenon in the recent development of financial markets. During the COVID-19 crisis, FinTech has played an unprecedentedly prominent role in stabilizing and reigniting the economy (Core and De Marco 2021, Kwan et al. 2021, Bao and Huang 2021, Fu and Mishra 2021). By definition, FinTech is a broad concept that refers to the use of technology in providing financial services (FSB 2019). What makes it stand out in the long history of financial innovation is that the disruption this time has been initiated by players outside the financial markets rather than within the old system. Digital platforms for marketplace lending and credit issued by big technology companies (BigTech), such as Ant Group, Amazon, or Mercado Libre, have posed serious challenges to the lending model of traditional financial intermediaries (Boot et al. 2021).

Figure 1 shows that BigTech credit has overtaken credit issued by decentralized platforms in recent years. BigTech credit accounts for 2%-3% of gross domestic product (GDP) in countries like China and Kenya. These BigTech credits are particularly important for micro, small, and medium-sized enterprises (MSMEs), which are the backbone of entrepreneurship and economic growth. Armed with information, distribution, and monitoring technologies built into the ecosystem of BigTech digital platforms, BigTech lenders are able to reduce reliance on traditional collateral and thus cover more borrowers that have been unserved or underserved by traditional financial institutions (Petersen and Rajan 1994, Berger and Udell 1995, Cornelli et al. 2022). BigTech credit has become a top concern for economic policy making (Carstens et al. 2021, Adrian 2021). As recognized by Philippon (2016) and Lagarde (2018), the disruption by FinTech brings a "brave new world" for monetary policy makers and requires re-evaluation of the effectiveness of monetary policy transmission through these new lenders. Despite the burgeoning literature on FinTech, little is known about its implications for monetary policy transmission.[1] This paper bridges this gap by exploring monetary policy transmission mechanisms through BigTech and conventional banks.

[1] See Allen et al. (2021) for a survey of FinTech research and policy discussion.

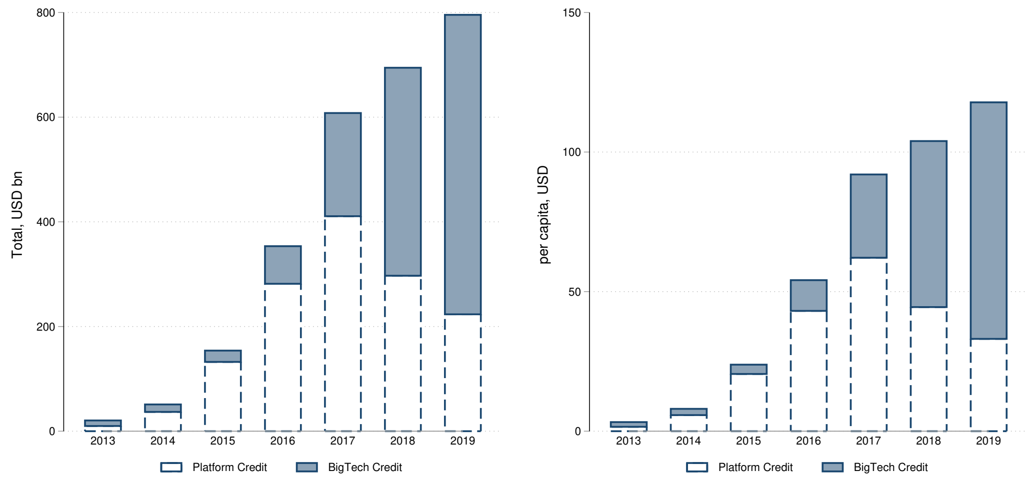

Figure 1: Global FinTech Credit

Data source: Cornelli et al. (2020).

We employ a unique data set covering the full borrowing history of sampled MSMEs from a major BigTech lender and traditional banks in China. We accessed credit data from the Ant Group, one of the dominant BigTech companies both domestically and internationally, and match with these MSMEs' borrowing history from traditional banks. Our data set covers monthly observations of both BigTech credit and bank credit to firms from January 2017 to December 2019. Combined with variations in monetary policy, our data set provides an ideal laboratory for investigating monetary policy transmission mechanisms through BigTech lenders and traditional banks. The findings based on the evidence from China may shed light on regulatory and monetary policies in other countries as well.

Our identification strategy focuses on the extensive margin, captured by a new lending relationship between a bank and a firm, and the intensive margin, captured by newly issued loans to a firm that has already borrowed from the bank. We explore the relative response of BigTech lending to changes in monetary policy, compared with traditional bank lending. After controlling firms' demand for credit, our estimates capture the impact of monetary policy through the credit supply of different types of banks. In addition, we examine the real impact on firms of BigTech credit relative to conventional bank loans by comparing sales growth in response to changes in monetary policy.

The main findings of the paper are the following. We find that BigTech loans tend to be smaller, and BigTech banks grant credit to more new borrowers, compared with conventional banks, in response to expansionary monetary policy. In other words, when monetary policy eases, BigTech lenders are more likely to establish new lending relationships with firms, compared with traditional banks. BigTech banks' advantages in information, monitoring, and risk management are the potential mechanisms. Compared with traditional bank loans, BigTech lending amplifies monetary policy to a larger extent for firms that have online businesses, rather than firms that have only offline businesses, and when BigTech lending is compared with secured bank loans, rather than unsecured banks loans. However, BigTech and traditional bank credits to firms that have already borrowed from these banks respond similarly to monetary policy changes. Overall, BigTech credit amplifies monetary policy transmission mainly through the extensive margin relative to traditional bank loans. In addition, monetary policy has a stronger impact on the real economy through BigTech lending than traditional bank loans.

This study relates to three branches of the literature. First, we contribute to the literature on monetary policy transmission by focusing on a new player, BigTech lenders, and comparing their responses to monetary policy with those of traditional banks. The bank lending channel of monetary policy (Bernanke and Blinder 1988, 1992, Kashyap and Stein 1995) depends on cross-sectional heterogeneity in various dimensions, including liquidity, size, income gap, leverage, and market power (Kashyap and Stein 2000, Brissimis et al. 2014, Drechsler et al. 2017, Gomez et al. 2021, Wang et al. 2021). The risk tolerance and risk exposure of financial intermediation may amplify monetary policy shocks, as is found by Coimbra et al. (2022) and Di Tella and Kurlat (2021). Heterogeneity in lenders' technological characteristics is a missing link in the literature.[2] Hasan et al. (2020) and Hasan and Li (2021) examine the role of regional FinTech penetration and banks' in-

[2]There are studies focusing on firms' technology adoption and its effect on monetary policy, but they are limited to non-financial firms. For instance, Consolo et al. (2021) find that firms' information technology investment weakens the credit channel of monetary policy transmission, and Fornaro and Wolf (2021) study the impact of monetary policy on firms' technology adoption decisions.

house technology development in the effectiveness of monetary policy. De Fiore et al. (2022) study BigTech's response to monetary policy based on cross-country annual data and model the role of BigTech as facilitating matching between sellers and buyers.

The key innovation of our study is that we focus on the monetary transmission mechanism through BigTech lending relative to traditional bank lending by exploring quasi-loan-level data between MSMEs and two types of lenders, BigTech and traditional banks. The evidence that BigTech lending amplifies monetary policy also adds to the recent literature that investigates the role of nonbanks in monetary policy transmission (e.g., Elliott et al. 2019, Chen et al. 2018).

Second, our study is related to the burgeoning studies on the relationship between FinTech lenders and banks. We contribute to the literature by directly comparing the lending behaviors of these two types of lenders to the same MSME borrowers through the lens of a unique data set. As summarized in Stulz (2019), Boot et al. (2021), Thakor (2020) and Berg et al. (2021), the recent wave of financial technologies is new and has brought an abundance of data and codification of soft information. These developments have strengthened screening and monitoring, which rationalize the empirical finding that compared with banks, FinTech lenders rely more on hard information. On the one hand, many studies examine whether FinTech lending substitutes for or complements bank lending. For instance, using U.S. mortgage lending and personal credit data, Buchak et al. (2018b), Di Maggio and Yao (2021), and Jagtiani (2021) show that FinTech lenders use different information to set interest rates relative to banks and are more likely to serve nonprime consumers. Using consumer lending data from LendingClub and banks in the United States, Jagtiani and Lemieux (2018) and Hughes et al. (2022) show that FinTech penetrates areas that are underserved by banks. Bharadwaj et al. (2019) and Erel and Liebersohn (2020) find that FinTech could improve financial access and resilience. Tang (2019) shows that peer-to-peer lending substitutes bank lending for infra-marginal bank borrowers but complements bank lending with respect to small loans. Liu et al. (2022) compare syndicated loans by a BigTech lender and a traditional bank in China and find that BigTech loans tend to be smaller, have higher interest rates, and are repaid far before maturity. Other recent studies, such as Pierri and Timmer (2022), Lin et al. (2021), Kwan et al. (2021), He et al. (2021), and Hasan and Li (2021), focus on technology adoption by banks and examine its impact on lending. Although Stulz (2019) highlights the special role of BigTech credit, there is little evidence on the difference in corporate lending between BigTech lenders and banks, in particular their responses to monetary policy shocks. This study fills this gap in the literature.

Third, this paper also contributes to the literature on financial innovation and economic growth, by highlighting the impact of BigTech credit on firm performance. Many studies focus on the real effects of the innovations of non-financial firms, such as Akerman et al. (2015), Beaudry et al. (2010), and Autor et al. (2003). These studies dwarf those on technological innovation in the financial sector, which may spur economic growth. For instance, Beck et al. (2016) show that banking innovation is associated with higher growth in countries and industries with better growth opportunities. Gorton and He (2021) find that banking innovation contributes to economic growth by allowing banks to offer longer maturity loans to the real sector with higher productivity. By contrast, research on the real effects of FinTech or BigTech credit is quite limited. Chen et al. (2022), Eça et al. (2021), Ahnert et al. (2021), and Beck et al. (2022) document that access to FinTech credit reduces sales volatility, increases sales growth, and spurs firm investment and entrepreneurship. In this study, we provide further evidence to show that, compared with traditional bank lending, BigTech credit increases MSMEs' sales growth in response to changes in monetary policy, echoing the real impact of monetary policy as in Gertler and Gilchrist (1994).

The rest of the paper is structured as follows. Section 2 describes the institutional background of BigTech credit in China, the data construction, and the variables used in the paper. Section 3 illustrates the identification strategies and reports the empirical results. Section 4 provides further discussion. Section 5 concludes.

2 Data and Variables

China has gradually become a leading player in BigTech credit. According to both the total and per capita BigTech credit of the top six countries from 2013 to 2019 (see Figure A1 in the appendix), China's BigTech credit has dominated other countries since 2017. On the one hand, aided by advantages in information, technology, distribution, and monitoring built into BigTech platforms' ecosystems, BigTech companies have access to millions of unserved and underserved credit users at very low cost, particularly MSMEs. On the other hand, the government's regulatory tolerance in the early stage development of FinTech has played an important role in supporting the rapid expansion of BigTech credit (see Chui 2021). Does BigTech credit substitute for or complement traditional bank lending to firms since both types of credit providers may face the same pool of potential credit users? Is BigTech credit more responsive to financial market conditions, such as the monetary policy stance, particularly in developing countries like China? China's BigTech credit differs from that of other countries in many dimensions. One important difference is that unlike in the United States and other advanced economies, BigTech lending in China is dominated by business lending rather than mortgage lending. Will BigTech credit reduce firms', particularly MSMEs', financial constraints and boost their growth?

To address these questions, we use data from the biggest BigTech credit provider in China, MYBank. MYBank is owned by the Ant Group, which is an affiliate company of the Alibaba Group and operates virtually without physical branches. Since its launch in 2015, MYBank has followed the same rules and policies of the China Banking and Insurance Regulatory Commission (CBIRC) as traditional banks.[3] MYBank mainly serves households and MSMEs such as e-commerce sellers and QR code offline merchants. The Ant Group owns the world's largest digital payment platform, Alipay, which is easy to access and use by both merchants and customers. Both e-commerce sellers and QR code

[3]The China Banking Regulatory Commission (CBRC) was the agency that regulated the banking sector in China. In April 2018, it was merged with the China Insurance Regulatory Commission (CIRC) to form the CBIRC.

offline merchants leave digital footprints when they use Alipay to settle online or offline transactions. Armed with this information and an advanced risk management model, MYBank offers loans with a "contact-free feature," without any visits to physical bank branches, under a so-called "310" model. That is, MYBank promises the completion of user registration and loan application within 3 minutes, money transfer to an Alipay account within 1 second, and 0 human intervention. More institutional background on MYBank and other BigTech lenders in China can be found in Frost et al. (2019), Huang et al. (2020), Hong et al. (2020), Hau et al. (2021), Gambacorta et al. (2022), and Liu et al. (2022).

There are similarities and differences between MYBank and traditional banks. Both types of banks are regulated by the CBIRC, attract deposits, and lend to credit users. They may have different lending models. Traditional banks usually require in-person interaction and inspection to issue loans and therefore take time to approve loan applications. MYBank issues loans very quickly by using various soft and hard information from the Ant Group and its parent company, the Alibaba Group. The repayment schedule could be different too. Loans from MYBank can be repaid early without any cost (Liu et al. 2022). Figure 2 shows the main financial indicators for MYBank and other traditional banks from 2015 to 2021, including the deposit-to-asset ratio, profitability calculated as the ratio of net income to assets, capital adequacy calculated as the ratio of capital to risk-weighted assets, and the ratio of nonperforming loans (NPLs) to assets. The figure shows that after the year of its launch, 2015, MYBank has tended to depend less on external finance via attracting deposits, have a slightly lower capital adequacy ratio than traditional banks on average, but have lower profitability and NPL ratio. Lower profitability may be associated with higher competition in the credit market, and the lower NPL ratio would imply that MYBank may have better risk management via abundant information and advanced technologies.

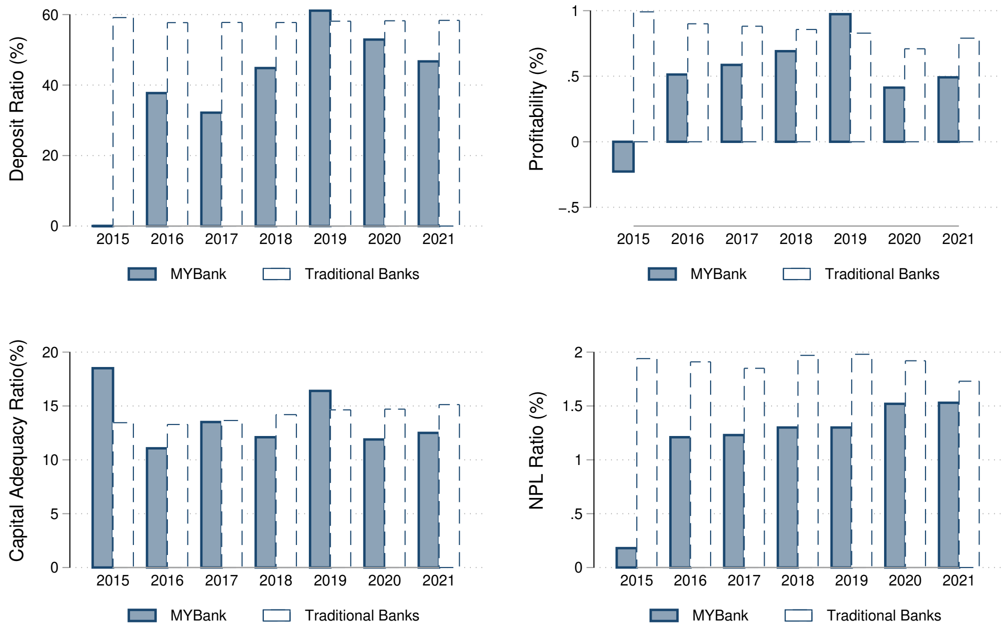

Figure 2: Main Indicators for MYBank and Traditional Banks

Sources: Annual Report of MYBank; CBIRC.

2.1 Data Construction

MYBank serves both households and firms in China. For our purpose, we mainly focus on MYBank's entrepreneurial customers. We explore how monetary policy affects credit expansion and contraction differently through MYBank and traditional banks. Both online and offline entrepreneurial customers settle transactions via Alipay and leave their digital footprints on the ecosystem of the Ant Group. Moreover, the business activities of online merchants on the digital platforms operated by the Alibaba Group provide additional information for MYBank to evaluate the risk of these merchants. MYBank's lending model might respond to monetary policy quite differently compared with traditional banks.

Due to MYBank's data regulation policy, we obtained a 10% random sample of its firm customers from January 2017 to December 2019. We dropped inactive firms by the following criteria: (i) a firm needs to be registered before 2019; (ii) a firm's owner is younger than 60 years; and (iii) the number of transactions should be greater than five per month during 70% of a firm's life cycle. There are around 340,000 firms drawn from MYBank's database. Table A1 in the appendix presents the sector distribution of the firms and shows that most of them are in the retail industry. The firm characteristics in our data set include business location, age and gender of the business owner, and the firm's monthly sales. The data set also provides a network score for each firm, which measures the firm's centrality in the Ant Group network based on its sales and payments history.[4] This score can be treated as the "network collateral" or "reputation" a firm has on this BigTech platform. The higher is the score, the more active is the firm in the ecosystem of this BigTech platform, and the more harmful it is to the firm's profits when the firm loses access to the ecosystem of the platform.

The MYBank database also provides detailed information on the borrowing history of each firm. We observe a firm's newly granted loans from MYBank, which is the BigTech credit in this study. We then retrieve traditional bank credits for each firm as well. That is, for each firm, we observe its access to BigTech credit and bank credit; whether the firm uses credit or not; and if the firm uses credit, how much it has used. For traditional bank credits granted to a firm, we can further distinguish between secured and unsecured bank loans. However, due to data limitations, we only observe the aggregate credits granted by traditional banks, rather than detailed information on bank loans from a specific traditional bank. Therefore, our final data set is at the firm-lender-month level and we focus on two types of lenders: the BigTech lender, MYBank, and other traditional bank lenders as a whole.[5]

There are three major caveats in the data structure due to data limitations. First, we cannot break down the loans among traditional banks since they are treated as an

[4]The network score is a rank calculated by using a PageRank algorithm. This algorithm was first introduced by Larry Page, one of the founders of Google, to evaluate the importance of a particular website page. The calculation is done by means of webgraphs, where webpages are nodes and hyperlinks are edges. Each hyperlink to a page counts as a vote of support for that webpage. In the case of the Ant Group network score, customers and QRcode merchants can be considered as interconnected nodes (webpages) and payment funding flows can be considered as edges (hyperlinks).

[5]In each month, it is possible for a firm to originate new credit multiple times. Therefore, we may have several origination records in each month for each firm. For the purpose of the analyses, we compile all the origination records that occur each month into one aggregate origination record at the firm-month level.

aggregate bank lender. Second, we use only one BigTech lender, MYBank. Although it is a dominant BigTech player, we may underestimate the responses of BigTech credits to monetary policy.[6] Third, we cannot observe the loan-level information of interest rates, repayment schedules, and default history due to data disclosure policy. Nevertheless, the use of proprietary data from MYBank and the simultaneous observations of BigTech and traditional bank credits to the same firms allow us to present a more granular view of BigTech credit and disentangle various monetary policy transmission mechanisms through BigTech lenders and traditional banks.

2.2 Summary Statistics

Table 1 presents the summary statistics of the variables used in this study. Panel A shows that in a given month, the average shares of firms that use BigTech and bank credit are 5.8% and 1.3%, respectively, and only 0.3% of firms obtained secured loans and 1.1% of firms had access to unsecured loans from traditional banks. The average amount of credit granted by the BigTech lender is around 21,934 Chinese yuan (3,400 dollars), and the average amounts of secured and unsecured bank credits are 532,792 yuan (84,500 dollars) and 147,867 yuan (18,700 dollars), respectively. The large difference in average loan amounts between these two types of lenders might imply that BigTech lending is complementary to traditional bank credits. Panel B in 1 shows that offline firms are the majority in our sample as only 1.6% are online sellers. The monthly sales of the sampled firms are 10,386 yuan (1,600 dollars) on average, suggesting that our sample data mainly consist of micro and small firms. The business owners are relatively young, with an average age of 38 years, and generally balanced in gender.

[6] Another important BigTech lender in China is WeBank, founded by Tencent, but it focuses on consumer credit. The BigTech lender in this paper, MYBank, founded by Alibaba, focuses on business credit.

Table 1: Summary Statistics

Variables	N	Mean	St. Dev.
	Panel A: Credit		
Credit use -All	15,139,162	0.036	0.185
Credit use -BigTech	7,569,581	0.058	0.234
Credit use -Bank	7,569,581	0.013	0.113
Credit use -Bank unsecured	7,569,581	0.011	0.104
Credit use -Bank secured	7,569,581	0.003	0.051
Loan amount -All	173,484	38,015.87	134,803.90
Loan amount -BigTech	158,795	21,934.73	38,508.80
Loan amount -Bank credit	14,689	211,860.50	406,918.30
Loan amount -Bank secured credit	2,389	532,792.40	673,866.10
Loan amount -Bank unsecured credit	12,438	147,867.70	282,328.60
	Panel B: Firm Characteristics		
Network Centrality	15,139,162	37.52	21.047
Sales	15,139,162	10,386.64	67,164.41
Online	15,138,972	0.016	0.124
Owner Age	15,139,162	38.332	8.845
Owner Gender-Male	15,139,162	0.512	0.500
	Panel C: Macroeconomic Conditions		
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

We are interested in the transmission mechanism of monetary policy through a BigTech bank and traditional banks. Monetary policy in our paper is measured by the seven-day pledged interbank repo rate for deposit institutions (DR007). This interbank rate is emphasized in the Quarterly Monetary Policy Executive Reports of China as playing "an active role to cultivate the market base rate." This implies that the central bank, the People's Bank of China, uses this interbank rate as a *de facto* intermediate target (McMahon et al. 2018). We adopt the monthly change in this rate ($\Delta DR007$) to capture changes in the monetary policy: a positive value indicates a tightening of monetary policy and a negative value indicates an expansionary monetary policy. China has been experiencing a gradual transition from a quantity-based rule to price-based monetary policy, and our sample covers a recent period, 2017M1-2019M12; therefore, $\Delta DR007$ might be a good measure of monetary policy in China. Furthermore, recent studies, such as Chen et al. (2018) and Kamber and Mohanty (2018), provide evidence that the impulses of monetary policy transmission in China are similar to those in advanced economies. Therefore, the transmission of monetary policy through BigTech and traditional banks in this study might apply for other economies.

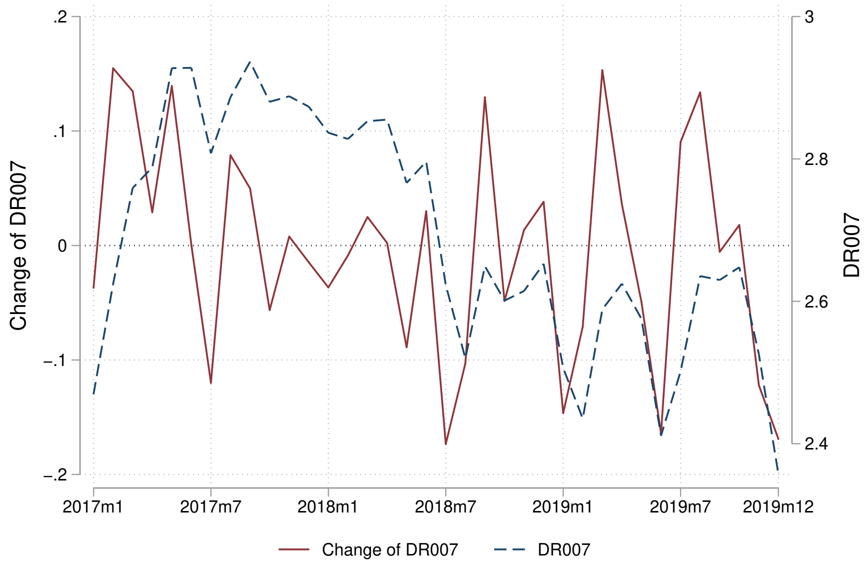

Figure 3: Monetary Policy Rate

Figure 3 Figure 3 displays the time series of the level and change in the monetary policy rate, DR007. There are large variations in the monetary policy rate in our sample period. The tightening and easing cycles occur in turn and neither dominates the whole sample period; therefore, this interbank rate will be useful for our identification. Other macroeconomic control variables include the logarithm of GDP and bank branch density, measured as the number of branches per thousand population, both at the city level. They are summarized in panel C in Table 1.

3 Empirical Evidence

3.1 Identification Strategy

We adopt the following specification for the baseline analysis:

$$Credit_{ibt} = \alpha + \beta MP_t \times D(BigTech)_b + \delta_b + \theta_{it} + \epsilon_{ibt} \quad (1)$$

where i, b and t indicate firm, lender, and month, respectively. There are two lenders in our data set: the group of traditional banks as a whole and the BigTech lender, MYBank. The variable $D(BigTech)_b$ is a dummy variable that equals 1 for the BigTech lender. The variable MP_t captures monetary policy, for which we use changes in the intermediate target rate ($\Delta DR007$) in the baseline regression. A positive $\Delta DR007$ indicates a tightening of monetary policy and a negative value indicates an easing. A lender fixed effect, δ_b , captures the time-invariant differences between traditional banks and BigTech lenders. A firm-time fixed effect, θ_{it}, absorbs any confounding factors that are firm-time variant, including firms' credit demand. With this specification, we will compare lending by the two types of lenders to the same firm at the same time. Thus, an estimate of β captures the difference in response to monetary policy arising from the credit supply side. Later we will also show the results when we specify firm and time fixed effects separately instead of a firm-time fixed effect. In that case, we control a set of firm characteristics, including the age of the business owner, the logarithm of sales, the network centrality score of the firm in the Ant Group system, and the logarithm of the GDP of the city where the firm is located. All these control variables (except owner's age) are in lagged terms to deal with reverse causality.

For the explained variable, $Credit_{ibt}$, we are interested in the impact of monetary policy on both the extensive and intensive margins, as in Khwaja and Mian (2008) and Bittner et al. (2020). Fortunately, our data provide firms' complete borrowing histories from both traditional banks and the BigTech lender. For the extensive margin, we construct a dummy variable, $D(\textit{New Lending Relationship})_{ibt}$, which equals one if firm i

starts to obtain credit from bank b at time t. That is, firm i was not bank b's client before t, but it becomes a client at time t and thereafter. This variable indicates the formation of a new lending relationship between firm i and bank b. We adopt a linear probability specification for the dichotomous dependent variable to facilitate the interpretation of the interaction term in the estimation.

For the intensive margin, we focus on the logarithm of the amount of credit, $Ln(Loan)_{ibt}$, which is a conventional way of studying the credit channel of monetary policy. Here the sample is restricted conditional on (i) the firm has already established a lending relationship with a lender; (ii) the loan amount is positive; and (iii) the firm obtains credit from both traditional banks and the BigTech lender, and therefore observations of firms borrowing from only one lender are not included. In other words, we conduct a quasi-loan-level regression, and our strategy is to compare the amounts of lending to the same firm from different lenders at the same time. Therefore, the number of observations when investigating the intensive margin is largely reduced relative to the extensive margin. For both the extensive and intensive margins of lending, we focus on coefficient β. As a higher MP_t means a tightening of monetary policy in the baseline estimation, a significant and negative β indicates that BigTech lenders are more responsive to monetary policy than traditional banks and *vice versa*.

One of the key assumptions for identification is that there are no other confounding shocks that affect both monetary policy and the relative lending behavior of traditional banks and the BigTech lender. Aggregate shocks that symmetrically affect these two types of lenders do not threaten the identification, as they are absorbed in the time fixed effect and will not contaminate the estimate of the coefficient of the interaction term. The other concern about identification is the differentiation between credit demand and credit supply. Benefiting from the data structure, we are able to minimize this concern since we control credit demand through a firm-time fixed effect and can ensure that our estimates arise from the credit supply side.

3.2 Baseline Results

Table 2 presents the estimates of the baseline specification from an extensive or intensive view of the impact of monetary policy on firms' borrowing through the two types of banks. A key finding from columns (1) and (2) is that the coefficients of the interaction term of monetary policy and the BigTech dummy are negative and statistically significant for the extensive margin, implying that the BigTech lender is more responsive than traditional banks in expanding to new customers when monetary policy eases. More specifically, when the monetary policy rate decreases by one standard deviation, the probability of a BigTech lender building a new lending relationship with a firm is 0.25 percentage point higher than that of a traditional bank. Considering that the average probability of lending is 3.6% (see Table 1), this impact is economically large. BigTech credit amplifies the transmission of monetary policy through financial intermediation. This finding echoes those of Coimbra et al. (2022) and Di Tella and Kurlat (2021), but focuses on firm-level borrowing.

Columns (1) and (2) in Table 2 also consider different sets of control variables. Column (1) uses bank, firm, and month fixed effects and other firm- and city-level control variables. The results show that firms with higher sales and located in more developed regions are more likely to establish new lending relationships with BigTech lenders or traditional banks. In addition, the business owners' age and network centrality are positively associated with the probability of building a new lending relationship. Column (2) uses firm-month fixed effect instead as a robustness check, and the results in these two columns are quite similar.

Table 2: Baseline Results

DepVar	D(New Lending Relationship)		Ln(Loan)	
	(1)	(2)	(3)	(4)
Δ DR007 × D(BigTech)	-0.026***	-0.026***	-0.080	-0.020
	(0.0003)	(0.0005)	(0.134)	(2.553)
Owner Age	0.002***		0.002	
	(0.0001)		(0.011)	
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 × Month FE	NO	YES	NO	YES

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

Does BigTech credit amplify monetary policy through the intensive margin as well? Columns (3) and (4) in Table 2 report the regression results and show that the coefficients of the interaction term of monetary policy and the BigTech dummy are insignificant for the intensive margin. That is, BigTech is not significantly different from traditional banks in terms of the amount of newly issued credit when lending to the same borrower. At first glance, this finding seems to contrast with the standard bank lending channel as in Bernanke and Blinder (1988) and Kashyap and Stein (2000). Firms in our sample data are mainly micro and small firms, and their credit demand might be discontinuous at the monthly level, but we have controlled for various fixed effects to isolate firms' demand side from the supply side of financial intermediation. Thus, the main reason for the lack of effect on the intensive margin might come from the credit supply side. Based on the syndicated loans of MYBank and a traditional bank, Liu et al. (2022) find that the amount of loans to MSMEs is usually quite inflexible irrespective of firms' risk characteristics. We reach a similar finding as theirs but focus on the bank lending channel through changes in the financial conditions faced by financial intermediaries.

3.3 Robustness of the Results

When exploring differences between BigTech credit and bank credit, a potential concern might be the comparability of these two types of lenders with respect to credit size and usage. Table 1 shows that the size of the average traditional bank credit is much larger than that of the average BigTech credit. The difference in lending scale might lie in the purposes of the loans. For instance, firms could borrow a large amount from traditional banks for long-term investment while borrowing a smaller amount from the BigTech lender to satisfy short-term liquidity demand, for instance, to bridge debt or finance trade credit. In this case, when monetary policy changes, the responses of the two types of lenders would be less comparable. To mitigate concern about comparability, we propose the following argument. On the one hand, it is not easy for lenders to know exactly how borrowers use their funds, and therefore we are less concerned about the purposes and sizes of the loans when examining building new lending relationships. On the other hand, we limit the sample of bank credits to those that are smaller than the 75th percentile in the distribution of BigTech credit. That is, we reconstruct the sample by only keeping the bank credits that are similar in size to the BigTech credits and rerun the baseline estimation.

Table 3 shows that the estimates are very similar to the baseline results for the extensive margin.[7] For the intensive margin, the magnitudes become much larger than the baseline estimates after we restrict the sample to loans of similar size. This finding

[7]The observations in our data are aggregated over loans for each firm in each month, and the 75th percentile cutoff applies to the loan level. Therefore, the number of firm-month observations is the same as in the baseline specification.

implies that the BigTech lender tends to be more responsive to monetary policy on the intensive margin as well, although the difference is statistically insignificant. Overall, these results mitigate the concern about comparability and further support our baseline findings.

Table 3: Robustness Check: Bank Credit and BigTech Credit with Loans of Similar Sizes

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)
Owner Age	0.002***		0.003	
	(0.0001)		(0.011)	
L.Sales	0.001***		0.013***	
	(0.00004)		(0.003)	
L.Network Centrality	0.0001***		-0.0005	
	(0.00002)		(0.001)	
L.Regional GDP	0.001***		0.049**	
	(0.0002)		(0.024)	
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

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

The discussion above focused on bank lending at the firm-month level. What is the impact of monetary policy on bank lending at a more aggregate level? For a better understanding of the overall impact of monetary policy on lending by the two types of banks, we aggregate firms' bank credit and BigTech credit to the city level. This combines the effects of monetary policy on the extensive and intensive margins on different types of lenders. We then examine whether aggregate credit at the city level shows a larger difference for the BigTech lender than for banks in response to monetary policy. In addition, by comparing aggregate BigTech lending and bank lending, we mitigate the concern about not observing bank loans granted by individual banks within the traditional bank group. The specification is similar to the baseline specification, except now the control variables are at the city level, we use city and city-time fixed effects instead of firm and firm-time fixed effects, and the dependent variable is the logarithm of lending amount at the city-lender-time level.

Table 4: Robustness Check: City-Level Aggregates

	(1)	(2)
MP × 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 × Time FE	NO	YES

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

Table 4 shows that BigTech credit reacts more aggressively than traditional bank credit to monetary policy changes. Specifically, when monetary policy eases by one standard deviation, the BigTech lender issues 41.73% more credit than traditional banks to MSMEs, which implies a very large impact on the aggregate economy. These results suggest that the stronger role of the BigTech lender comes from expanding financial access to MSMEs, which are usually underserved by traditional banks. The extent of building new lending relationships is so prominent that the response of BigTech credit at the city level becomes much stronger than bank credit.

To sum up, we have provided novel evidence that the BigTech lender amplifies the bank lending channel of monetary policy transmission, and it works mainly through the extensive margin of bank lending. In the following subsections, we investigate the potential amplification mechanisms of BigTech credit relative to conventional bank credit.

3.4 Mechanism Investigation

In this subsection, we propose two complementary explanations – the information channel and the risk channel – for the stronger response of BigTech credit relative to bank credit responding to monetary policy changes. We also test the predictions of these two potential mechanisms. A dominant feature of BigTech credit is related to the technological advantages of BigTech lenders. BigTech lenders have access to various hard and soft information about firms, which may mitigate the information asymmetry between lenders and borrowers (Boot et al. 2021, Stulz 2019, Di Maggio and Yao 2021). BigTech lenders also make use of big data to develop alternative risk management techniques and models, which may better predict default risk (Berg et al. 2020, Di Maggio et al. 2021). Financial intermediaries that are stronger in these two aspects might be more responsive to a change in monetary policy (Coimbra and Rey 2017, Coimbra et al. 2022).

To test the information channel, we split the full sample of firms into a subsample of online firms that sell products on digital platforms operated by the Alibaba Group, and a subsample of offline firms that do not conduct e-commerce. The prediction is that BigTech credit will respond more than traditional bank credit to monetary policy changes for the subsample of online sellers. This is because in addition to information on transactions through Alipay, MYBank also uses other information on online firms that run businesses on digital platforms operated by MYBank's parent company, the Alibaba Group. This kind of information is not directly available to traditional banks. For the risk assessment mechanism, we distinguish between bank credit that is secured by collateral and that without collateral, and compare BigTech credit with secured bank credit and unsecured bank credit separately. The prediction is that BigTech credit will respond more than secured bank lending, compared with the scenario between BigTech credit and unsecured bank lending. The reason is that banks require riskier firms to provide collateral to reduce the banks' lending risk. BigTech lenders' alternative risk assessment models may reduce such risk and could enable them to extend more credit to firms when the central bank cuts the interest rate.

Table 5: Mechanism Investigation: Offline and Online Firms

DepVar:	D(New Lending Relationship)		Ln(Loan Amount)	
Firm Type:	Offline	Online	Offline	Online
	(1)	(2)	(3)	(4)
$\Delta DR007 \times$ D(BigTech)	-0.026***	-0.053***	-2.232	-2.208
	(0.0004)	(0.0005)	(19.639)	(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

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

Table 5 shows the results of testing the information channel. We split the firms in our sample data into two subsamples, offline and online sellers. As described in section 2, a large fraction of the offline sellers are self-employed corner shop owners or peddlers who sell low-value goods and often use Alipay QR codes as the cashier. The BigTech lender then obtains transaction information, such as cash flow and sales, via Alipay. In contrast, online sellers run businesses on digital platforms operated by the Alibaba Group, and most of them only have a digital appearance and a small share of sellers may have physical offline stores. We do not include the physical branches in our sample data. The BigTech lenders have access to various information on these online sellers, including their customer profiles, product varieties, service satisfaction, and so forth. In terms of lending behavior, traditional banks depend on visiting the physical stores to gather soft information on the borrowers. BigTech lenders depend on data obtained from the digital world, which is the hard information on the borrower. These abundant data are particularly useful for BigTech lenders, and this information advantage will be larger between BigTech lenders and online sellers compared with offline sellers.

Results in Table 5 show that the BigTech lender grants credit to more firms, compared with traditional banks, when monetary policy is expansionary. Moreover, for the BigTech lender, the probability of expanding credit to new online firms is double that for lending credit to offline firms, compared with traditional bank lending. Specifically, when the interest rate declines by one standard deviation, BigTech lenders' probability of expanding lending relationships to offline sellers is 0.25 percentage points greater than that of traditional banks, but it increases to 0.50 percentage points for online sellers. This finding confirms our prediction that BigTech lenders that use more information would respond more aggressively to monetary policy changes. Nevertheless, the coefficients for the intensive margin are still insignificant for both subsamples.

Table 6: Mechanism Investigation: Secured and Unsecured Bank Loans

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 × Time FE	YES	YES	YES	YES

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

Table 6 presents the results when we consider traditional banks' secured and unsecured loans separately. It shows that the gap between BigTech credit and secured bank credit in responding to monetary policy changes is larger than that between BigTech credit and unsecured bank credit. Again, this is significant for the extensive margin but not for the intensive margin. These findings are consistent with the credit risk assessment hypothesis that BigTech lenders react to monetary policy change in a stronger way because they may have better models for evaluating risk and bear more risks.

4 Further Discussion

In this section, we further discuss our empirical findings. First, we investigate whether the BigTech lender's stronger response to monetary policy is related to heterogeneity in competition between banks and BigTech lenders. Second, we explore whether BigTech credit responds asymmetrically to monetary policy easing and tightening. Third, we focus on whether BigTech credit depends on heterogeneity across firm sizes and network scores. Finally, we examine whether the stronger impact on BigTech lenders has any real effects.

4.1 Competition between Banks and BigTech Lenders

An important debate on financial innovation is whether conventional banks and BigTech lenders, or FinTech lenders in general, are complements or substitutes (Buchak et al. 2018a, Tang 2019, Jagtiani and Lemieux 2018, Erel and Liebersohn 2020). To address this debate, we consider a measure of credit market competition, by using bank branch density at the city level, which is defined as the number of bank branches per thousand population.[8] Our hypothesis is that BigTech lenders are more likely to face stronger competition from banks and substitute for bank credit when bank branch density is high, while a complementary relationship is more likely in places with fewer bank branches. We assign the bank branch density to each firm based on the city where it is located and split the full sample into subsamples of high versus low branch density based on the median value in the sample data.

[8]The bank branch data are from the CBIRC, which documents the exact location of each bank branch, covering all banks. We aggregate the number of branches by city-year. The population data are from the bureau of statistics of each city.

Table 7: Discussion: Bank Branch Density

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 × Time FE	YES	YES	YES	YES

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

Table 7 reports the results for the two subsamples. Columns (1) and (2) report that the estimates are very close in the two subsamples, and they are the same as that in the baseline estimation. For the intensive margin, the results in columns (3) and (4) show that the magnitude of the coefficient in the subsample of high branch intensity is much larger than that in the subsample of low branch intensity, although they are both statistically insignificant. These findings suggest that the stronger reaction to monetary policy change by BigTech lenders than banks does not necessarily rely on market competition between these two types of financial intermediaries. MSMEs are likely unserved or underserved by banks due to information asymmetry and risk management, and therefore the bank branch density does not matter in the regressions. This is consistent with our proposed mechanisms of information and risk management technology advantages.

4.2 Asymmetric Effects of Monetary Policy

Macroeconomic policy may have an asymmetric impact on bank lending via a nonlinear response (see, for instance, Elenev et al. 2021 and others). In this subsection, we distinguish between monetary policy easing and tightening and investigate whether the BigTech lender responds differently in these two policy regimes. We construct a dummy variable indicating monetary policy tightening, $D(Tightening)_t$, for when the change in the monetary policy rate is positive, and interact it with the absolute values of the changes in the monetary policy rate in addition to the BigTech lender dummy. Specifically, we estimate the following:

$$\begin{aligned} Credit_{ibt} = \alpha' + \beta_1'|MP_t| \times D(BigTech)_b + \beta_2' D(BigTech)_b \times D(Tightening)_t \\ + \beta_3' D(BigTech)_b \times |MP_t| \times D(Tightening)_t + \delta_b + \theta_{it} + \epsilon_{ibt} \end{aligned} \tag{2}$$

Table 8: Discussion: Asymmetric Effect between Easing and Tightening

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

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

The first two columns in Table 8 report an asymmetric impact between monetary easing and tightening with respect to the extensive margin. Specifically, the transmission-enhancing role of the BigTech lender only appears when monetary policy is *loosening*, and the magnitude is large. When the monetary policy rate decreases by one standard deviation, the probability of a BigTech credit provider lending to a new firm is 0.97 percentage point higher than that of a traditional bank, while it is 0.25 percentage point higher in the baseline results. By contrast, when the monetary policy is tightened by one standard deviation, the credit contraction on the extensive margin is smaller for the BigTech lender than banks by a magnitude of 0.88 percentage point. The last two columns in Table 8 show that the impact on the intensive margin is insignificant and indifferent between monetary policy tightening and easing.

4.3 Heterogeneous Effects across Firms

Firms with different sizes and network scores may have different chances to obtain credit from financial intermediaries. We divide the full sample into four subsamples, each corresponding to the first to fourth quartiles of the size distribution, and then repeat the baseline estimation for each subsample.

The results in Table 9 show that the BigTech lender is more responsive to monetary policy changes on the extensive margin for all four groups of firms. Moreover, the magnitude of the impact increases with firm size. When the monetary policy rate decreases by one standard deviation, the probability of a BigTech lender building a new lending relationship with a firm in the fourth quartile of the size distribution is 0.37 percentage point higher than that of a traditional bank, while the effect for firms in the first quartile is only 0.12 percentage point. When we explore the intensive margin, the coefficient changes from positive in the first quartile to negative in the fourth quartile, but it remains statistically insignificant across the size distribution.

Table 9: Discussion: Heterogeneity across Size

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

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

Table 10: Discussion: Heterogeneity across Network Centrality

DepVar	D(New Lending Relationship)		Ln(Loan)	
	(1)	(2)	(3)	(4)
Δ DR007 $\times$ D(BigTech)	0.010***	0.010***	-0.025	-0.204
	(0.001)	(0.001)	(0.363)	(8.942)
Δ DR007 $\times$ Network Centrality	-0.0001***		0.003	
	(0.000)		(0.005)	
D(BigTech) $\times$ Network Centrality	0.002***	0.002***	0.008***	0.003
	(0.000)	(0.000)	(0.001)	(0.018)
D(BigTech) $\times$ Network Centrality$\times$ Δ DR007	-0.001***	-0.001***	-0.001	-0.004
	(0.000)	(0.000)	(0.006)	(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
Firm FE	YES	-	YES	-
Month FE	YES	-	YES	-
Firm $\times$ Month FE	NO	YES	NO	YES

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

We interact the network score with monetary policy and the BigTech lender dummy and examine the coefficient of the triple interaction term. Table 10 shows that the higher is the network centrality of a firm, the more pronounced is the effect that the BigTech lender is more responsive to monetary policy than traditional banks on the extensive margin. This result is in line with the advanced risk assessment technologies of BigTech lenders, as firms with higher network centrality have more network collateral on the BigTech platform. Therefore, the platform can lever more effective risk management for these firms.

4.4 Real Effects of BigTech Credit

In this subsection, we investigate how monetary policy affects the real economy through BigTech credit. The literature mainly examines the impact of monetary policy on firms' investment (Gertler and Gilchrist 1994, Cloyne et al. 2018, Ottonello and Winberry 2020). Instead, we explore firms' sales to capture the real effect since many MSMEs in our sample do not have accounting-approved balance sheet statistics. We use firms' monthly sales as the dependent variable to capture firms' growth and specify the following alternative equation:

$$Ln(Sale)_{it} = \alpha_0 + \gamma_1 BigTech_{it-1} + \gamma_2 BigTech_{it-1} \times MP_t + \Gamma' X_{it-1} + \theta_i + \eta_t + \epsilon_{it} \quad (3)$$

where the dependent variable, $Ln(Sale)_{it}$, is the logarithm of sales of firm i in month t. We use two variables to capture the usage of BigTech credit in the previous period, $BigTech_{it-1}$. First, we use a dummy variable to indicate whether a firm has been granted a loan by the BigTech lender. Second, we examine the amount of the BigTech loan. A set of control variables, X_{it-1}, includes age of business owner, network score, and GDP in the region where the firm operates. The regression includes firm and time fixed effects, θ_i and η_t, respectively. In particular, we are interested in estimates of γ_1 and γ_2. When monetary policy tightens, we expect firms to have lower sales. Therefore, a negative γ_2 implies that the use of BigTech credit strengthens the impact of monetary policy on the real economy and *vice versa*.

Table 11 shows that the usage of BigTech credit is associated with a stronger response of firms' sales in response to monetary policy. Specifically, given the same change in monetary policy, column (1) shows that firms that accessed BigTech credit in the previous period are more responsive in sales growth by 10.7% than those that did not use BigTech credit. Column (2) shows that firms that had one standard deviation more BigTech credit are associated with a stronger response in sales growth by 5%. These results suggest that BigTech credit not only responds to monetary policy in a stronger way than traditional banks, but also it relaxes firms' financial constraints and facilitates the transmission of monetary policy to the real economy.

Table 11: Discussion: Real Effects of BigTech Credits

BigTech:	Dummy of Usage	Amount of Usage
DepVar: Ln(Sale)	(1)	(2)
$\Delta DR007\times$ L.BigTech	-0.107***	-0.011***
	(0.037)	(0.004)
L.BigTech	0.114***	0.012***
	(0.007)	(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

Note: *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

5 Conclusion

In this paper, we explored the transmission mechanism of monetary policy through two types of financial intermediaries: traditional banks and BigTech credit providers. BigTech lenders may have advantages in information, technology, distribution, and monitoring embedded in the digital platforms of BigTech companies. Thus, BigTech lenders may apply an alternative lending model to MSMEs. We found that a BigTech lender is more responsive to monetary policy on the extensive margin after controlling credit demand, and this effect is more pronounced when the monetary policy is easing rather than tightening and for larger firms with network centrality. The difference between the two types of lenders is larger in the subsample of online sellers than offline sellers, and the difference is also larger when comparing BigTech credit with secured bank credit than comparing BigTech credit with unsecured bank credit. These findings suggest that the information advantages and risk management models of the BigTech lender amplify the transmission of monetary policy. In addition, financial access to BigTech credit shows a more pronounced real effect in response to monetary policy. Nevertheless, on the intensive margin, BigTech and traditional credits respond similarly to monetary policy changes.

The policy implication is that monetary policy makers should account for the amplification mechanism of FinTech –BigTech lenders in particular– in financial markets. Moreover, coordination between macroeconomic policies and BigTech regulation policies is necessary to improve the use of BigTech credit for financial access and serve the real economy.

References

Adrian, T. (2021). Bigtech in financial services. *Speech. International Monetary Fund, Washington, DC.*

Ahnert, T., Doerr, S., Pierri, M. N., and Timmer, M. Y. (2021). Does IT help? Information technology in banking and entrepreneurship. *IMF Working Paper.*

Akerman, A., Gaarder, I., and Mogstad, M. (2015). The skill complementarity of broadband internet. *Quarterly Journal of Economics*, 130(4):1781–1824.

Allen, F., Gu, X., Jagtiani, J., et al. (2021). A survey of fintech research and policy discussion. *Review of Corporate Finance*, 1(3-4):259–339.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4):1279–1333.

Bao, Z. and Huang, D. (2021). Shadow banking in a crisis: Evidence from fintech during COVID-19. *Journal of Financial and Quantitative Analysis*, 56(7):2320–2355.

Beaudry, P., Doms, M., and Lewis, E. (2010). Should the personal computer be considered a technological revolution? Evidence from US metropolitan areas. *Journal of Political Economy*, 118(5):988–1036.

Beck, T., Chen, T., Lin, C., and Song, F. M. (2016). Financial innovation: The bright and the dark sides. *Journal of Banking & Finance*, 72:28–51.

Beck, T., Gambacorta, L., Huang, Y., Li, Z., and Qiu, H. (2022). Big techs, QR code payments and financial inclusion. *BIS Working Paper.*

Berg, T., Burg, V., Gombović, A., and Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. *Review of Financial Studies*, 33(7):2845–2897.

Berg, T., Fuster, A., and Puri, M. (2021). Fintech lending. *NBER Working Paper.*

Berger, A. N. and Udell, G. F. (1995). Relationship lending and lines of credit in small firm finance. *Journal of Business*, 68(3):351–381.

Bernanke, B. and Blinder, A. (1992). The federal funds rate and the channels of monetary transmission. *American Economic Review*, 82(4):901–21.

Bernanke, B. S. and Blinder, A. S. (1988). Credit, money, and aggregate demand. *American Economic Review*, 78(2):435–439.

Bharadwaj, P., Jack, W., and Suri, T. (2019). Fintech and household resilience to shocks: Evidence from digital loans in Kenya. *NBER Working Paper*.

Bittner, C., Bonfim, D., Heider, F., Saidi, F., Schepens, G., and Soares, C. (2020). Why so negative? The effect of monetary policy on bank credit supply across the euro area. *Working Paper*.

Boot, A., Hoffmann, P., Laeven, L., and Ratnovski, L. (2021). Fintech: What's old, what's new? *Journal of Financial Stability*, 53:100836.

Brissimis, S. N., Iosifidi, M., and Delis, M. D. (2014). Bank market power and monetary policy transmission. *International Journal of Central Banking*, 10(4):173–214.

Buchak, G., Matvos, G., Piskorski, T., and Seru, A. (2018a). Beyond the balance sheet model of banking: Implications for bank regulation and monetary policy. *NBER Working Paper*.

Buchak, G., Matvos, G., Piskorski, T., and Seru, A. (2018b). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, 130(3):453–483.

Carstens, A., Claessens, S., Restoy, F., and Shin, H. S. (2021). Regulating big techs in finance. *BIS Bulletin, No.45*.

Chen, K., Ren, J., and Zha, T. (2018). The nexus of monetary policy and shadow banking in China. *American Economic Review*, 108(12):3891–3936.

Chen, T., Huang, Y., Lin, C., and Sheng, Z. (2022). Finance and firm volatility: Evidence from small business lending in China. *Management Science*, 68(3):2226–2249.

Chui, M. (2021). Money, technology and banking: What lessons can China teach the rest of the world? *BIS Working Paper*.

Cloyne, J., Ferreira, C., Froemel, M., and Surico, P. (2018). Monetary policy, corporate finance and investment. *NBER Working Paper*.

Coimbra, N., Kim, D., and Rey, H. (2022). Central bank policy and the concentration of risk: Empirical estimates. *Journal of Monetary Economics*, 125:182–198.

Coimbra, N. and Rey, H. (2017). Financial cycles with heterogeneous intermediaries. *NBER Working Paper*.

Consolo, A., Cette, G., Bergeaud, A., Labhard, V., Osbat, C., Kosekova, S., Basso, G., Basso, H., Bobeica, E., Ciapanna, E., et al. (2021). Digitalisation: channels, impacts and implications for monetary policy in the euro area. *ECB Occasional Paper*.

Core, F. and De Marco, F. (2021). Public guarantees for small businesses in Italy during COVID-19.

Cornelli, G., Frost, J., Gambacorta, L., and Jagtiani, J. (2022). The impact of fintech lending on credit access for us small businesses. *FRB of Philadelphia Working Paper*.

Cornelli, G., Frost, J., Gambacorta, L., Rau, P. R., Wardrop, R., and Ziegler, T. (2020). Fintech and big tech credit: a new database. *BIS Working Paper*.

De Fiore, F., Gambacorta, L., and Manea, C. (2022). Big techs and the credit channel of monetary policy. *Working Paper*.

Di Maggio, M., Ratnadiwakara, D., and Carmichael, D. (2021). Invisible primes: Fintech lending with alternative data. *NBER Working Paper*.

Di Maggio, M. and Yao, V. (2021). Fintech borrowers: Lax screening or cream-skimming? *Review of Financial Studies*, 34(10):4565–4618.

Di Tella, S. and Kurlat, P. (2021). Why are banks exposed to monetary policy? *American Economic Journal: Macroeconomics*, 13(4):295–340.

Drechsler, I., Savov, A., and Schnabl, P. (2017). The deposits channel of monetary policy. *Quarterly Journal of Economics*, 132(4):1819–1876.

Eça, A., Ferreira, M., Prado, M., and Rizzo, A. E. (2021). The real effects of fintech lending on SMEs: Evidence from loan applications. *ECB Working Paper*.

Elenev, V., Landvoigt, T., and Nieuwerburgh, S. V. (2021). A macroeconomic model with financially constrained producers and intermediaries. *Econometrica*, 89(3):1361–1418.

Elliott, D., Meisenzahl, R., Peydró, J.-L., and Turner, B. C. (2019). Nonbanks, banks, and monetary policy: US loan-level evidence since the 1990s. *Working Paper*.

Erel, I. and Liebersohn, J. (2020). Does fintech substitute for banks? eevidence from the paycheck protection program. *NBER Working Paper*.

Fornaro, L. and Wolf, M. (2021). Monetary policy in the age of automation. *Working Paper*.

Frost, J., Gambacorta, L., Huang, Y., Shin, H. S., and Zbinden, P. (2019). Bigtech and the changing structure of financial intermediation. *Economic Policy*, 34(100):761–799.

FSB (2019). Fintech and market structure in financial services: Market developments and potential financial stability implications. *Financial Stability Board, Basel, Switzerland*.

Fu, J. and Mishra, M. (2021). Fintech in the time of COVID-19: Technological adoption during crises. *Journal of Financial Intermediation*, 50:100945.

Gambacorta, L., Huang, Y., Li, Z., Qiu, H., and Chen, S. (2022). Data vs collateral. *Review of Finance (forthcoming)*.

Gertler, M. and Gilchrist, S. (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. *Quarterly Journal of Economics*, 109(2):309–340.

Gomez, M., Landier, A., Sraer, D., and Thesmar, D. (2021). Banks' exposure to interest rate risk and the transmission of monetary policy. *Journal of Monetary Economics*, 117:543–570.

Gorton, G. B. and He, P. (2021). Economic growth and bank innovation. *NBER Working Paper*.

Hasan, I., Kwak, B., and Li, X. (2020). Financial technologies and the effectiveness of monetary policy transmission. *Working Paper*.

Hasan, I. and Li, X. (2021). Technology adoption and the bank lending channel of monetary policy transmission. *Working Paper*.

Hau, H., Huang, Y., Shan, H., and Sheng, Z. (2021). Fintech credit and entrepreneurial growth. *Swiss Finance Institute Research Paper*.

He, Z., Jiang, S., Xu, D., and Yin, X. (2021). Investing in lending technology: It spending in banking. *Working Paper*.

Hong, C. Y., Lu, X., and Pan, J. (2020). Fintech adoption and household risk-taking. *NBER Working Paper*.

Huang, Y., Zhang, L., Li, Z., Qiu, H., Sun, T., and Xue, W. (2020). Fintech credit risk assessment for smes: Evidence from China. *IMF Working Papers*.

Hughes, J. P., Jagtiani, J., and Moon, C.-G. (2022). Consumer lending efficiency: Commercial banks versus a fintech lender. *Financial Innovation*, 8(1):1–39.

Jagtiani, J. (2021). Which lenders are more likely to reach out to underserved consumers: Banks versus fintechs versus other nonbanks? *FRB of Philadelphia Working Paper*.

Jagtiani, J. and Lemieux, C. (2018). Do fintech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business*, 100:43–54.

Kamber, G. and Mohanty, M. S. (2018). Do interest rates play a major role in monetary policy transmission in china? *BIS Working Paper*.

Kashyap, A. K. and Stein, J. C. (1995). The impact of monetary policy on bank balance sheets. In *Carnegie-Rochester Conference Series on Public Policy*, volume 42, pages 151–195.

Kashyap, A. K. and Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3):407–428.

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–42.

Kwan, A., Lin, C., Pursiainen, V., and Tai, M. (2021). Stress testing banks' digital capabilities: Evidence from the COVID-19 pandemic. *Working Paper*.

Lagarde, C. (2018). Central banking and fintech: A brave new world. *Innovations: Technology, Governance, Globalization*, 12(1-2):4–8.

Lin, C., Ma, C., Sun, Y., and Xu, Y. (2021). The telegraph and modern banking development, 1881–1936. *Journal of Financial Economics*, 141(2):730–749.

Liu, L., Lu, G., and Xiong, W. (2022). The big tech lending model. *Working Paper*.

McMahon, M., Schipke, A., and Li, X. (2018). China's monetary policy communication: Frameworks, impact, and recommendations. *IMF Working Paper*.

Ottonello, P. and Winberry, T. (2020). Financial heterogeneity and the investment channel of monetary policy. *Econometrica*, 88(6):2473–2502.

Petersen, M. A. and Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *Journal of Finance*, 49(1):3–37.

Philippon, T. (2016). The fintech opportunity. *NBER Working Paper*.

Pierri, N. and Timmer, Y. (2022). The importance of technology in banking during a crisis. *Journal of Monetary Economics*, 128:88–104.

Stulz, R. M. (2019). Fintech, bigtech, and the future of banks. *Journal of Applied Corporate Finance*, 31(4):86–97.

Tang, H. (2019). Peer-to-peer lenders versus banks: Substitutes or complements? *Review of Financial Studies*, 32(5):1900–1938.

Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, 41:100833.

Wang, Y., Whited, T. M., Wu, Y., and Xiao, K. (2021). Bank market power and monetary policy transmission: Evidence from a structural estimation. *Journal of Finance*, 77(4):2093–2141.

Additional Figures and Tables

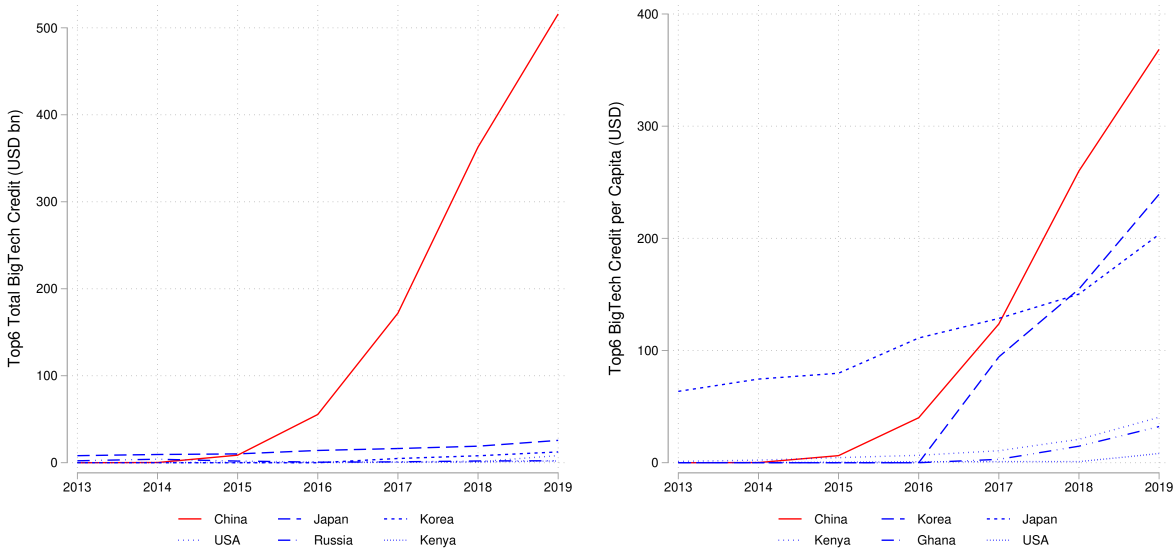

Figure A1: Top Six Countries in BigTech Credit

Data source: Cornelli et al. (2020).

Table A1: 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%