# How Does BigTech Credit Affect Monetary Policy Transmission?

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## Abstract

This paper investigates whether and how BigTech credit works differently from bank credit in transmitting monetary policy. Through the lens of a unique dataset covering the full borrowing history of sampled firms from both BigTech and traditional bank lenders in China, we compare the extensive and intensive margin by the two types of lenders in reaction to monetary policy changes to the same firm at the same time. We find that the BigTech lender is more responsive to moentary policy changes in the extensive margin but not the intensive margin, and advantages in data abundance, screening and monitoring of the BigTech credit are the possible mechanisms. Moreover, the use of BigTech credit is also associated with a stronger real effects from monetary policy.


**Keywords**: Financial Technology; Technology Companies; Monetary Policy; Bank Credit

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# 1 Introduction

Financial technology (FinTech) has been a major phenomenon in the recent development of the financial market. Defined by FSB (2019), FinTech is a broad concept referring to the use of technology in providing financial services. What makes it stand out in the long history of financial innovation is that the disruption is generated by players outside the financial market rather than within the old system, and the newly established digital platforms and big technology companies (BigTech) pose serious challenge to the lending business of traditional financial intermediaries. In the recent COVID-19 crisis, technology-equipped financial service has been unprecedentedly prominent in circuiting the economy (Core and De Marco 2021, Kwan et al. 2021, Bao and Huang 2021, Fu and Mishra 2021).

The interaction between BigTech and traditional banks is the key to understanding the substance of finance and shaping the future landscape of the financial market. Moreover, BigTech lenders challenge the void of regulation and have become a top concern in economic policymaking. As recognized by Philippon (2016) and Lagarde (2018), FinTech brings a "brave new world" for monetary policymakers. Despite the growing literature on FinTech, little is known about its implication for monetary policy. This paper fills in the gap by answering the following two questions. First, whether and how does BigTech credit work differently from bank credit in transmitting monetary policy? Second, what is the real effect of the response to monetary policy from BigTech credit?

To answer these questions, we employ a unique dataset covering the full borrowing history of the sampled micro, small and medium enterprises (MSMEs) from a major BigTech lender and traditional banks in China. Specifically, we first access the credit data from the Ant Financial, one of the dominating BigTech companies both domestically and internationally, and match with these MSMEs' bank borrowing history accessed from the Credit Reference Center of the People's Bank of China. Thus, we construct a dataset that allows the monthly observation of both BigTech credit and bank credit to the same firm from 2017 January to 2019 December. Combined with the variations in monetary policy, this dataset provides a good laboratory to investigate the different responses to monetary policy changes by BigTech lender and traditional banks. In addition, the evidence from China, whose scale of BigTech credits is the largest worldwide in both absolute and per capita terms, has general values for other countries to reflect on regulatory and monetary policies regarding BigTech credits.[1]

Our identification strategy is to compare the extensive and intensive margin, which are captured by the new lending relationship and loan amount, respectively, by the BigTech lender and traditional banks in response to monetary policy changes to the same MSMEs at the same time. We specify the firm-month fixed effect which saturates the credit demand effect, thus, our estimates capture the impact on the supply side. When examine the real effect of BigTech credit, we compare the sale in responses to monetary policy changes for firms that use BigTech credit and those do not, for which we conduct a propensity score matching exercise to address the endogeneity concern.

The main findings are threefold. First, monetary policy changes are associated with a more pronounced responses in the BigTech lender than the traditional banks, but the transmission-enhancing role of BigTech lender is only present in the extensive margin while there is no significant difference between the two types of lenders in the intensive margin. In other words, when monetary policy eases, the BigTech lender is more likely to establish new lending relationships with but does not necessarily issue more credits to the same MSMEs compared to traditional banks. Second, the more responsive effect of BigTech lender is stronger when the MSMEs are online sellers than offline sellers and when compare with secured than unsecured banks loans, suggesting BigTech lenders' advantage in data abundance and risk management techniques in screening and monitoring being the mechanisms. Third, firms' use of BigTech credit is associated with larger real effects of monetary policy. Specifically, when monetary policy eases, firms show a higher sale growth if they have used BigTech credit than those have not.

[1]According to estimates by (Cornelli et al. 2020), the BigTech credits per capita in 2019 for France, United States, and China are \$6.82, \$25.11, and \$368.47, respectively.

This paper relates to three branches of literature. First, we contribute to the massive literature on monetary policy transmission by focusing on the new player of BigTech financial intermediation and comparing its responses to monetary policy with traditional banks. The transmission of the bank lending channel (Bernanke and Blinder 1988, 1992, Kashyap and Stein 1995) has been shown to be affected by the 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). Recently, the role of risk-tolerance and risk exposure of the financial intermediation is recognized to amplify the effects of monetary policy shocks in Coimbra et al. (2021) and Di Tella and Kurlat (2021). Meanwhile, the heterogeneity in lenders' technological characteristics is a missing link in the literature. We fill this gap and discuss the implication of technology adoption for monetary policy transmission.[2] Moreover, the evidence of BigTech lender in this study also adds to the recent endeavors investigating nonbanks in monetary policy transmission (e.g., Elliott et al. 2019, Chen et al. 2018).

Second, we stand on the increasing studies on the relationship between FinTech lenders and banks and we are innovative in directly comparing the lending behaviors of the two types of lenders to the same MSME borrowers through the lens of a unique dataset. As summarized in Stulz (2019), Boot et al. (2020), Thakor (2020) and Berg et al. (2021), the recent wave of financial technologies is new and abrupt in terms of data abundance and codification of soft information that strengthens screening and monitoring, which explains the increasing empirical findings that FinTech lenders reply more on hard information than banks. For instance, using the U.S. mortgage lending and personal credit data, Buchak et al. (2018b) and Di Maggio and Yao (2021) show that FinTech lenders use different information to set interest rates relative to banks, respectively. Also, using the digital loan data in Kenya, Bharadwaj et al. (2019) find that financial technology

[2] There are studies focusing on firms' technology adoption and its effect for monetary policy, but they are limited to firms not financial intermediaries. 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.

could improve financial access and resilience. On the other hand, recent studies including Pierri and Timmer (2021), Lin et al. (2021), Kwan et al. (2021), and He et al. (2021) focus on the technology adoption by banks and examine its impact on lending. Although Stulz (2019) highlight the special role of BigTech credits, there is little evidence on the difference in corporate lending between BigTech lenders and banks, in particular their responses to monetary policy shocks, and this paper fills in this gap in the literature.

Lastly, we speak to the literature on financial innovation and economic growth and we contribute by highlighting the impact of BigTech credit on firm performance. The big literature studying the real effects of innovation of non-financial firms, such as Akerman et al. (2015), Beaudry et al. (2010), and Autor et al. (2003), dwarfs that of technological innovation in the financial sector. Regarding banking innovation, Beck et al. (2016) show that it is associated with higher growth in countries and industries with better growth opportunities, and Gorton and He (2021) find that it 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 very limited, exceptions include Chen et al. (2019) and Eça et al. (2021) documenting that fintech credit access reduces sales volatility and spurs firm investment. In this study, we provide further evidence to show that the use of BigTech credit enhances the sale growth of MSMEs, thus the real impact of monetary policy (Gertler and Gilchrist 1994).

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

## 2 Data and Variables

China is a leading player of BigTech development. The ability to build and maintain a large user base is the key factor behind BigTech's expansion into the financial industry in

China, and the government's regulatory tolerance in the early stage supports its florescence (Chui et al. 2021). At the same time, it also differs from other countries in many dimensions. For instance, unlike the U.S., the fintech lending in China is dominated by business lending rather than mortgage lending, thus the BigTech credit generates deep interaction with banks' corporate loans and firms' investment and growth.

We access the data from MYbank, which is an online bank without physical branches owned by the Ant Financial Group and one of biggest BigTech lender in China. Almost all the customers of MYbank are micro and small business, consisting of e-commerce sellers (online firms) and QRcode merchants (offline firms). Different from traditional bank loans which require in-person interaction and inspection, MYbank loans are granted with a "contact-free feature" based on big data and machine learning, without any visits in physical bank branches. It operates on the so-called "3-1-0" model, that is, promising 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 detailed descriptions of the business model of MYbank and other BigTech lenders can be found in Frost et al. (2019), Huang et al. (2020) and Hau et al. (2021).

Specifically, we start the dataset construction by drawing the 10% random sample of the customers of MYbank. We have dropped inactive firms by requiring that (1) the firm need to be registered before 2019; (2) the firm owner are younger than 60 years old; (3) the number of customers should be about 5 per month in 70% of firm's life cycle. We do not access the full sample of MYbank's customers due to data privacy rules and computing limits of large data size. As a result, around 340,000 firms are drawn. Our sample period is from January 2017 to December 2019. We observe firm characteristics including location, age and gender of the business owner, and its monthly sales. Another unique characteristic is the network score, which is a measurement of the firm's centrality in the Ant Financial network based on their payments history.[3]

[3]The network score is obtained as a rank calculated using a PageRank algorithm. This algorithm was 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

The next step is to retrieve the borrowing history of each firm. First, we observe the monthly statistics of the firm's newly issued loans in the MYbank, which is the definition of BigTech credit in this study. Second, we access the counterpart of traditional bank credits for each firm from the Credit Reference Center of the People's Bank of China. That is, for each firm, we observe its BigTech credit and bank credit at the same time. Within bank credits, we can distinguish secured and unsecured loans. However, we only have the aggregated bank credits but do not observe the granular decomposition of the firm's bank credits by each specific bank. Thus, our final dataset is at the firm-lender-month level, while there are only two lenders: the BigTech lender MYbank and other traditional bank lenders as a whole. Admittedly, there are three major caveats in the data structure. First, we cannot break down the loans among traditional banks and they are seen as an aggregate bank lender, which refrains us from discussing the role of conventional bank-level characteristics such as capitalisation and bank size. Second, we use only one lender, i.e., the MYbank, to represent BigTech credit, though it is the dominating BigTech player, thus we may underestimate the responses of BigTech credits and are unable to uncover the interactions within different BigTech lenders. Third, we cannot observe the loan-level information of interest rates and default history due to data disclosure policy, which impedes further investigation of the riskiness of different loans. Even though, the simultaneous observation of BigTech credit and traditional bank credit is already one step further in the literature, and we leave to the future research to the tackle the challenges of these caveats.

Table 1 presents the summary statistics of variables used in this study. The average credit amount obtained from BigTech lender is around 21,841 Chinese yuan (3,400 dollars), and the average amounts of secured and unsecured bank credit are 536,947 yuan (84,500 dollars) and 118,832 yuan (18,700 dollars), respectively. These numbers indicate that the loans issued from the BigTech lender are much smaller than those from traditional banks. Besides, the monthly sales of the sampled firms are 10,414 yuan (1,600

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).

dollars) on average, showing that our sample is mainly consisted of very small firms. As for the business owners, they are relatively young with an average age of 38 years old and generally balanced in gender.

**Table 1:** Summary Statistics

| Variables | N | Mean | St. Dev. |
|---|---|---|---|
| *Panel A: Credit* | | | |
| Credit use -All | 16,281,080 | 0.034 | 0.181 |
| Credit use -Bigtech | 8,140,540 | 0.055 | 0.229 |
| Credit use -Bank | 8,140,540 | 0.012 | 0.110 |
| Credit use -Bank unsecured | 8,140,540 | 0.002 | 0.050 |
| Credit use -Bank secured | 8,140,540 | 0.006 | 0.075 |
| Loan amount -All | 178,838 | 38,852.850 | 168,685.800 |
| Loan amount -Bigtech | 163,241 | 21,841.590 | 38,277.230 |
| Loan amount -Bank credit | 15,597 | 216,895.700 | 525,568.800 |
| Loan amount -Bank secured credit | 2,528 | 536,947.300 | 718,637.600 |
| Loan amount -Bank unsecured credit | 8,141 | 118,832.700 | 426,258.500 |
| *Panel B: Firm Characteristics* | | | |
| Network Centrality | 16,153,432 | 37.501 | 20.997 |
| Sales | 16,281,080 | 10,414.670 | 68,203.850 |
| Online | 16,280,882 | 0.015 | 0.123 |
| Owner Age | 16,276,528 | 38.328 | 8.866 |
| Owner Gender-Male | 16,281,080 | 0.511 | 0.500 |
| *Panel C: Macroeconomic Condition* | | | |
| DR007 | 16,281,080 | 2.637 | 0.150 |
| $\Delta$ DR007 | 16,281,080 | $-0.017$ | 0.095 |
| GDP-city (bn) | 15,918,248 | 195.182 | 210.853 |
| Bank branch density-city | 15,731,950 | 0.110 | 0.039 |

# 3 Empirical Evidence

## 3.1 Identification Strategy

We adopt the following specification in the baseline analysis:

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

where $i, b, t$ indicate firm, lender, and month, respectively. There are two lenders in our dataset, one is the group of traditional banks without knowing which specific banks they are, and the other is the BigTech lender MYbank. $D(BigTech)_b$ is a dummy variable indicating the BigTech lender when it equals to one. $MP_t$ is the variable capturing monetary policy, and we use the change in DR007 ($\Delta DR007$) in the baseline regression. A positive $\Delta DR007$ indicates the tightening of monetary policy and a negative one indicates accommodating monetary policy. $\delta_b$ is the bank fixed effect which captures the time-invariant differences between traditional banks and BigTech lenders. $\theta_{it}$ is the firm-time fixed effect, which absorbs any confounding factors that are firm-time-variant, including firms' credit demand. With this specification, we are comparing the credit lending by two types of lenders to the same firm at the same time, thus, the estimates of $\beta$ capture the differences in responses to monetary policy arising from the credit supply side. Also, later we show the results when we specify firm- and time- fixed effects instead of firm-time fixed effect. In that case, we control an array of variables of firm characteristics, including the age of the business owner, the logarithm of sales, the network centrality score of the firm in the Ant Financial system, and the logarithm of GDP of the city where the firm is located, and we use the lagged term of the latter three variables to mitigate the reverse causality concern.

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), and we are able to do that because the data allows the observation of the firms' complete borrowing history in both traditional banks and the BigTech lender. Specifically, for the extensive margin, we construct a dummy variable $D(\textit{New Lending Relationship})_{ibt}$ that equals to one if firm $i$ starts to obtain credit from bank $b$ at time $t$. That is, firm $i$ is not bank $b$'s client before $t$, but becomes a client at time $t$ and thereafter. This variable indicates the formation of new lending relationship between firm $i$ and bank $b$. Note that we adopt a linear probability specification for the dichotomous dependent variable to faciliate the interpretation of the interaction term in the estimation.

For the intensive margin, we look at the logarithm of the amount of credit $Ln(Loan)_{ibt}$, which is the conventional way of studying the lending channel of monetary policy. Note here the sample is restricted conditional on (i) the firm has already established a lending relationship with the lender; (ii) the loan amount is positive; and (iii) the firm obtains credit from both traditional banks and the BigTech lender, i.e., the observations that the firm only borrow from one lender are not included. In other words, here we are conducting a quasi-loan-level regression, and our strategy is to compare the lending amount to the same firm from different lenders at the same time. Therefore, the number of observations when investigate the intensive margin is largely reduced in relative to the extensive margin.

In both extensive and intensive margin investigations, the coefficient of most interest is $\beta$. As a higher $MP_t$ means a tightening of monetary policy in the baseline estimation, a significant and negative $\beta$ indicates that BigTech lenders are more responsive to monetary policy than traditional banks, *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 behaviour of traditional banks and BigTech lenders. Aggregate shocks that symmetrically affect these two types of lenders do not threat the identification, as they are absorbed in the time fixed effect and will not contaminate the estimates of the coefficient of the interaction term. However, certain shocks that target particularly at the relative development of BigTech credits pose a concern. One such shock is the regulation policies on the financial business provided by BigTech companies in China. The other concern on identification which typically appears in empirical studies on the lending channels of monetary policy is the differentiation between credit demand and credit supply. Benefiting from the data structure, we are able to minimize this concern since we saturate the credit demand impact in the firm-time fixed effect and can ensure that the estimates arise from credit supply side.

## 3.2 Baseline Results

Table 2 presents the estimates from the baseline specification. A general observation is that the coefficients of the interaction term of the change in monetary policy and the BigTech dummy are negative and statistically significant for the extensive margin but insignificant for the intensive margin, suggesting that the BigTech lender is more responsive than traditional banks in expanding new customers when monetary policy eases, but is not significantly different from traditional banks in terms of intensive credit amount when lending to the same borrower.

More specifically, from columns (1)-(2), when the monetary policy rate decreases by one standard deviation, the probability of a BigTech lender to build a new lending relationship with the firm is 0.25 percentage points higher than that of a traditional bank.[4] Considering the average probability of new lending relationship is 3.4% (see Table 1), this impact is economically large. From columns (3)-(4), the intensive margin of monetary policy transmission is statistically similar between the two lenders, since the coefficients of the interaction term is insignificant. For the other control variables, the results are consistent that on average, firms with higher sales and that locate in a more developed region are more likely to establish lending relationships and obtaining more credits, from either 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.

[4] $0.095 \times 0.026 = 0.0025$.

**Table 2:** Baseline Results

| *DepVar* | D(New Lending Relationship) | | Ln(Loan) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta$ 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 |

Next, to better interpret the overall impact combing the extensive and intensive margins of monetary policy on different lenders, we aggregate the bank credit and BigTech credit to the city level, and then examine whether the city's aggregated SME credits show a larger change from BigTech lender than banks in response to monetary policy changes. By comparing the aggregated BigTech lending and bank lending, we can also further mitigate the concern that we cannot detect the individual banks within the traditional bank group. The specification is similar as above, except that now the control variables are at city-level and 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 city-lender-time level. Table 3 shows the results. Our main finding that BigTech credits react in a more significant way than traditional banks to monetary policy remain in the aggregate data.

Specifically, when monetary policy eases by one standard deviation, the BigTech lender issues more credits than banks to the MSMEs in the city by 41.73%, which implies a very large impact to the aggregate economy.[5]

**Table 3:** Baseline Results: 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 | - |
| Time FE | YES | - |
| City $\times$ Time FE | NO | YES |

These results suggest that the stronger role of BigTech lender comes from expanding financial access to MSMEs, which are under-served by banks, and the scale of extending lending relationships is so large that the responses in total BigTech credit amount are also larger than bank credits, even though the amounts issued by the two lenders are not significantly different for each loan on average. Thus, we have shown novel evidence, using both loan-level and city-aggregated specifications, that BigTech lender strengthens the lending channel of monetary policy transmission, mainly through the extensive margin. In the following subsections, we investigate what are the mechanisms behind the transmission-enhancing role of BigTech credit.

[5] $0.093 \times 4.487 = 0.4173$.

### 3.3 Mechanism Investigation

We propose two explanations of the stronger response from BigTech lenders in relative to banks, and test the predictions of these possible mechanisms. The technological advantage of BigTech lenders are twofold. One is the data abundance that helps mitigate information asymmetry (Boot et al. 2020, Stulz 2019, Di Maggio and Yao 2021), and the other is credit assessment techniques that can better predict default risk (Berg et al. 2020, Di Maggio et al. 2021). Financial intermediaries that are stronger in these two aspects can be more responsive to the change in monetary policy environment (Coimbra and Rey 2017, Coimbra et al. 2021).

First, to test the data abundance mechanism, we split the full sample of firms into a subsample of online firms that sell products on the digital platform and a subsample of offline firms that do not conduct e-commerce, and the prediction is that the stronger impact from BigTech compared with banks would be more significant for the subsample of online sellers because they will generate more data that is only accessible to BigTech lenders. Second, to test the credit assessment mechanism, we distinguish between bank credits that is secured by collaterals and those without collaterals, and then compare the BigTech credits with secured bank credits and unsecured bank credits separately. The prediction is that the role of BigTech credit will be stronger when compared with the secured bank lending, because taking collateral is one important way for banks to manage risk and indicates that the firm risk is likely higher and in stronger need of risk assessment, thus the advantage of risk assessment for BigTech lender would be more significant.

Table 4 shows the results in testing the first mechanism. We separate the firms into two subsamples, i.e., offline and online sellers. As described in Section 2 , a large fraction of the offline sellers is mom-and-pop stores and pedlars selling small goods who use the Alipay QR codes as cashier and the BigTech lender obtains their information mainly from the cash flows and sales. In contrast, the online sellers do business in the Taobao e-commerce market. Most of them only have digital appearance and a small share also have physical stores offline, but we do not include the physical branches in our definition and sample construction.The BigTech lenders own various aspects of information of these online sellers, including their customer profiles, products variety, service satisfaction, etc. In terms of lending behavior, traditional banks depend on the visit of physical stores to collect soft information of the borrower and BigTech lenders depend on the data shown in the digital world which is the hard information of the borrower. Data abundance is particularly important for BigTech lenders and this information advantage is larger between BigTech lender and online sellers compared to offline sellers.

**Table 4:** Mechanism Investigation: Offline and Online Firms

| DepVar: | D(New Lending Relationship) | | Ln(Loan Amount) | |
|---|---|---|---|---|
| Firm Type: | Offline | Online | Offline | Online |
| | (1) | (2) | (3) | (4) |
| $\Delta DR007$ × 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 × Time FE | YES | YES | YES | YES |

Results show that the relative stronger responses to monetary policy at the extensive margin from BigTech lenders in the sample of online sellers doubles that of offline sellers, meanwhile the coefficients of the intensive margin are insignificant in both subsamples. More specifically, when the monetary policy eases by one standard deviation, the probability of expanding lending relationship by BigTech lenders is larger than that by banks by 0.25 percentage points to offline sellers, but this number increases to 0.50 percentage points to online sellers. These findings imply the mechanism of data abundance is at display, and the reduction in information asymmetry is an important channel of the larger role of BigTech lenders when responding to monetary policy changes.

Table 5 presents the results when we distinguish between secured and unsecured loans within the bank lending. 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, and 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 can react to monetary policy change in a stronger way because they have better models to evaluate risk and bear riskiness, possibly benefiting from machine learning, artificial intelligence, and big data techniques. This interpretation is particularly relevant when we consider the risk-taking channel of monetary policy (Borio and Zhu 2012, Jiménez et al. 2014, Dell'Ariccia et al. 2017), as the function of risk evaluation becomes even more important, though a full discussion of the role of BigTech lenders in the risk-taking channel is beyond the scope of this paper.

**Table 5:** 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) |
| $\Delta DR007$ × 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 |

# 4 Discussion

In this section we provide further discussions about our findings. First, we examine whether the stronger response of BigTech lender shows heterogeneity regarding the competition relationship between banks and BigTech lenders. Second, we test the asymmetric impact between monetary policy easing and tightening. Third, we examine whether the stronger impact from BigTech lenders has real effects.

## 4.1 Competition Between Banks and BigTech Lenders

First, we account for the unsettled debate whether banks and BigTech lenders, or FinTech lender in general, are complements or substitutes (Buchak et al. 2018a, Erel and Liebersohn 2020).

To do that, we first measure the bank branch density at city-level, which is calculated as the number of bank branches per thousand people.[6] The hypothesis is that BigTech lenders are more likely to be faced with stronger competition with banks and substitute bank credits when the bank branch density is high, while a complementary relationship is more likely in places with less bank branches. Then we assign the bank branch density to each firm based on the city it is located at and split the full sample to subsamples of high- and low- branch density based on the median value. Table 6 shows the results using the subsamples. From columns(1) and (2), we see that the estimates are very close in the two subsamples, and the magnitudes of the coefficients are the same as that in the baseline estimation. For the intensive margin results shown in columns (3) and (4), the magnitude of coefficients in the subsample of high branch intensity is much larger than than in the subsample of low branch intensity, however, they are both statistically insignificant. These findings suggest that the stronger reaction to monetary policy change from BigTech lenders than banks do not necessarily rely on the competition relationship between these two types of financial intermediaries. This is consistent with our proposed mechanisms of data and technique advantages.

[6]The bank branch data is from the China Banking and Insurance Regulatory Commission (CBIRC), which documents the exact location of each bank branches, covering all banks. We aggregate the number of branches by city-year. The population data is from the bureau of statistics of each city.

**Table 6:** Mechanism Investigation: Bank Branch Density

| DepVar: | D(New Lending Relationship) | | Ln(Loan Amount) | |
|---|---|---|---|---|
| Bank Branch Density: | High | Low | High | Low |
| | (1) | (2) | (3) | (4) |
| $\Delta DR007$ × 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 |

## 4.2 Asymmetric Effects of Monetary Policy

Second, we distinguish between monetary policy easing and tightening. We construct a dummy variable indicating monetary policy tightening $D(Tightening)_t$, i.e., when the change in monetary policy rate is positive, and interact it with the change in 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 **??** shows the results. In the first two columns, two findings are worth noting. First, the second row shows that when monetary policy tightens, the probability of expanding new lending relationships is reduced to a larger extent for BigTech lender than banks. Second, combing the first and third row, we observe an asymmetric impact between easing and tightening. Specifically, the transmission-enhancing role of 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 lender to build a new lending relationship with a firm is 0.97 percentage points higher than that of a traditional bank, meanwhile the number in the baseline results is 0.25.[7] By contrast, when the monetary policy is tightened by one standard deviaion, the credit contraction in the extensive margin is smaller for the BigTech lender than banks by a magnitude of 0.88 percentage points.[8]

# 5 Conclusion

In this paper, we show that BigTech credits behave differently from traditional banks in response to monetary policy changes. First, the BigTech lender is more responsive to monetary policy changes in the extensive margin but not the intensive margin after controlling the credit demand, and this effect is more pronounced when the monetary policy is easing than tightening. Second, the differences between the two types of lenders are larger in the subsample of online sellers than offline sellers and when the comparison is between BigTech credit and secured bank credit than that between BigTech credit and unsecured bank credit, suggesting that data abundance and risk management techniques are the mechanism behind the transmission-enhancing role of BigTech lender. Lastly, the financial access to BigTech credit also show a more pronounced real effect in response to monetary policy.

The policy implications from our findings are that monetary policymakers need to account for the increasing role of FinTech, BigTech lenders in particular, in the financial market. Moreover, a coordination between macroeconomic policies and BigTech regulation policies is necessary to exploit the positive effect of BigTech credit in financial access and real economy.

[7] $0.095 \times 0.102 = 0.0097$.

[8] $0.095 \times (0.195-0.102) = 0.0088$.

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