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

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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 credit amplifies monetary policy transmission mainly through the extensive margin. Specifically, the BigTech bank is more likely to grant credit to 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. In addition, the usage of BigTech credit is associated with a stronger response of firms' sales in response to monetary policy.

Keywords: Financial Technology; Bank Lending; Monetary Policy Transmission

JEL Codes: E52; G21; G23

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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. As of the year 2018, MSMEs account for 99.8% of establishments, 79.4% of employment, and 68.2% of sales in the Chinese economy. 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.

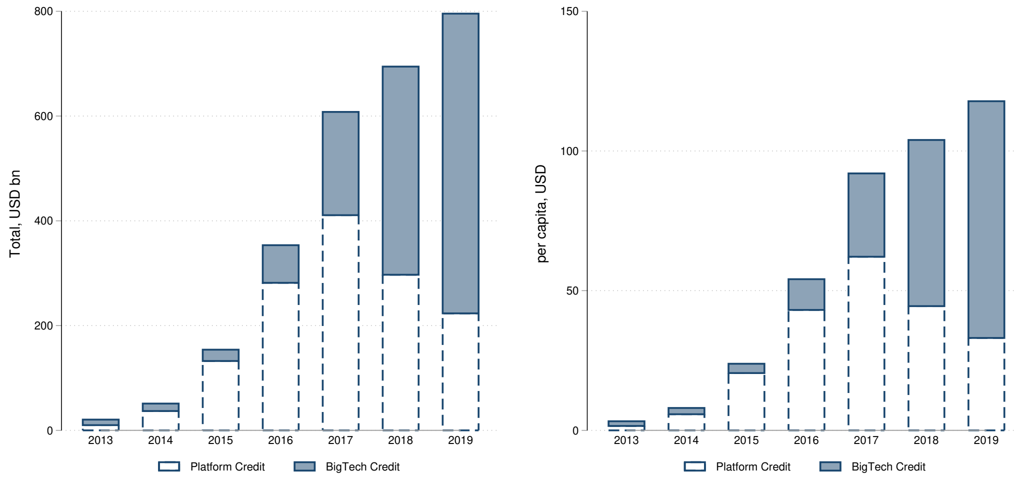


Figure 1: Global FinTech Credit

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

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

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] Recently, Hasan et al. (2020) and Hasan et al. (2022) examine the role of regional FinTech penetration and banks' in-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. Zhou (2022) emphasizes the role of social network in helping FinTech enhance the transmission of monetary policy to the mortgage market.

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. (2022), 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

[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.

whether FinTech lending substitutes for or complements bank lending. For instance, using U.S. mortgage lending and personal credit data, Buchak et al. (2018), Di Maggio and Yao (2021), and Dolson 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. Suri et al. (2021) and Erel and Liebersohn (2022) find that FinTech could improve financial access and resilience. Gopal and Schnabl (2022) document that FinTech lenders substituted for the reduction in bank lending to small business after the 2008 financial crisis. Tang (2019) and Beaumont et al. (2022) show that FinTech 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. Buchak et al. (2021) use Chinese data to show that FinTech facilitates the interest rate liberalization of banks through competition in deposit-like products. Other recent studies, such as Pierri and Timmer (2022), Lin et al. (2021), Kwan et al. (2021), He et al. (2021), Hasan et al. (2022), and Modi et al. (2022), 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 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).

[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.

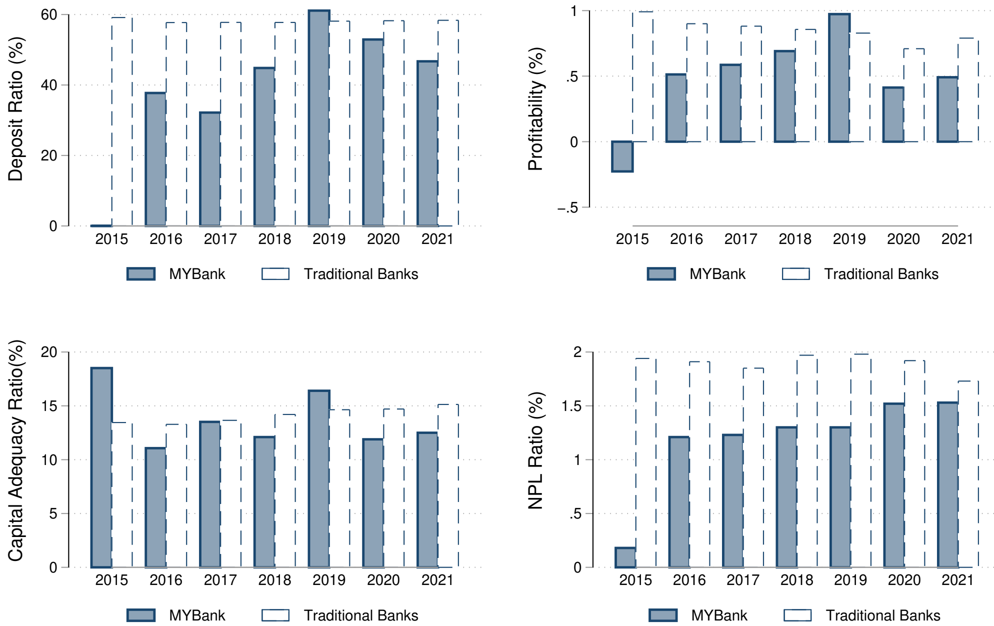


Figure 2: Main Indicators for MYBank and Traditional Banks

Sources: Annual Report of MYBank; CBIRC.

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.

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 A2 in the appendix presents the sector distribution of the firms and shows that most of them are in the retail industry, and Table A3 indicates that the retail industry amounts to almost 30% of the total establishments and sales in the economy. 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]

[4]The network score is a rank calculated by using a PageRank algorithm. This algorithm was first intro-

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 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

duced 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.

[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.

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.

Table 1 presents the summary statistics of the variables used in this study, and we report the definition of each variable in Table A1 in the appendix. 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. These statistics show that Bigtech credit does serve a special groups of MSMEs, which is consistent with the role of FinTech in small business lending documented by Beaumont et al. (2022) and Gopal and Schnabl (2022). While we highlight the importance of MSMEs, those in retail industry in particular, in terms of employment and economic growth for Chinese economy, we recognize that this sample of firms is not necessarily representative of the entire picture. Our study suggests a new mechanism of monetary policy transmission, that is, how MSMEs obtain credits from BigTech lenders in response to MP changes, which is different from the traditional bank lending channel.

2.2 Monetary Policy Variable

The choice of monetary policy variable is not obvious in the Chinese context. After 1999, the intermediate targets of the central bank, the People's Bank of China (PBC), are twofold: quantity-based money supply and priced-based market interest rates (McMahon et al. 2018, Huang et al. 2019, Chen et al. 2018). Between the quantity- and price-based targets, the emphasis on the former has declined in recent years. This can be demonstrated in the following ways. First, we observe the disappearance of M2 or credit aggregate targets since 2018 in the State Council's Annual Report on the Work of Government, which covers the most important economic plans for the following year but still specifies the GDP growth targets. Second, in recent years, there have been continuous waves of interest rate liberalization that started with money market rates and abandoned the ceiling on bank deposit rates in 2015. These developments have facilitated the transition toward a modern price-based monetary policy framework. Third, we show in the appendix that the explanatory power of output and inflation gaps for M2 growth has been decreasing, and meanwhile, that interbank rates have become stronger and outperformed M2 growth rates in recent periods.[7] To sum up, though we agree with Chen et al. (2018) that the quantity-based monetary policy rules are dominating for earlier years (their sample ends in 2016), price-based interest rates are more appropriate as the intermediate targets for our more recent period, i.e., 2017-2019.

Among various interest rate variables, we use the seven-day interbank pledged repo rate (DR007) in this paper. The reasons are the following. The Monetary Policy Executive Report in the third quarter of 2016 stated that "DR007 moves around the open market operation 7-day reverse repo rate. The DR007 can better reflect the liquidity condition in the banking system and has an active role to cultivate the market base rate".[8] This implies

[7]The debates remain on whether the Taylor rule applies to China's monetary policy, however, estimations from such specifications as shown in the appendix provide evidence on the relative effectiveness between quantity and price rules. See Figure A2 for details.

[8]The Monetary Policy Executive Report is issued quarterly by the PBC since 2001 and it is one of the main communication tools of the central bank (McMahon et al. 2018).

that the PBC uses this interbank rate as a *de facto* intermediate target (McMahon et al. 2018), and this rate is closely watched by the market. Also, to match the monthly frequency of our data, the interbank rate is better than other instruments such as the required reserve ratio (RRR) that change at a much lower frequency. Moreover, as can be seen in Figure A2 in the appendix, comparing DR007 with other rates including shibor and R007, DR007 attaches more importance to the output and inflation gaps.

Therefore, following Jiménez et al. (2014), 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. Finally, recent studies, such as Fernald et al. (2014), Chen et al. (2018), Kamber and Mohanty (2018), and Das and Song (2022) 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 to other economies.

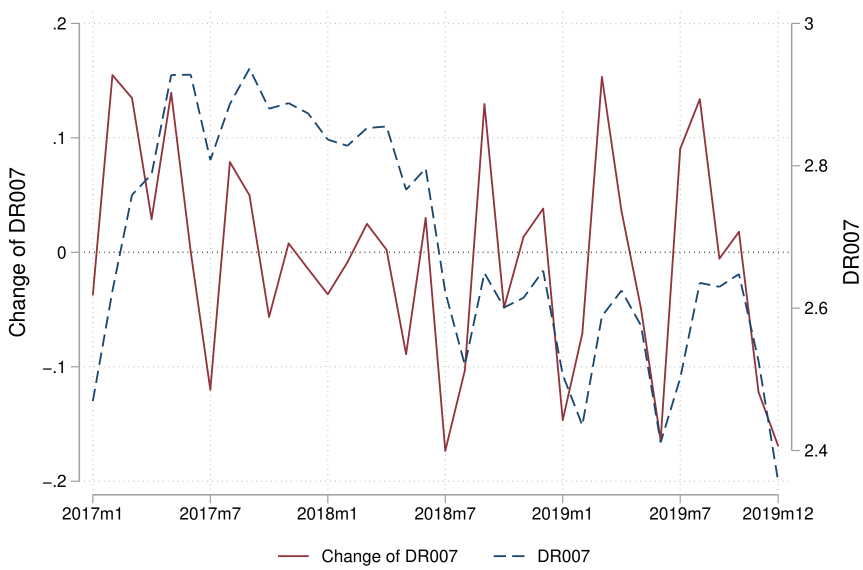


Figure 3: Monetary Policy Rate

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, which is 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.

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 (in Chinese Yuan)	173,484	38,015.87	134,803.90
Loan amount -BigTech (in Chinese Yuan)	158,795	21,934.73	38,508.80
Loan amount -Bank credit (in Chinese Yuan)	14,689	211,860.50	406,918.30
Loan amount -Bank secured credit (in Chinese Yuan)	2,389	532,792.40	673,866.10
Loan amount -Bank unsecured credit (in Chinese Yuan)	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

3 Empirical Evidence

3.1 Identification Strategy

We adopt the following specification for the baseline analysis:

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

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. (2022). 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 $\times$ 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 $\times$ 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. In the same vein, Zhou (2022) also provide evidence that FinTech affects mortgage market in terms of composition rather than in the intensive margin. 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 con- cern 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.[9] 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 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

[9] 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.

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 $\times$ 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	-
Month FE	YES	-
City $\times$ Month 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 are likely to have lower monitoring cost and more relaxed earning-based borrowing constraint, thus higher capacity of lending and tolerance of value-at-risk, which result in more responsiveness to changes in monetary policy (Coimbra and Rey 2022, Coimbra et al. 2022, Hasan 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 $\times$ Month FE	YES	YES	YES	YES
Other Controls	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 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.

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 $\times$ Month FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

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

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. 2022, Tang 2019, Jagtiani and Lemieux 2018, Erel and Liebersohn 2022). 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.[10] 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.

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 × Month FE	YES	YES	YES	YES
Other Controls	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

[10] 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.

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:

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

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.

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
Other Controls	YES	YES	YES	YES

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

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 $\times$ Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES	YES	YES	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.

Table 10: Discussion: Heterogeneity across Network Centrality

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

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

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. 2022, 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: 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
Firm FE	YES	YES
Month FE	YES	YES
Other Controls	YES	YES

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

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.

4.5 Other Contract Terms and Regulation Policy of BigTech Loans

In this subsection, we use an extended dataset to study the impact of monetary policy on other terms of BigTech loans besides the likelihood of granting credit and loan amount and address the concerns on the confounding effect arising from the regulation policy of BigTech credit. Specifically, we obtain a dataset that extends the time coverage to the end of 2021 and includes the information on outstanding amount, interest rate, and maturity of BigTech loans, allowing us to examine the role of regulation which only became substantial in 2021 and test how other terms are affected by monetary policy.

However, due to data and business privacy reasons, the extended dataset bears two main caveats. On one hand, the interest rate information is not disclosed as the original value but normalized to fall between zero and one, thus, the interpretation of findings on interest rate shall be treated with caution. On the other hand, the additional information is not available for traditional bank loans, meaning that we cannot compare the impact of monetary policy on other contract terms between BigTech and traditional bank loans, which is key to our previous analysis, and that is why we do not use the extended dataset in the baseline. To sum up, the extended dataset is at the firm-month level for BigTech credit, and the cross-sectional variation only lies at the borrowing firm level but not at the lender level. Even so, it is valuable for us to dig into other important terms of the BigTech credit and provide insights on the impact of regulation policy and monetary policy transmission.

Given the different structure of the extended dataset, we cannot specify borrower-month fixed effect to isolate the demand effect and control other macroeconomic variables, therefore we adopt the method of local projections (Jordà 2005) to account for the change in credit demand over time and mitigate the concern on other confounding macroeconomic factors:

$$Loan\ Term_i^{t+h} - Loan\ Term_i^t = \alpha_0^h + \Sigma_{k=0}^{k=2}(\beta_k^h MP_{t-k} + \zeta_k^h Macro_{t-k}) + \gamma^h \Gamma_{i,t-1} + \delta_i^h + \epsilon_{i,t}^h \tag{4}$$

where *Loan Term* indicates the various dimensions of BigTech loans, including the logarithm of outstanding loans, the logarithm of newly issued loans, the normalized interest rate index, and the maturity, and the dependent variable is the cumulative change in these terms between t and $t+h$. We set $h = 1, 2, ...12$ as the horizon. The same as the baseline analysis, MP_t is the monetary policy variable proxied by the change in policy rate $\Delta DR007_t$. *Macro* indicates an array of macroeconomic conditions including GDP growth rate, inflation, value-added growth rates of state-owned enterprises and private enterprises to mitigate concerns on potential confounding effects. These time-series data of the Chinese macroeconomy are compiled by Higgins and Zha (2015) and Chang et al. (2016) and obtained from the Center for Quantitative Economic Research by the Federal Reserve Bank of Atlanta. We include the current and two-period lagged terms of monetary policy and macroeconomic variables to account for their own dynamics. $\Gamma_{i,t-1}$ indicates a set of firm-level control variables, including the logarithm of outstanding loans, logarithm of sales, network centrality, logarithm of consumption, and the ratio of outstanding loans to sales, that capture firms' credit demand and determinants of loan terms. Same as in the baseline, they are specified in lagged form to mitigate the concern on reverse causality from loan terms to firm performances. Note that the specification of these firm-level controls is not the same as in the old results, do we need to specify that? In addition, the specification of owner age in the old results is a bit strange. δ_i is the firm fixed effect that absorbs all firm characteristics that do not vary with time, and $\epsilon_{i,t}$ is the error term. We are interested in the estimates of β_0^h with $h = 1, 2, ...12$, as it captures the impact of a one unit (100 basis points) increase in monetary policy rates in t

on loan terms over the twelve months horizon. Here we restrict the sample to end in 2019 to avoid the disruption by the pandemic and at the same time stay consistent with the main analysis above; later we will discuss the findings with extended periods when bringing in BigTech regulation policies.

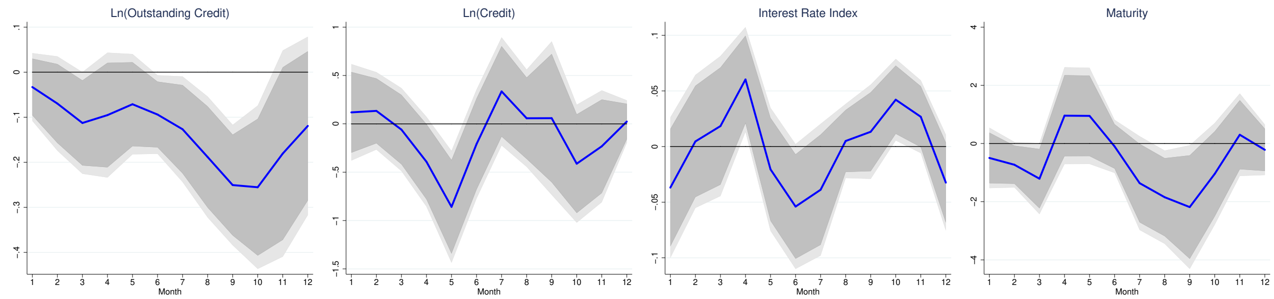


Figure 4: Local Projection

Figure 4 shows the results. First, we observe that an increase in monetary policy rate is associated with a significant decline in both outstanding and new loans issued by BigTech. Specifically, the decline in outstanding credit became statistically significant three months after monetary policy changes and is persistent ten months after, and the reduction in new credit is significant four months after the shock and the impact peaks in the fifth month, though it is temporary as the effect becomes insignificant in the longer horizon. In terms of magnitude, a one standard deviation increase in monetary policy rate (0.095) is associated with a decrease in the outstanding credit by 2% and a decrease in the new credit by 8% in the most affected horizon. Second, monetary policy tightening is also associated with significantly increased interest rate and decreased maturity in the short horizon. Specifically, a one standard deviation increase in monetary policy rate is associated with an increase in the interest rate index by by 0.01 unit and a decrease in the loan maturity by 0.11 months within a quarter. These findings are consistent with conventional monetary policy transmission (Bernanke and Gertler 1995, Black and Rosen 2018). Furthermore, the opposite findings on quantity (outstanding and newly issued loan amount) and price (interest rate) are helpful in disentangling the credit demand and credit supply effect and suggest that the results are driven by credit supply by the BigTech lender.

Next, we discuss the regulation policy on BigTech credit and its impact on credit terms. One possible alternative perspective of our analysis is that BigTech is possible to take regulatory arbitrage when issuing credit if it is treated as a part of the shadow banking sector, thereby mitigating monetary policy transmission (Xiao 2020, Hasan et al. 2020). It is important to note that the MYBank in our analysis is the banking business of the BigTech company Alibaba, and it self is a commercial bank that is regulated in the same way as traditional banks. Thus, the BigTech credit in our paper is not subject to different regulation policies. At the same time, we also recognize that the regulation policy on BigTech credit might affect the lending decisions of MYBank indirectly via other financial businesses of the BigTech company or the firms' alternative borrowing channels. Thus, it is worthwhile to formally address the issue of BigTech regulation.

For this purpose, we construct a measurement for BigTech regulation policy in the following way. First, we search and summarize the launch of government policies targeting internet lending in China from 2017 to 2021.[11] We obtain the announcement dates of each regulation policy and adjust the date if it is not a trading day to the nearest trading day after the announcement. Table A4 in the appendix lists the 27 specific regulation policies we use. Second, we calculate the abnormal return of Alibaba and Tecent within three days after the regulation policy announcement.[12] Alibaba and Tencent are the holding companies of the two largest BigTech lenders in China, i.e., MYBank and WeBank. In addition to Aliababa, we account for Tencent in this analysis because its stock market reactions are important to measure the stringency of BigTech regulation policies and its stock data has a longer time coverage, although we do not have its microlevel BigTech credit data. Third,

[11]Internet lending is a broad concept covering all lending activities in online platforms, which include BigTech credit.

[12]We calculate the abnormal return as the deviation between the actual return of the company and the CAPM predicted return by regressing the actual return on the return of the Hang Seng index, which is the aggregated Hong Kong stock market index.

we access the search frequency indicators of the keywords “Ant Financial” and “FinTech” in Baidu, which the largest search engine in China and the Chinese version of Google. Finally, with the abnormal stock returns of Alibaba and Tencent, and the search index of “Ant Financial” and “FinTech”, we conduct a principal component analysis (PCA) and extract the first component as the measurement of BigTech regulation policy. In this process, we reverse the sign of abnormal stock returns to ease the interpretation of the measurement so that an increase in the index indicates a tighter regulation. [13]

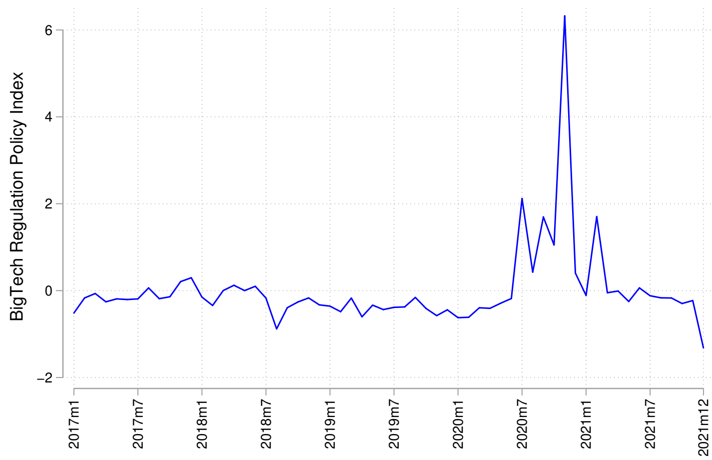


Figure 5: BigTech Regulation Policy Index

Figure 5 presents our BigTech credit regulation policy index. A notable observation is that is not much variation in the regulation stringency before mid 2020, this is consistent with the market consensus that the regulation was very lax in the early period of the BigTech development. Moreover, the regulation measurement spiked in November 2020, which coincided with Jack Ma’s controversial speech in the Bund Summit in October 2020 and the regulation on BigTech’s financial services tightened thereafter. While our baseline sample

[13]Table A5 in the appendix shows a good performance of the PCA. All variables have positive loading on the first factor which comprises about 62% of the common variation across the set of observed variables, therefore, we use the first factor as a summary index of the regulation policy. Moreover, the abnormal return of Aliabab and the search index for Ant Financial show the largest loadings, which is meaningful and an advantage for us concerning the MYBank data used in this study.

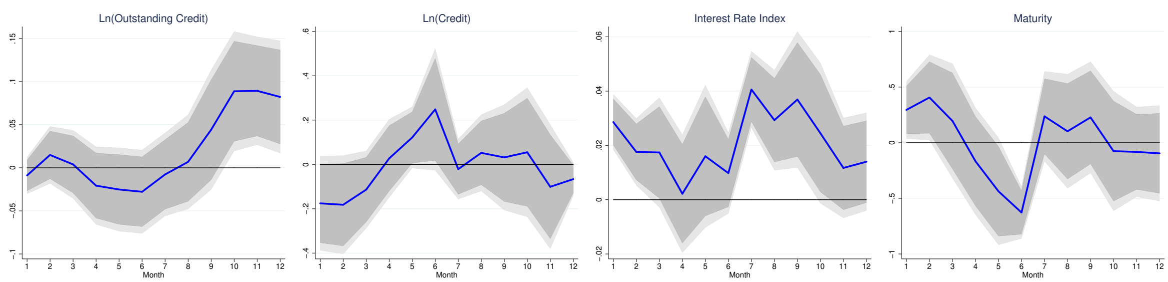
ends in 2019 when regulation did not play a significant role in the expansion of BigTech credit, we can use the extended dataset that covers 2017-2021 to investigate the impact of regulation on BigTech credit.

We alter the local projection specification to account for the regulation stringency in parallel with monetary policy. We also need to take care of the disruptions brought by the COVID pandemic which started in 2020. The altered specification is as follows:

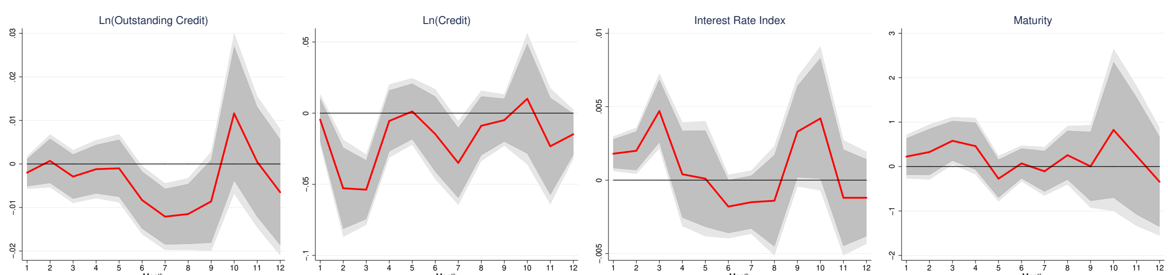
$$Loan\ Term_i^{t+h} - Loan\ Term_i^t = {\alpha'_0}^h + D(Before)_t \Sigma_{k=0}^{k=2} ({\beta'_{mp,k}}^{h,before} MP_{t-k} + {\beta'_{reg,k}}^{h,before} Reg_{t-k})$$
$$+ D(After)_t \Sigma_{k=0}^{k=2} ({\beta'_k}^{h,after} MP_{t-k} + {\beta'_k}^{h,after} Reg_{t-k}) + \Sigma_{k=0}^{k=2} {\zeta'_k}^h Macro_{t-k} + {\gamma'}^h \Gamma_{i,t-1} + {\delta'_i}^h + {\epsilon'_{i,t}}^h \quad (5)$$

where $D(Before)$ and $D(After)$ are two dummies indicating the period before and after COVID, respectively. Reg_t is our constructed BigTech regulation stringency index, and the rest are the same as before. In this specification, we treat monetary policy and regulation policy in the same way. We report the results on monetary policy (${\beta'_{mg,0}}^{h,before}$ and ${\beta'_{mg,0}}^{h,after}$) in Figure A3 in the appendix, which confirm our previous findings that monetary policy tightening contracts BigTech credit even after controlling for regulation policy in the pre-COVID period, meanwhile they show that the role of monetary policy becomes less significant in the post-COVID period. Here we focus on the estimates of ${\beta'_{reg,0}}^{h,before}$ and ${\beta'_{reg,0}}^{h,after}$, which capture the impact of regulation policy on the BigTech loan terms before and after the pandemic disruption. Results are presented in Figure 6.

It indicates that the regulation policy plays different roles in the pre- and post-COVID periods. Before COVID, panel (a) shows that when the regulation was relatively weak, a more stringent regulation policy is associated with an increase in the outstanding BigTech credit as well as the interest rate over a ten-month horizon. In addition, the loan maturity increases in the first two months after regulatory tightening, and then decreases in half a year. The same sign changes in quantity and price suggest that the effects likely driven by the credit demand, as firms take more BigTech loans in longer maturities after observing a more restrictive regulation policy. In comparison, the results are different after COVID, when regulation became more substantial and restrictive. Panel (b) shows that regulation tightening is associated with a significant decrease in loan amount and a significant increase in interest rate, meanwhile an insignificant change in maturity structure. These findings show that credit supply is the driver and the BigTech lender contracts credits after observing a more pronounced regulatory constraint. Overall, we provide evidence showing that BigTech lender reacts to regulation policies and policymakers can combine monetary and regulatory policies to adjust BigTech credits in the market.



(a) Before COVID



(b) After COVID

Figure 6: Local Projection: Impact of Regulation Policy

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.

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Additional Figures and Tables

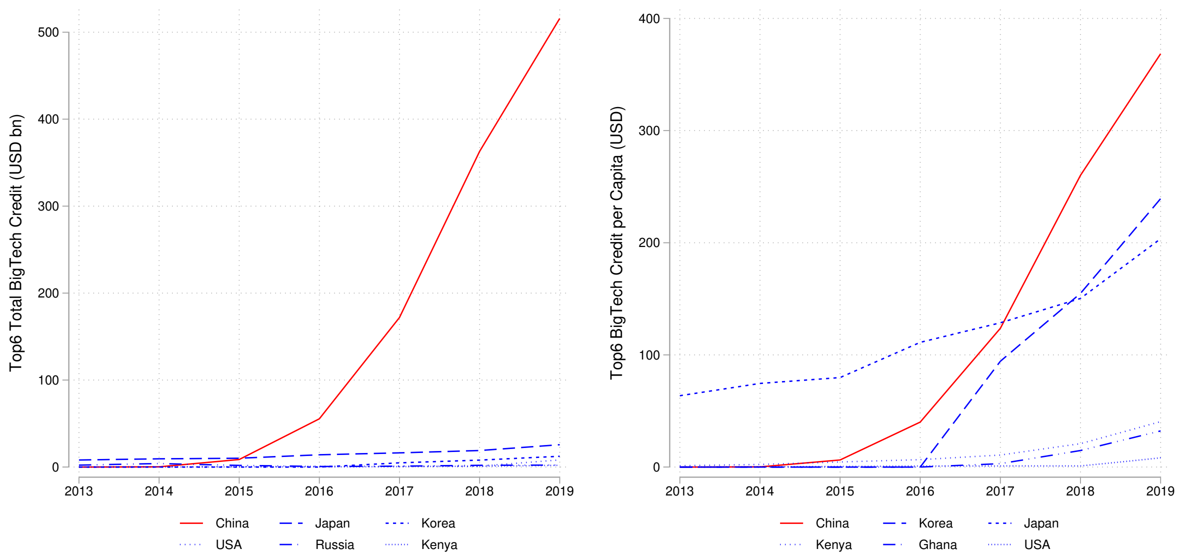


Figure A1: Top Six Countries in BigTech Credit

Data source: Cornelli et al. (2020).

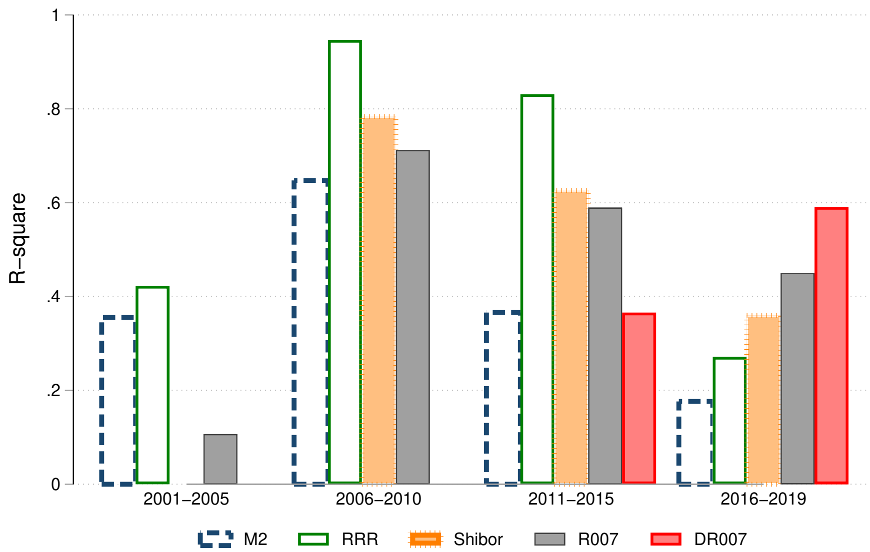


Figure A2: R-square using different variables to capture monetary policy

Note: To compare different variables and choose one to best capture the monetary policy framework in China, we evaluate the performance of regressing various monetary policy candidate variables on the output and inflation gaps and simply compare the R-square from the specification: $mpvar_t = \alpha + \beta_y outputgap_t + \beta_\pi inflationgap_t + \epsilon_t$. The output and inflation gap data are from Chang et al. (2016) and Chen et al. (2018). $mpvar_t$ is either the M2 growth rate, the change in required reserve ratio (RRR), Shibo (1-month) rate (Shanghai interbank offered rate), R007 (weighted average 7-day repurchase rate for the whole market organization), or DR007 (weighted average 7-day repurchase rate in which deposit institution uses interest rate bonds as the pledge in the interbank market). We estimate this equation using quarterly data in four sample periods: 2001-2006, 2006-2010, 2011-2015, and 2016-2019. We stop the data in 2019 to avoid the disruptive impact of the coronavirus pandemic.

Table A1: Variable Definition

Variables	Definition	Source
	Panel A: Credit	
Credit use -All	A dummy that equals to one if the firm obtains credit from either the BigTech lender or traditional banks.	MYBank
Credit use -BigTech	A dummy that equals to one if the firm obtains credit from the BigTech lender.	MYBank
Credit use -Bank	A dummy that equals to one if the firm obtains credit from traditional banks.	MYBank
Credit use -Bank unsecured	A dummy that equals to one if the firm obtains unsecured loans, i.e., loans without collateral, from traditional banks.	MYBank
Credit use -Bank secured	A dummy that equals to one if the firm obtains secured loans, i.e., loans with collateral requirements, from traditional banks.	MYBank
Loan amount -All	The total amount of credit (in RMB) the firm obtains from either the BigTech lender or traditional banks.	MYBank
Loan amount -BigTech	The amount of credit (in RMB) the firm obtains from the BigTech lender.	MYBank
Loan amount -Bank credit	The amount of credit (in RMB) the firm obtains from traditional banks.	MYBank
Loan amount -Bank secured credit	The amount of secured loans (in RMB) the firm obtains fromtraditional banks.	MYBank
Loan amount -Bank unsecured credit	The amount of unsecured loans (in RMB) the firm obtains fromtraditional banks.	MYBank
	Panel B: Firm Characteristics	
Network Centrality	A rank calculated by using a PageRank algorithm. The calculation is done by means of webgraphs, where webpages are nodes and hyperlinksare edges. Each hyperlink to a page counts as a vote of support for that webpage. In the case of theAnt Group network score, customers and QRcode merchants can be considered as interconnected nodes(webpages) and payment funding flows can be considered as edges (hyperlinks)	MYBank
Sales	The amount of sale values (in RMB) of the firm.	MYBank
Online	A dummy that equals to one if the firm sells product in the e-commerce platform of Alibaba.	MYBank
Owner Age	The age of the firm owner.	MYBank
Owner Gender-Male	A dummy that equals to one if the firm owner is a male.	MYBank
	Panel C: Macroeconomic Conditions	
DR007	The level of the even-day pledged interbank repo rate for deposit institutions (DR007).	People's Bank of China (PBoC)
Δ DR007	The monthly change of the even-day pledged interbank repo rate for deposit institutions (DR007)	People's Bank of China (PBoC)
GDP-city (bn)	The GDP (in billions of RMB) of the city that the firm locates at.	Local Bureau of Statistics
Bank branch density-city	The number of bank branches per thousand population in the city that the firm locates at.	China Banking and Insurance Regulatory Commission (CBIRC), Local Bureau of Statistics

Table A2: 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%

Table A3: Impact of MSMEs and Retail Sector on Chinese Economy, 2018

% in Total Economy	MSME	Retail Sector
Establishments	99.8	29.8
Employment	79.4	10.46
Sales	68.2	29.94

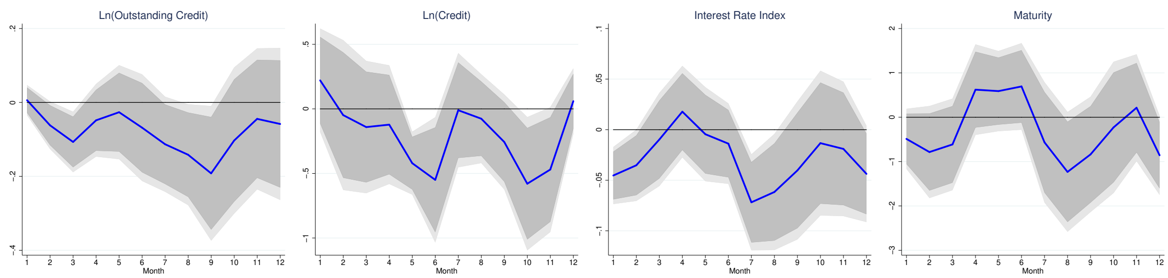
Note: MSME refers to micro, small, and medium-sized enterprises. The data source is the China Economic Census Book 2018.

Table A4: Regulation Policy on Internet Lending

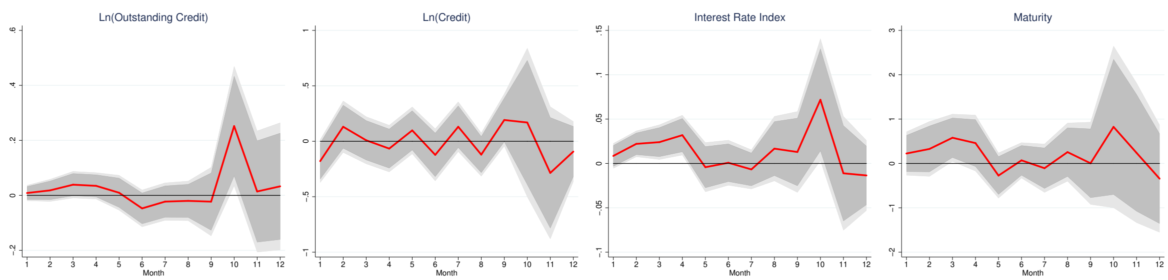
Announcement Date	Policy Document	Issuing Entity
February 23, 2017	Guidelines for Online Lending Fund Depository Business	China Banking Regulatory Commission
June 16, 2017	Notice on Further Improving the Special Rectification of Internet Financial Risks	People's Bank of China; and other agencies
August 24, 2017	Guidelines for Information Disclosure of Business Activities of Online Lending Information Intermediary Institutions	China Banking Regulatory Commission
November 21, 2017	Notice on Immediate Suspension of the Establishment of New Online Micro-loan Companies	Office of the Leading Group for Special Rectification on Internet Financial Risks
December 8, 2017	Notice on Issuing the Implementation Plan for Special Rectification of Risks in Business of Small Loan Companies Online Micro-loan	Office of the Leading Group for Special Rectification on P2P Online Lending Risks
December 12, 2017	Standards for Individual Online Lending Funds Depository Business; Standards for Individual Online Lending Funds Depository Systems	National Internet Finance Association
December 13, 2017	Notice on Carrying Out Compliance Inspections and Rectification of P2P Online Lending Institutions	Office of the Leading Group for Special Rectification on P2P Online Lending Risks
March 17, 2018	Self-Regulatory Convention for Collection of Overdue Debts in Internet Lending	National Internet Finance Association
August 17, 2018	Notice on Conducting Compliance Inspections of P2P Online Lending Institutions	Office of the Leading Group for Special Rectification on P2P Online Lending Risks
August 17, 2018	108 Articles on Compliance Inspection Issues for Online Lending Information Intermediary Institutions	Office of the Leading Group for Special Rectification on P2P Online Lending Risks
August 21, 2018	Notice on Preventing Risks of Fabricated Borrowing Projects and Malicious Fraud in P2P Online Lending	National Internet Finance Association
January 21, 2019	Opinions on Properly Handling the Classification, Disposal, and Risk Prevention of Online Lending Institutions	Office of the Leading Group for Special Rectification on Internet Financial Risks; Office of the Leading Group for Special Rectification on P2P Online Lending Risks
January 23, 2019	Notice on Further Implementing Compliance Inspections and Subsequent Work for P2P Online Lending	Office of the Leading Group for Special Rectification on P2P Online Lending Risks
April 8, 2019	Work Plan for Conditional Record-filing Pilot of Online Lending Information Intermediary Institutions	Office of the Leading Group for Special Rectification on Internet Financial Risks; Office of the Leading Group for Special Rectification on P2P Online Lending Risks
August 23, 2019	Financial Technology (FinTech) Development Plan (2019-2021)	People's Bank of China
September 4, 2019	Notice on Strengthening the Construction of Credit System in P2P Online Lending	Office of the Leading Group for Special Rectification on Internet Financial Risks; Office of the Leading Group for Special Rectification on P2P Online Lending Risks
November 15, 2019	Guidance on the Pilot Transformation of Online Lending Information Intermediary Institutions into Small Loan Companies	Office of the Leading Group for Special Rectification on Internet Financial Risks; Office of the Leading Group for Special Rectification on P2P Online Lending Risks
July 12, 2020	Interim Measures for the Management of Internet Loans by Commercial Banks	China Banking and Insurance Regulatory Commission
September 7, 2020	Notice on Strengthening the Supervision and Management of Small Loan Companies	China Banking and Insurance Regulatory Commission
September 11, 2020	Pilot Measures for the Supervision and Administration of Financial Holding Companies	People's Bank of China
September 11, 2020	State Council Decision on Implementing Access Management of Financial Holding Companies	State Council
November 3, 2020	Public Solicitation of Opinions on the 'Interim Measures for the Management of Online Small Loan Business (Draft for Comments)'	China Banking and Insurance Regulatory Commission; People's Bank of China
February 19, 2021	Notice on Further Standardizing the Internet Loan Business of Commercial Banks	China Banking and Insurance Regulatory Commission
December 29, 2021	General Technical Requirements for Financial Big Data Platforms	People's Bank of China
December 29, 2021	Financial Big Data Terminology	People's Bank of China
December 29, 2021	Financial Technology Development Plan (2022-2025)	People's Bank of China

Table A5: Regulation Policy Index: Principal Component Analysis

	Factor 1	Factor 2	Factor 3	Factor 4
Share Variation	0.616	0.251	0.079	0.055
Abnormal Return Alibaba	0.556	0.177	-0.809	-0.079
Abnormal Return Tecent	0.250	0.896	0.365	0.027
Search Index Ant Financial	0.558	-0.292	0.385	-0.674
Search Index FinTech	0.563	-0.282	0.254	0.734



(a) Before COVID



(b) After COVID

Figure A3: Local Projection: Impact of Monetary Policy After Controlling for Regulation Policy