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Abstract

This paper studies whether and how banks' technology adoption affects the bank lending channel of monetary policy transmission. We construct a new measurement of bank-level technology adoption, which can tell whether the technology is related to the bank's lending business and which specific technology is adopted. We find that lending-related technology adoption significantly strengthens the transmission of the bank lending channel, meanwhile, adopting technologies that are not related to lending activities significantly mitigates that. By technology categories, the adoption of cloud computing technology displays the largest impact on strengthening the bank lending channel. Moreover, higher exposure to BigTech competition is significantly associated with a weaker reaction to monetary policy shocks.

Keywords: bank lending channel, monetary policy transmission, technology adoption

JEL classification: G21, G23

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1 Introduction

In recent years, financial technologies (FinTech) have grown to an important factor that reshapes the landscape of the finance sector and the way financing business is served. Financial innovation happened all the time, what marks the current wave of FinTech different is the disintermediation and disruption brought by players outside the traditional financial market, i.e., big technology (BigTech) companies, and traditional banks are passive to cope with these challenges. On one hand, in response to the advancing competition from BigTech's participation in the financing market, banks have become increasingly enthusiastic to develop in-house technologies. The effects of banks' technology adoption in the FinTech era is particularly important to understand the substance of finance and its interaction with the real economy. On the other hand, as stated in Philippon (2016) and Lagarde (2018), FinTech brings a "brave new world" for monetary policymakers. In the recent COVID-19 crisis, technology has shown an important role in meeting the increased financial services demand and distributing government-guaranteed credit, thus fulfilling the monetary policy.[1] Despite these perceptions, it remains a missing link in the literature and little is known about the general implication of technology adoption on monetary policy transmission.

The research questions in this paper are twofold. First, we examine whether and how bank-level technology adoption affects the bank lending channel of monetary policy. Second, we separate and compare the role of banks' technology adoption and that of exposure to the financial services provided by BigTech companies. To the best of our knowledge, we are the first to study the heterogeneity in the bank lending channel of monetary policy arising from technology adoption.

To begin with, we construct a new measurement of bank-level technology adoption. To investigate the effects of technology in banking, a lack of appropriate bank-level technology adoption data is the biggest challenge. The existing method

[1] See Erel and Liebersohn (2020) and Kwan et al. (2021) for evidence from the U.S. Paycheck Protection Program (PPP), and Core and De Marco (2021) for evidence from the Italian public guarantee scheme.

in the literature relies on the spending on internet technology (IT), such as the number of personal computers and the expense on specific hardware and software (Pierri and Timmer 2021, Kwan et al. 2021). However, this method cannot tell which technology the bank is adopting, moreover, it does not include recent technologies in which BigTech companies have advantages when extending their business in the finance field, such as artificial intelligence, big data, and cloud computing.

We tackle this measurement problem by utilizing banks' patents application in specific technology areas. Specifically, we collect the patents application documents of banks, which include a detailed technical description of the invention and the purpose or application scenarios of the patent. Based on careful reading and extraction of the patent files, our patent-based technology adoption measurement has two unique features. On one hand, it can tell whether the technology adoption is lending-related or not. On the other hand, it classifies the technology into the following six categories: artificial intelligence (AI), big data, cloud computing, digitalization, machine learning, and blockchain. In addition, adopting the method in Chen and Srinivasan (2019), we construct an alternative measurement of technology adoption using textual analysis of the disclosure of technology-related words in banks' reports. Using textual analysis can also classify technologies into lending-related or not and the aforementioned six categories. By definition, the patent-based measurement tells more tangible information and actual usage of technologies in the banking business, while the text-based one accounts more for banks' perception than the actual application of technologies, but these two measurements display consistent patterns and characteristics of banks' technology adoption, and our main findings survive using either measurement.

Next, we examine the role of technology adoption in monetary policy transmission by interacting the bank-level technology adoption measurement or its various subcomponents with monetary policy shocks, which is constructed using the methodology in Chen et al. (2018), and test whether and how the response in bank loan growth is affected. Local projections (Jordà 2005) are utilized to investigate the dynamic impacts of technology adoption. Importantly, we address the concern that banks' technology adoption might be determined by their exposure to competition from BigTech financial services. The higher penetration of the BigTech, the more motivated the banks are in adopting similar technologies to cope with the competition. We measure banks' exposure to BigTech competition by the regional BigTech financial service usage index weighted by the location of banks' branches, then we separate banks' technology adoption that is orthogonal to the BigTech exposure and compare the effects between them. In a further step, we mitigate the endogeneity concern by employing the branch-weighted distance to Hangzhou, the technology hub, and the ratio of college enrollment as instrumental variables (IV) for banks' technology adoption, and main findings remain.

The dataset used in this paper is based on the quarterly data of 19 Chinese listed banks from 2008Q1 to 2018Q4, combined with our bank-level measurement of technology adoption and exposure to BigTech penetration, and economy-wide monetary policy shocks. The Chinese banking industry provides a good laboratory to study the influence of FinTech and the responses of traditional banks in technology adoption because China is the leading and largest player in the FinTech area and the findings can yield significant implications for the other countries that are catching up in terms of FinTech development. Besides, our sample starts from 2008Q1 as FinTech arises in recent years and banks' technology adoption is limited before that. Thus, different from studies based on data in the 1990s or 2000s, the evidence in this study reflects the effects of the more recent and disruptive financial innovations.

Our main findings are threefold. First, lending-related technology adoption significantly strengthens the transmission of the bank lending channel, meanwhile, adopting technologies that are not related to lending activities significantly mitigates the transmission. When faced with an expansionary monetary policy shock, the higher the banks' technology adoption with the purpose of improving the lending business, or the lower the technology adoption not targeted at the lending business, the larger the increase in loan growth. Specifically, a one standard deviation change towards an easing monetary policy brings a 0.16 standard deviation increase in banks' loan growth, and an increase in adopting lending-related technology by one standard deviation enlarges the transmission to 0.25 standard deviations, meanwhile, an increase in adopting non-lending-related technology by one standard deviation dampens the transmission to 0.07 standard deviations. Second, when we distinguish between different technology categories, the adoption of cloud computing technology displays the largest impact on strengthening the bank lending channel. In contrast, adopting other types of technologies does not show a consistent and significant impact. Third, it is important to take account into the banks' exposure to BigTech competition, as it is significantly associated with weaker reactions to monetary policy shocks. In addition, after considering the BigTech exposure, the transmission-enhancing role of lending-related technology adoption is still present.

As far as we know, this paper provides the first evidence of the impact of banks' technology adoption on the bank lending channel of monetary policy transmission. Though the potential influence of FinTech on the effectiveness of monetary policy is acknowledged in both policy-making and academic discussions (Smets 2016, Philippon 2016), few studies formally address this issue. By identifying the specific technologies banks adopt and judging whether the adoption is related to the lending business, we are able to have granular measurements disclosing the breadth of capacity instead of expenses on technology, thus we can specify the mechanisms linking technology adoption to the effectiveness of bank lending channel. Moreover, we are also innovative in examining banks' exposure to BigTech competition and banks' technology adoption at the same time, therefore we can provide micro-level evidence on the substitution-complementarity relationship between BigTech and traditional banks, which is an important perspective in FinTech research that lacks granular evidence.

The findings in this study have important implications. With the rapid development of FinTech, monetary policymakers need to account for the interaction between banks' technology adoption and the relationship between banks and BigTech lenders in adjusting monetary policy. Also, the different effects from different categories of technology adoption and exposures to BigTech competition echo the argument in Lagarde (2018) that monetary policymakers and financial regulators will have to further expand their focus from financial entities to financial activities. In addition, academic investigation on banks' technology adoption should not be limited to bank performance, as it bears significant macroeconomic impacts which is worth further research.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 describes the data used in this paper. Section 4 presents the empirical methodology and empirical results. Section 5 concludes.

2 Literature Review

This paper relates to three branches of literature. First, we add to studies on the macroeconomic impacts of banks' technology adoption by discussing its influence on the bank lending channel of monetary policy transmission. Second, we relate to factors determining monetary policy transmission and bring in the new and influencing determinant of technology adoption. Third, this paper lies in the expanding literature on the relationship between FinTech and traditional banks, and we contribute by comparing banks' exposure to BigTech competition and in-house technology adoption.

To begin with, discussions on the macroeconomic impacts of the technological progress in the banking industry are very limited, though catching more and more attention in recent years with the rise of FinTech. Theoretically, De Nicolo et al. (2021) provide a general equilibrium framework, in which banks adopt technology in response to an aggregate productivity increase, resulting in reduced information asymmetry, lower lending rates, and higher banking sector efficiency. On the empirical side, early studies such as Berger (2003) provide descriptive evidence on improvements of costs and lending capacities, but follow-up studies are scant. Exceptions including Pierri and Timmer (2021) and Beck et al. (2016), both examining the effects of information technology on financial stability though provide opposite findings. Pierri and Timmer (2021) find that pre-crisis IT adoption enhances financial stability in the post-crisis years while Beck et al. (2016) show that financial innovation brings more risk-taking and fragility. In addition, using the evidence from the distribution of telegraph stations and banks in the early 19th century and that from banks' digital capabilities in the recent coronavirus pandemic crisis, respectively, Lin et al. (2021) and Kwan et al. (2021) document the importance of information technology as a growth engine for banking.

The scant empirical evidence and inconclusive findings in the literature are partly due to the difficulty of gauging the operation of multi-dimensional technologies, in particular, the more advanced financial technologies originated from BigTech companies. The existing measurement relies on the total expenses or broad adoption such as the number of personal computers, or IT and R&D expenses on different hardware or software, and it does not include in-house inventions and does not allow granular classification of technologies, meanwhile, evidence shows that banks are leading the innovation efforts by inventing FinTech-related patents (Jiang et al. 2021).[2] Moreover, the type of technologies employed by commercial banks captured by those measurements, especially when the study period is the 2000s or earlier, can be very different from today's use of more advanced technologies such as machine learning, big data and cloud computing. Our measurement of technology adoption contributes to the literature in that we make use of the specific technologies invented by banks in the form of patents, and we can tell the specific technologies adopted and the purpose of adopting them, thus capture a more detailed and informative landscape of the technology adoption in

[2] Also see the Wall Street Journal report "Big Banks Stake Fintech Claims With Patent Application Surge": `https://www.wsj.com/articles/BL-CIOB-9707`

nowadays banking industry.

Second, we are the first to provide evidence of technology adoption as a factor determining the bank lending channel in monetary policy transmission. Studies have noted the cross-sectional differences in the way banks respond to monetary policy shocks to understand the bank lending view of monetary transmission, and have shown that the source of heterogeneity of transmission includes liquidity, size, income gap, leverage, and market power (Kashyap and Stein 2000, Gomez et al. 2021, Brissimis et al. 2014, Drechsler et al. 2017). The role of technology adoption has been documented to affect banks' lending activities by extending credit access and reducing agency costs (Petersen and Rajan 2002, Berger and DeYoung 2006), but not been examined as a factor in the bank lending channel of monetary policy transmission. Buchak et al. (2020) and Wang et al. (2021) reflect the implications of FinTech development on monetary policy by equaling FinTech lenders to shadow banks and discussing the relationship between FinTech lenders and banks, however, they do not consider the consequences of technology adoption by banks. The evidence shown in this paper suggests that technological progress within banks and the technological pressure outside banks are both important factors to explain banks' heterogeneous responses to monetary policy shocks.

Third, this study relates to the investigations of the relationship between traditional banks and FinTech lenders. Hauswald and Marquez (2003) propose that technological progress affects competition in financial services through two opposite dimensions: information processing and information access. While improved ability to process information shields competition and increases bank profitability, improved access to information intensifies competition due to informational spillovers. Among recent studies, Fuster et al. (2019) document that FinTech lenders process mortgage applications faster and adjust supply more elastically than non-FinTech lenders, Bartlett et al. (2018) and Boot et al. (2021) show that FinTech would make the loan markets more competitive, Buchak et al. (2020) indicate that FinTech lenders substitute for banks in loans that are easily sold, while Erel and Liebersohn (2020) provide an argument of complementarity between them based on the evidence from the paycheck protection program (PPP). However, on one hand, the existing literature does not take account of the fact that traditional banks have adopted strategies such as developing in-house technologies in response to the competition from non-bank FinTech lenders, on the other hand, the current findings rely on the data from US or EU, where the FinTech credit scale is very small compared to that of banks,[3] thus its implications on the dynamic relationship between the two types of players are limited.

We make contributions in this strand of literature by accounting for the relationship of substitution or complementarity through comparing the roles of traditional banks' in-house technology adoption and their exposure to the penetration of financial services provided by external FinTech lenders, i.e., BigTech companies. More specifically, we can measure both bank-level exposure to BigTech competition and in-house technology adoption, thus we can examine their effects on the bank lending channel simultaneously after taking account into their mutual influences. Besides, we provide evidence using the bank and BigTech data in China, which is the lead player in FinTech development and its scale of BigTech credits is the largest worldwide in terms of both absolute and per capita values (Cornelli et al. 2020).

3 Data and Variables

Investigation of the effects of monetary policy requires high-frequency data, and annual data could not capture the volatile monetary shocks. Moreover, as suggested by the literature and policy practices, China's monetary policy decisions are made quarterly (details will follow). Therefore, this study requires quarterly bank financial data, and this requirement results in the availability of 19 listed

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

banks in 2008Q1-2018Q4.[4] As shown in Table 1, our sample includes the largest 5 state-controlled commercial banks (the Big5), 8 joint-stock commercial banks, and 6 urban and rural commercial banks, and they account for 56% of the total assets in the Chinese banking industry. We combine the bank financial variables with the measurement of technology adoption and exposure to BigTech competition, and monetary policy shocks to generate the final dataset. This section describes the construction of bank-level variables and monetary policy shocks in detail.

3.1 Bank-level Variables

3.1.1 Bank's Technology Adoption

As mentioned before, using IT spending to measure technology adoption cannot consider in-house technology development and the latest technological progress, and we solve these caveats by constructing a new measurement. Specifically, we employ the information of technological patent applications by banks. Patents application is a good demonstration of the outcome of the bank's IT and R&D expenses and reports the exact technologies the bank has actually adopted or plans to adopt. Chen et al. (2019) also make use of patent filing data to identify and classify FinTech innovations. Moreover, Cipher (2018) shows that banks do protect their investment in technology through patenting and they are catching up with technology companies. By extracting the information from patent application documents, we can identify the exact technology and tell the primary purpose of adopting this technology in the bank's business. In particular, we can judge whether the technology is invented to improve the bank's lending business, which is the key to understanding the effects of technology on a bank's lending behavior and its transmission of monetary policy.

To do that, we first search the patent documents filed by banks under these

[4] There are 172 non-listed banks that do not have the quarterly balance sheet and financial statement. There are 45 listed banks as of 2020, however, the other 26 banks either became publicly listed in very recent years thus only have less than four entries of consecutive quarterly data, or do not have valid loan data. These non-listed and listed-but-lack-information banks are relatively very small.

three International Patent Classification (IPC) codes: G06Q20, G06Q30, G06Q40. These three codes cover the general definition of FinTech as digital computing technologies that are used or to be used in financial services (Chen et al. 2019). The higher-level code G06Q covers data processing systems or methods that are specifically adapted for the administrative, commercial, financial, managerial, supervisory, or forecasting purpose, and its subcategory of Q20 indicates the granular classification that applies for payment architectures, schemes, or protocols, Q30 for e-commerce, and Q40 for finance, insurance, or tax strategies. Loosely speaking, these three codes cover the computing patents that have applications in payment, e-commerce, and finance.

Our patent documents are sourced from the China National Intellectual Property Administration (CNIPA), the China patent office, and we keep all the search results filed by any Chinese banks. In this step, we obtain the patent number, the applicant bank, the names of inventors, the application date, the title of the patent, the IPC codes, the abstract of the patent, and detailed descriptions of the technologies and purposes of the patent.

Next, based on careful reading of the descriptions in the patents file, we assign granular categories of technology to each patent, and classify whether the invention is lending-related, i.e., whether the patents are designed to be used in the bank's lending business. More specifically, on one hand, we create a granular classification by assigning the main technologies adopted in each patent into one of the following categories: (1) artificial intelligence (AI), if the main technologies employed in the patent are described as "artificial intelligence", "smart []", "automation [technology]", and "neural networks"; (2) big data, the same for "big data", "data science", "data mining", and "data analysis"; (3) cloud computing, for "cloud computing", "cloud platform", and "cloud [technology]"; (4) digitalization, for "digitalization", "electronic[zation]", "digital strategy", and "digital market"; (5) machine learning, for "machine learning", "deep learning", "biometric identification", "image identification", "sentiment identification", "sentiment analysis", "natural language processing", "face recognition", and "identification"; and (6) block chain, for "block chain".

On the other hand, we judge whether the mentioned technology in the patent is related to banks' lending activities or not. This lending-related classification is subjective based on reading the descriptions of the purpose of the invention. Take the patent 201010272295X filed by the China Construction Bank in 2010 as an example, its patent title is "credit business risk monitoring system and method thereof", and the patent document includes the description "...which solves the problem that credit business risk monitoring has strong subjectivity and low executing efficiency". We can know that this patent is used to solve the problems in credit risk monitoring and to improve the precision and efficiency of the lending decision, therefore, we assign this patent lending-related. Meanwhile, for another patent 2011101800941 filed by the China Construction Bank in 2011, the patent title is "safety processing device and method for telephone banking system", and its purpose is to "improve the security and reliability of telephone banking transaction and open higher authority telephone banking transactions by performing the voiceprint recognition process...", based on this we determine that this patent is to improve the digitalization but not related to the bank's lending business.

Table 1 presents a list of the sample banks with their nature and asset size, and the number of technology patents for each of them in the years 2008 and 2018. Note that we construct the measurement of technology adoption at annual frequency, as it is rare for a bank to have technology patents every quarter, and then we match this measurement to quarterly financial variables.[5] 13 out of the 19 banks in the sample have filed at least one technological patent in the sample period.

[Table 1 here]

Figure 1 summarizes our measurement of bank's technology adoption based on

[5]As we will explain later, we construct an alternative measurement of technology adoption based on textual analysis of banks' annual reports, which are available yearly only.

patent applications. It shows the sum of technological patents filed by banks each year by the six categories of technologies in the left panel, and that by lending-related or not in the right panel. First, we observe that there is a clear jump in 2013-2014 in the total number of technology patents filed by banks. This jump is only for the technology patents that are not lending-related, meanwhile, the technologies that are related to or invented for the purpose of improving lending do not show a jump. The timing of the jump is in coincidence with the launch of the epoch-making money market investment product, Yu'e Bao, by the Ant Financial in 2013, and this year is also recognized as the first year of the internet financing era in China. The presence and penetration of the BigTech company Alibaba in the financial business could be a strong motivation for traditional banks to catch up in technology. Second, the distribution across different types of technologies is unequal. The largest share lies in digitalization technologies, followed by big data and machine learning; in contrast, banks are less interested in blockchain, AI, and cloud computing. This pattern indicates that banks are keen on catching up with the digitalization trend and then gradually shift their focus on specific technologies such as big data and machine learning in which BigTech companies have a dominating advantage. Third, a majority of technological patents developed by banks are not related to the lending and loan business. In the years 2008-2013, the total number of lending-related technology patents is only 7 per year on average, while that of non-lending-related patents is 37; after 2013, the lending-related technology invention slightly increased to an average of 19 per year and the lending-irrelevant patents substantially increased to 185 per year.

[Figure 1 here]

In addition to the measurement based on patent applications, alternatively, there are increasing applications of textual analysis in measuring technology-prone. For instance, Pierri and Timmer (2021) measure bank executives' tech-prone by reading and counting the mentioning of tech-related words in their biographies, and Chen and Srinivasan (2019) use textual analysis of the disclosure of digital-related words in corporate financial reports and conference calls to measure by which magnitudes firms go digital. Therefore, we provide an alternative measurement of banks' technology adoption by manually collecting the mentioning of specific technological terms in banks' annual reports.[6]

Specifically, we count the mentioning of the six types of technologies based on the same word crowds (or "dictionary") as used in the classification of patents, and we also judge whether the mentioned technology is related to banks' lending activities and construct a measurement of perception of lending-related technologies. The judgment of whether the technology is related to lending depends on the exact contexts in the reports. For example, for the paragraph "we use the new core system and big data technology to integrate information, and to issue credit lines for small and medium firms by analyzing their credit status and ability to repay the loan...."(China Construction Bank, 2017), we decide that it falls into the technology category of big data and the mentioning of big data here is lending-related because the bank tends to apply the technology to improve its lending decisions and manage the risk.

Figure 2 shows the sum of technological terms mentioned by banks in each year by the six categories of technologies in the left panel, and that by lending-related or not in the right panel. This text-based measurement shows very similar patterns as that from the patent-based measurement. Banks are paying increasing attention to technologies over time. In the beginning, banks barely mentioned any of those technologies in their reports, and they brought up substantially more technological terms after 2013-2014. Moreover, the perception of technology largely focuses on those that are not related to lending. The perception of AI, instead of digitalization as suggested by the patent-based measurement, is the highest in recent years, indicating that banks' recognition is ahead of actual efforts and inventions in the

[6]For listed banks (and firms) in China, the quarterly reports usually only disclose earning and financial performance, and do not include informative disclosure on the bank's strategy or perception of technologies; this information is only available in the annual reports.

AI technology.

[Figure 2 here]

However, the text-based measurement is flawed in the sense that the mentioning of technology terms does not reflect actual expenses and acquirement of these technologies for banks, and the mere perception might underestimate the costs burden and the improved information processing capacities for banks. Therefore, between the patent-based and text-based measurements of technology adoption, we use the former in the main analysis and the latter in the robustness check.

3.1.2 Banks' Exposure to BigTech Penetration

Bank's technology adoption is not exogenous. Due to the rapidly rising BigTech financial services in China (Cornelli et al. 2020), the relationship between BigTech and traditional banks could be a driving force for banks to adopt more technologies to either compete or cooperate with BigTech companies. Besides, the competition with BigTech financial service could be a factor affecting the bank lending channel on its own. Thus, it is necessary to isolate banks' technology adoption from its exposure to BigTech competition. To do this, we first need a measurement of the latter and then derive the non-competition component of technology adoption.

First, the banks' exposure to BigTech competition is constructed as the branch-weighted BigTech penetration across regions:

$$BigTechCompetition_{it} = \Sigma_c \frac{\#Branch\ of\ Bank\ i\ in\ ct}{\#Total\ Branch\ of\ Bank\ it} BigTech_{ct}$$

where c denotes county, and $BigTech_{ct}$ is the penetration of BigTech financial services in county c at time t. For example, if bank i has 2 branches in county c_1 and 3 branches in county c_2, then its exposure to $BigTech$ competition is calculated as 40% of the BigTech penetration in c_1 plus 60% of that in c_2.

The county-level BigTech penetration $BigTech_{ct}$ is an index constructed based on the individual-level usage of various financial services provided by the Ant Financial. Ant Financial is one of the dominating BigTech companies both domestically and internationally. It is the parent company of Alipay, which is the largest mobile payment platform in the world and accounted for 55.32% of the third-party payment market in mainland China in 2018. A similar regional BigTech penetration data is also used in Hong et al. (2020). More specifically, the BigTech penetration dataset is developed by Guo et al. (2020) and launched by the Institute of Digital Finance of Peking University. We use the aggregated penetration of BigTech usage and its granular subcategorical measurements of payment, insurance, money fund, investment, credit, and credit evaluation service. These measurements are constructed based on the nondimensionalization of 20 individual-level indicators, and we report them in Table A1 in the appendix. A higher value indicates more penetration of BigTech in providing financial services in the county.

It is worth noting that the raw BigTech indicators display a clear time trend, with an annual growth rate over 25% for the aggregated BigTech penetration, reflecting the strong momentum of BigTech development in China. To deal with the trend issue and to focus on the cross-sectional difference between regions, we divide the raw index by the national average in each period and construct the relative BigTech adoption indicators across counties. Therefore, a value larger than 1 indicates that the county's BigTech penetration is more advanced than the national average, and a value smaller than 1 indicates that the county is lagging behind in BigTech penetration. In this way, we are able to erase the strong time trend meanwhile preserve the relative rank.[7]

For bank branch distribution, we collect the data of the exact location of bank branches from the China Banking and Insurance Regulatory Commission (CBIRC). Then we assign them to counties based on the address and merge them with the relative BigTech measurement. Table A2 in the appendix reports the top

[7]There are 2,793 counties in measuring BigTech penetration. The BigTech penetration data compiled by Guo et al. (2020) starts in 2011, and we assume the values for the years 2008-2010 the same as 2011. It is reasonable to do so because the relative measurement erases the time trend and we focus on the cross-sectional variation, and the BigTech financial services only became prevalent in the mid-2010s. Moreover, our main findings hold if we do not include the years 2008-2010.

5 banks in terms of exposure to BigTech in 2008, 2013, and 2018. It shows that there are variations across years, as new banks were added to the list and replaced old ones, and the pattern of subcategorical exposure to BigTech usage differs from each other, which helps to explore the mechanism of BigTech competition affecting monetary policy transmission.

Next, we regress banks' technology adoption measurement on the exposure to BigTech competition with bank and time fixed effects and use the residual in further analysis.[8] We standardize the residual and label it $\widetilde{Tech}$, which is the the component of technology adoption that is orthogonal to BigTech exposure. In parallel, we standardize the exposure to BigTech competition and label it as $\widetilde{BigTech\ Exposure}$, therefore we can examine and compare the relative impacts of pure technology adoption and exposure to BigTech competition.

3.1.3 Bank-level Outcome and Control Variables

We obtain the listed banks' financial and performance variables from the China Stock Market & Accounting Research Database (CSMAR) and WIND. We focus on the bank lending channel of monetary policy transmission, thus we use the loan growth as the main outcome variable to examine how banks' response in lending varies with different technology adoptions.

For control variables, we use bank size which is measured as the natural logarithm of bank assets, leverage which is measured as the liability to asset ratio and is approximate to the reciprocal of capital ratio, profitability which is measured as the income-to-cost ratio, and loan-to-deposit ratio. These are also the main characteristics shown in the literature that result in banks' heterogeneous responses to monetary policy (Kashyap and Stein 2000, Gomez et al. 2021, Brissimis et al. 2014, Drechsler et al. 2017, Acharya et al. 2020), and later we will conduct a horse race between these factors and technology adoption in the robustness check.

Table 2 shows the summary statistics of all variables used in this paper.

[8]The regression specification is: $Tech_{it} = \alpha + \gamma BigTech\ Exposure_{it} + \zeta_i + \theta_t + \epsilon_{it}$

[Table 2 here]

3.2 Monetary Policy Shock

Specification of monetary policy rule and identification of its shock are crucial to investigate the transmission of monetary policy to the economy.[9] There are controversies in modeling China's monetary policy framework because China is not inflation-targeting and it is in transition from quantity-based to price-based in recent years, thus, we clarify our choice of monetary policy shock measurement in this section. Even though the policy measurement is unique to China, the analysis and findings of monetary policy transmission from this study have general implications. Recent studies, for instance, Chen et al. (2018) and Kamber and Mohanty (2018), provide comparisons between the effectiveness of monetary policy transmissions in China and advanced economies and show that the transmission of monetary policy impulses to the rest of the economy in China is similar to the transmission process in advanced economies.

In the baseline analysis, we adopt the method in Chen et al. (2018) to measure monetary policy shocks in China. They describe that the primary goal of monetary policy in China is to achieve the annual GDP growth target instead of the inflation target, and the money supply (M2) growth rate is the most important intermediate target of China's monetary policy. Despite the interest rate liberalization, which is incomplete and unfinished, the importance of credit quantity targets is still essential in China. Since 1994, the State Council's Annual Report on the Work of Government would specify M2 growth targets, until 2018. The M2 growth target is the most important monetary indicator in the annual report, which is delivered by the Premier and considered to guide the government's economic work in the

[9]In the existing literature, many authors have studied the identification of monetary policy shock using a broad class of model specifications and identification schemes. Orphanides (2001) implements an availability of real-time data to a Taylor rule and analyzes monetary policy rule, and Romer and Romer (2004) consider quantitative and narrative information embedded in monetary policy documents to identify monetary policy and investigate the impact of monetary policy on the economy. More recently, Gertler and Karadi (2015) and Nakamura and Steinsson (2018) study monetary policy transmissions using high-frequency identification.

following year. Chen et al. (2018) capture the monetary policy decision process in China as the People's Bank of China (PBC) adjusts M2 growth rates on a quarterly basis[10] in response to inflation and GDP growth in the previous quarter. Specifically, the monetary policy rule is estimated as an endogenous quarterly M2 growth which is a function of the gap between actual and target inflation and the gap between actual and target GDP growth:

$$m_t = \gamma_0 + \gamma_m m_{t-1} + \gamma_\pi(\pi_{t-1} - \pi^*) + \gamma_{y,t-1}(y_{t-1} - y^*_{t-1}) + \epsilon_t \tag{1}$$

where m is the M2 growth rate, π is the CPI inflation rate, y is the GDP growth, and π^* and y^* are the growth targets for inflation and GDP set by the State Council, respectively.[11] The GDP growth target serves as a lower bound for monetary policy; the output coefficient $\gamma_{y,t-1}$ is thus time-varying. Then the estimated M2 growth rate ($\hat{m_t}$) is the endogenous M2 growth, and the monetary policy shock is calculated as the difference between the actual and endogenous M2 growth.

On the other hand, to account for the gradual transition to price-based monetary policy and the fact that the 7-day collateralized interbank repo rate between depository financial institutions is acting as the *de facto* policy rate, we adopt the quarterly change in the 7-day interbank fixing repo rate (FR007), which is a benchmark rate based on repo trading rate for the interbank market, as an alternative monetary policy measurement.[12] By definition, $\Delta FR007$ is based on the interest rate instead of M2 growth, and we use it as well as the FR007 level

[10]The quarterly frequency is based on the fact that the Monetary Policy Committee meets every quarter and the PBC releases a monetary policy executive report every quarter.

[11]Chen et al. (2018) set the quarterly inflation target at 0.875% (annualized rate of 3.5%) as the monetary policy executive reports released by the central bank indicate that the annual CPI inflation target is around 3-4 percent. The real GDP growth target is set by the central government of China. Specifically, it is decided at the Central Economic Work Conferee in December of each year and then is announced by the Premier of the State Council as part of the Annual Report on the Work of Government during the National People's Congress in the next spring.

[12]We use FR007 instead of DR007 (the 7-day pledged interbank repo rate for deposit institutions) because the latter is only available after 2014 and cannot cover the early sample. DR007 is mentioned in the Quarterly Monetary Policy Executive Reports as playing "an active role to cultivate the market base rate", which is a sign that the PBC is using DR007 as the *de facto* intermediate target. FR007 and DR007 have a correlation coefficient of 0.83.

in the robustness check to show that the choice of quantity-based or price-based monetary policy measurement does not alter the main findings in this study.

[Figure 3 here]

Figure 3 presents the time series of two monetary policy shock indicators. We observe large variations of monetary policy shocks in our sample period of 2008Q1-2018Q4. For the M2-based indicator, a positive value indicates expansionary monetary policy shock and a negative value indicates contractionary shock. For the FR007-based indicator, the opposite is true. The figure shows that the price-based and quantity-based monetary policy shock measurements move negatively with each other with a significant correlation coefficient of -0.40, suggesting that they are consistent with each other and expressing similar messages of monetary policy shocks in China.

4 Empirical Results

4.1 Baseline Results

To examine the role of banks' technology adoption in monetary policy transmission, we first adopt a simple specification to look into the correlations and then address concerns on identification by decomposing the technology adoption measurement and employing instrument variables for it. The basic regression specification is the following:

$$\textit{Loan Growth}_{it} = \alpha + \beta_1 MP_t \times Tech_{it-1} + \beta_2 MP_t + \beta_3 Tech_{it-1} + \Gamma Control_{it-1} + \delta_i + \epsilon_{it} \tag{2}$$

where i and t refer to bank and quarter, respectively. *Loan Growth*$_{it}$ is the bank's loan growth rate, MP_t is the monetary policy shock, and $Tech_{it-1}$ is banks' technology adoption. As explained in Section 3, in the main analysis, we use the M2-based shock as MP_t by which a larger value indicates an expansionary monetary policy shock, and we use the patent-based measurement of technology adoption as $Tech_{it-1}$. $Control_{it-1}$ is an array of control variables, including bank size, leverage, profitability, and loan-to-deposit ratio. We use the lagged term of technology adoption and other bank-level control variables to mitigate the concern on reverse causality. We control bank fixed effect in δ_i. We do not include the time fixed effects because we are interested in the estimates of the coefficients for monetary policy shock standalone (β_2), so that we can evaluate whether the bank lending channel works before accounting for banks' technology adoption. Specifically, a positive β_2 shows the smooth transmission of the bank lending channel, i.e., more expansionary monetary policy is associated with more lending, and a β_1 with the same sign of β_2 implies that the higher the bank's technology adoption the enhanced impact of monetary policy transmission, *vice versa*. Throughout all estimations in this study, we cluster the standard error at the bank level.

Table 3 shows the results. First, we observe that the conventional bank lending channel works. The coefficients of the monetary policy shock variable alone are significantly positive, indicating that an easing monetary policy shock induces a higher loan growth. More specifically, a one standard deviation change towards an easing monetary policy brings a 0.16 standard deviation increase in banks' loan growth.[13] Second, bank's technology adoption affects its monetary policy transmission but the effects depend on whether the technology adopted is lending-relevant or not. Results shown in columns (1) and (2) suggest that overall technology adoption is positively but insignificantly associated with the bank's response to monetary policy, however, results in columns (3) and (4) show that the adoption of lending-related technologies significantly strengthens the monetary policy transmission while the adoption of non-lending-related technologies dampens that. More precisely, adopting lending-related technology by one standard deviation more tends to enlarge the response of bank's loan growth to the

[13] $\frac{0.007 \times 75.54}{3.31} = 0.16$

same one standard deviation of monetary policy shock from 0.16 to 0.25 standard deviations, meanwhile adopting non-lending-related technology by one standard deviation more would mitigates the transmission from 0.16 to 0.07 standard deviations.[14] In other words, there is a strengthening effect by 56% from lending-related technology and a weakening effect by a similar scale from non-lending-related technology, which together result in an ambiguous effect of overall technology adoption.

[Table 3 here]

Then we examine the dynamic impact using Jordà (2005)-style local projection shown as follows.

$$\begin{aligned} Loan_{it+h-1} - Loan_{it-1} = \alpha + \beta_{1h} MP_t \times Tech_{it-1} + \beta_{2h} MP_t + \beta_3 Tech_{it-1} \\ + \Gamma_h Control_{it-1} + \delta_{ih} + \epsilon_{ith} \end{aligned} \tag{3}$$

where $h = 0, 1, 2, ..., 10$ indexes the forecast horizon. The coefficient β_{1h} measures how the cumulative response of bank loan in quarter $t + h$ to a monetary policy shock in quarter t depends on the bank's technology adoption in quarter $t-1$. We use the cumulative change in bank loan from $t-1$ to $t+h-1$ on the left-hand side. Figure 4 shows that banks adopting more lending-related technologies are consistently more responsive to the monetary policy shock for up to 3 quarters, while those adopting more non-lending-related technologies are consistently less responsive to the shock for up to 5 quarters.

[Figure 4 here]

4.2 Addressing Identification Concerns

There are two major concerns for the identification of the effect of technology adoption on bank's lending channel of monetary policy using the above specification. First, monetary policy shocks may be affected by other macroeconomic

[14] $\frac{0.007\times(2.70\times16.20+75.34)}{3.31} = 0.25; \frac{0.007\times(21.40\times(-2.01)+75.34)}{3.31} = 0.07.$

shocks. The way our monetary policy shock is measured, i.e., rule-based and already accounting for the information from inflation and economic growth, helps reduce this concern. Besides, the interaction specification compares how banks with different technology adoptions change their lending following changes in the monetary policy shocks. As long as other shocks affect all banks equally, banks' loan supply should not be contaminated by such shocks. Second, banks' technology adoption could be endogenous to lending, and there could be confounding factors affecting banks' technology adoption and lending. Using the lagged term of technology adoption and bank fixed effect mitigates the reverse causality and absorbs all time-invariant confounding characteristics, but still could not capture factors that vary with time and bank. We address this concern in two ways. First, we consider an important variable that has a potentially mutual relationship with banks' technology adoption and lending activities and decompose the technology adoption measurement. Second, we use instrumental variables (IV) for technology adoption and conduct two-stage least square estimations.

To begin with, as described in last section, we separate bank's technology adoption into two components, one from the exposure to BigTech competition ($\widetilde{BigTech\ Exposure}$) and the other one orthogonal to BigTech competition ($\widetilde{Tech}$, $\widetilde{Lending}$ *Tech*, or *Non-*$\widetilde{Lending}$ *Tech*). Note that all measurement denoted in tilde are standardized. Then we estimate the following specification and present the results in Table 4.

$$\begin{aligned}
&Loan\ Growth_{it} = \alpha + \beta_1 MP_t \times \widetilde{Tech}_{it-1} + \beta_2 MP_t \times \widetilde{BigTech\ Exposure}_{it-1} \\
&+\beta_3 MP_t + \beta_4 \widetilde{Tech}_{it-1} + \beta_5 \widetilde{BigTech\ Exposure}_{it-1} + \Gamma Control_{it-1} + \delta_i + \epsilon_{it}
\end{aligned} \tag{4}$$

[Table 4 here]

Results show that more exposure to the competition from BigTech financial services mutes the bank lending channel of monetary policy transmission. More specifically, if the bank has more branches in counties that show a larger adoption of BigTech financial services than the other counties, then the bank's response to monetary policy shocks is weakened. A one standard deviation increase in exposure to BigTech competition is associated with an over 40% decrease in banks' responses of loan growth to monetary policy shock. These results are consistent with the findings in Buchak et al. (2018) and Buchak et al. (2020) that the rise of BigTech is mainly driven by regulatory arbitrage and it mitigates monetary policy transmission as a part of the shadow banking sector, and they suggest that BigTech substitutes, instead of complements, the traditional banks. Moreover, after controlling the BigTech exposure, the same finding holds that lending-related technology adoption strengthens monetary policy transmission. A one standard deviation increase in the non-competition component of lending-related technology adoption is associated with an increase in banks' response to monetary policy shock by 28%.

Similarly, Figure 5 presents the dynamic effects from local projections of the three components of banks' technology adoption: exposure to BigTech competition, lending-related adoption, and non-lending related adoption. It shows that the transmission-enhancing role of lending-related technology and the transmission-mitigating role of exposure to BigTech competition are both temporary as their effects are only significant at impact. In contrast, the non-lending related technology adoption tends to weaken the monetary policy transmission in the long run and this effect is large, as a one standard deviation increase in non-lending related technology adoption is likely to fully counteract the increase (decrease) in loan growth from expansionary (contractionary) monetary policy shock in ten quarters.

[Figure 5 here]

Next, to further mitigate the concerns that bank technology adoption might be endogenous to other factors that affect lending, we perform an instrumental variable analysis. We use two instruments for technology adoption, including the weighted average distance to Hangzhou city and the weighted ratio of college enrollment. The idea with the first is that Hangzhou is the hub city for internet companies and the headquarter of Ant Financial is located there, the expansion of Ant Financial centers around its headquarter and gradually penetrates into nearby areas and then distant regions. Thus, the closer to Hangzhou the stronger the pressure from BigTech competition, and the bank is more likely to feel the importance of adopting technologies and develop in-house technologies. A similar instrumental variable is employed in Hong et al. (2020). We use the share of branches in each city as the weight, and compute the weighted distance to Hangzhou. We use both the geographical distance in kilometers and the train travel time in hours to measure the distance. As banks' distribution of branches changes over time, the distance IV is also time-variant for each bank. The idea with the second is that college students are more tech-savvy and they are more likely to adopt technology-equipped financial services. Banks are more motivated to develop and adopt technologies when they are faced with a higher-educated population. We compute the ratio of college-enrolled population in the total population in each city and again use bank branches' location as the weight. In addition, the distance to Hangzhou and college enrollment are arguably exogenous, as the distance is determined by geographical location and natural landscape and the college-student enrollment number is pre-set for each university by the Ministry of Education, and they are not directly linked to banks' lending behavior.

We employ these IVs for the decomposed technology adoption variables, i.e., the technology adoption that is orthogonal to BigTech competition ($\widetilde{Tech}$, $\widetilde{Lending\ Tech}$, or $\widetilde{Non\text{-}Lending\ Tech}$), and Table 5 report the first-stage regression results.[15] It shows that distance to Hangzhou is significantly and negatively correlated with the overall technology adoption and non-lending related technology adoption, but not the lending-related technology adoption, and college enrolled ratio is significantly and positively correlated with all the three technology adoption measurements.

[15]We also show the results employing IVs for the original technology adoption variables in the appendix Tables A3 and A4, and they are similar to the findings shown in Table 3.

Based on the F-statistics, weak IV concerns are relieved for the overall and non-lending related technology adoption, but not the lending-related one. Thus, we instrument the former variables using the two IVs and conduct the two-stage least square (2SLS) estimation for equation (4). Results shown in Table 6 are similar to that in Table 4, and the transmission-enhancing effects of lending-related technology adoption and transmission-weakening effects of BigTech exposure remain.

4.3 By Categories of Technology and BigTech Exposure

As described in Section 3, the granular data in this study allows us to distinguish banks' adoption of six different technologies (AI, big data, cloud computing, digitalization, machine learning, and blockchain) and banks' exposure to BigTech competition in six types of financial services (payment, insurance, money fund, investment, credit, and credit evaluation). To investigate the heterogeneous effects of various technologies and BigTech exposures, we first estimate the specification in equation (4) by categories of technology while controlling the aggregated exposure to BigTech competition, and then conduct the estimation by categories of BigTech exposure while controlling the aggregated technology adoption.

First, Table 7 shows the estimates by categories of technology adoption.[16] We first examine the effect of each category of technology one at a time in columns (1) to (6), and then test their roles at the same time as shown in column (7). Similar to the results using total technology adoption, we observe that the adoption of most types of technologies also does not significantly affect the functioning of the bank lending channel of monetary policy, but the adoption of cloud computing technology is an exception. Results in columns (3) and (7) show that an increase in adopting cloud computing technology by one standard deviation is associated with a significant increase in banks' response to monetary policy shock by 16% to 23%.

[16]Note here that we have separated the adoption of each technology from the exposure to BigTech competition using the same residual approach.

[Table 7 here]

Second, Table 8 shows the estimates by the category of financial services penetrated by BigTech. Exposure to BigTech usage of each type of financial service all tends to mitigate bank's transmission to monetary policy shocks, except the exposure to BigTech investment. In other words, when the bank's business is in areas that show higher usage of BigTech payment, insurance, money fund, credit, and credit evaluation services, the bank's loan response to monetary policy shocks is likely smaller. Moreover, this transmission-mitigating effect is the strongest for the exposure to BigTech credit evaluation service, which may mute two-thirds of the transmission. This result indicates that the biggest disadvantage of banks against BigTech lies in the data abundance and credit risk assessment, as BigTech companies are able to more precisely evaluate the borrowers based on their multi-dimensional behaviors, in addition to financing behaviors, in the platform (Berg et al. 2020). The more disadvantaged in credit evaluation, the less responsive the bank is when faced with monetary policy shocks.

[Table 8 here]

4.4 Robustness Checks

In this section, we conduct multiple robustness checks to show that the main findings hold when we use alternative measurements of monetary policy shock and bank technology adoption, and when we conduct a horse race with other factors that affect the operation of bank lending channel of monetary policy transmission.

First, we show the results using the price-based instead of the M2-based monetary policy shock measure. Specifically, Table 9 present the baseline estimates using the level and change of FR007 as MP_{t-1}. As an increase in FR007 indicates that monetary policy tightens rather than eases, the significant and negative coefficients of the interaction term between the price-based monetary policy and lending-related technology adoption in columns (3)-(4) and (7)-(8) suggest that banks' higher adoption of lending-related technologies strengthens its transmission of monetary policy, and the positive coefficients for the interaction term between monetary policy and non-lending related technology in columns (3)-(4) suggest the opposite role of adopting technologies that are not related to lending activities. These are consistent with the baseline findings.

[Table 9 here]

Second, we use three alternative measurements of bank-level technology adoption and then re-estimate the baseline specification. The alternative measurements include a count of technology terms mentioned in the banks' annual reports, a dummy taking a value of one if the bank has at least one technology patent, and a dummy taking a value of one if the bank has mentioned technology terms for at least once in its report. Results are shown in Table 10. Here we use the M2-based monetary policy shock measurement as in the baseline. We observe that the transmission-weakening role of BigTech exposure remains significant across different measurements of technology adoption, and the finding that the adoption of non-lending related technology mitigates banks' response to monetary policy shock also remains when we use the dummy measurement based on either patents or textual analysis.

[Table 10 here]

Third, we conduct a horse race with other factors that could affect the transmission of the bank lending channel of monetary policy. Specifically, in addition to using them as control variables, we also interact bank size, leverage, income-to-cost ratio, and loan-to-deposit ratio, in parallel to the key variables of interest, i.e., bank's technology adoption, with monetary policy shocks, and examine whether the role of technology adoption still holds in this horse race with alternative factors. Results shown in Table 11 indicate that banks with a higher leverage and a lower income-to-cost ratio tend to show a more efficient transmission of the lending channel when faced with monetary policy shocks. This is consistent with the findings in Gomez et al. (2021). Meanwhile, our evidence suggests that the roles of size and loan-to-deposit ratio are ambiguous in affecting banks' response to monetary policy shocks. More importantly, the transmission-enhancing role of lending-related technology is still present in this horse race, although the magnitudes of its effects are smaller than that of leverage and income-to-cost ratio.

[Table 11 here]

5 Conclusion

This study investigates the effects of technology adoption on the bank lending channel of monetary policy transmission. By constructing a patent-based measurement of bank-level technology adoption, we whether and how it affects the bank loan growth when faced with monetary policy shocks. We find that banks' technology adoption is associated with strengthened reaction to monetary policy shocks when the adoption is for lending-related purposes and is associated with a mitigated transmission when the adoption is not lending-related. By technology categories, the adoption of cloud computing technology displays the largest impact on strengthening the monetary policy transmission to bank loan growth. In addition, our findings suggest a substitute relationship between BigTech lenders and traditional banks as the exposure to BigTech competition significantly mutes the bank lending channel.

These findings are important to understand how monetary policy works in the FinTech era. Monetary policymakers need to account for the interaction between technological progress and traditional financial services in adjusting monetary policy. Also, various types of technology adoption and exposures to different dimensions of BigTech competition display different interactions with monetary policy shocks, implying that the policymakers will have to further expand their focus from financial entities to financial activities in the future.

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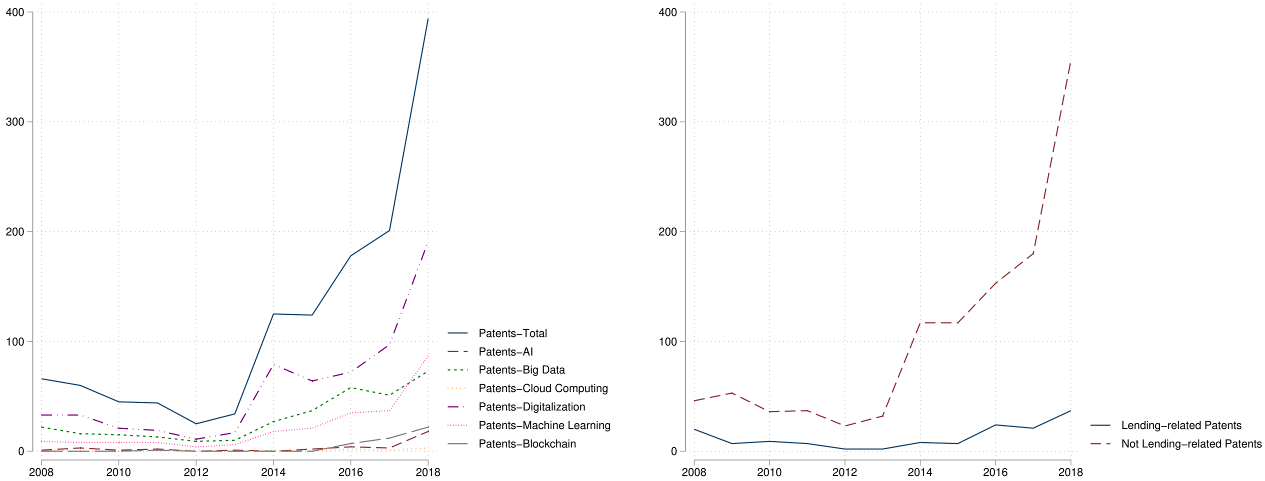

Figure 1: Banks' Technology Adoption: Patent-based

Notes: This figure shows the total number of technological patents filed by banks in each year. The left panel shows the aggregate number and the number of six subcategorical technologies, which are artificial intelligence (AI), big data, cloud computing, digialization, machine learning, and block chain. The right panel shows the number of lending-related and not lending-related patents separately. We identify the categories of technologies and whether the patent is lending-related based on the descriptions in the patent document.

Figure 2: Banks' Technology Adoption: Text-based

Notes: This figure shows the total number of technological terms mentioned by banks in their annual reports in each year. The left panel shows the aggregate count and the count of six subcategorical technological terms, which are artificial intelligence (AI), big data, cloud computing, digialization, machine learning, and block chain. The right panel shows the counts of lending-related and not lending-related mentioning separately. We identify the categories of technologies and whether the patent is lending-related based on the contexts when mentioning the technological terms.

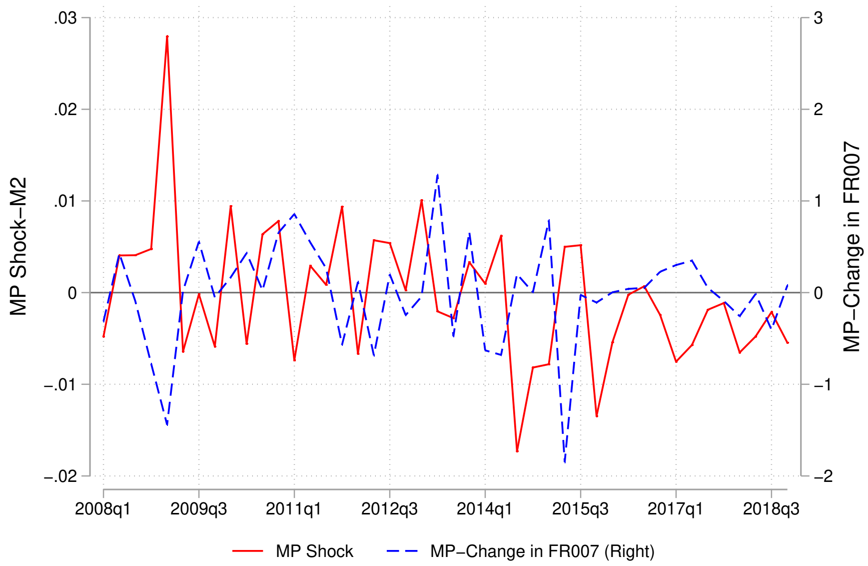

Figure 3: Monetary Policy Shocks

Notes: The red solid line indicates the M2-based measurement of monetary policy shocks (in decimal), reflecting the quantity-based monetary policy framework; the dashed blue line indicates the price-based measurement of monetary policy shocks (in percentage points), reflecting the price-based monetary policy framework. An increase in the M2-based shock or a decrease in the FR007-based shock denotes an expansionary monetary policy. The correlation between the two shock measures is -0.40.

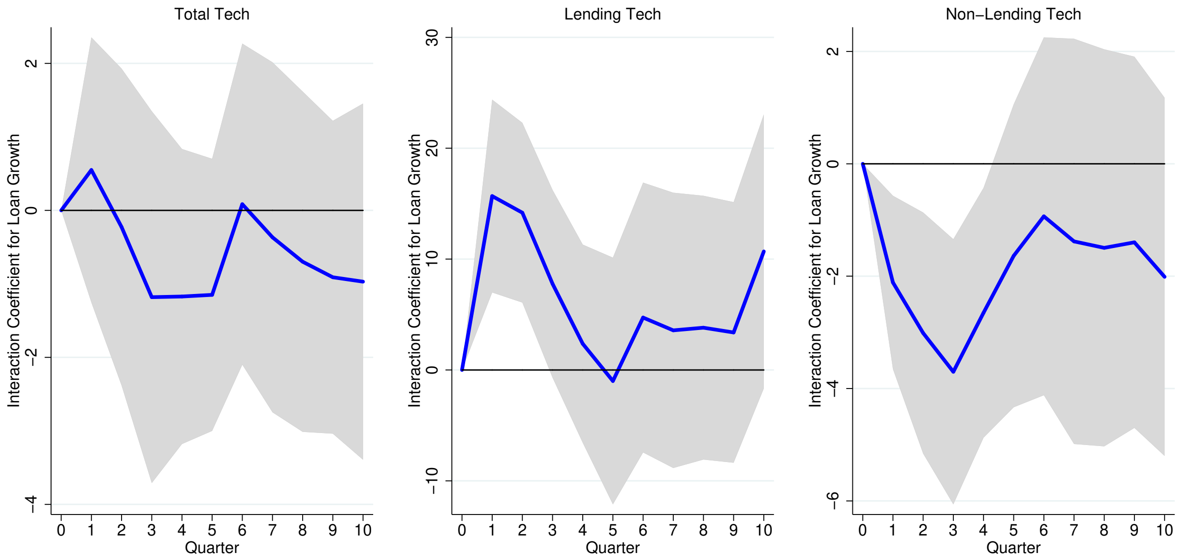

Figure 4: Local Projections of the Role of Technology Adoption

Notes: This figure presents the estimated coefficients of the interaction term between monetary policy shock and banks' technology adoption from a local projection estimation. The outcome variable is the cumulative changes of bank loan growth over the horizon of ten quarters. The left panel shows the results when we use the overall technology adoption measurement in the estimation. Then we distinguish between lending-related and non-lending-related technology adoptions and control them together in the estimation, and the coefficients of the interaction term between monetary policy and lending-related technology adoption and that between monetary policy and non-lending-related technology adoption are presented in the middle and right panels, respectively. The solid lines plot the point estimates and the shades correspond to the 95% confidence interval.

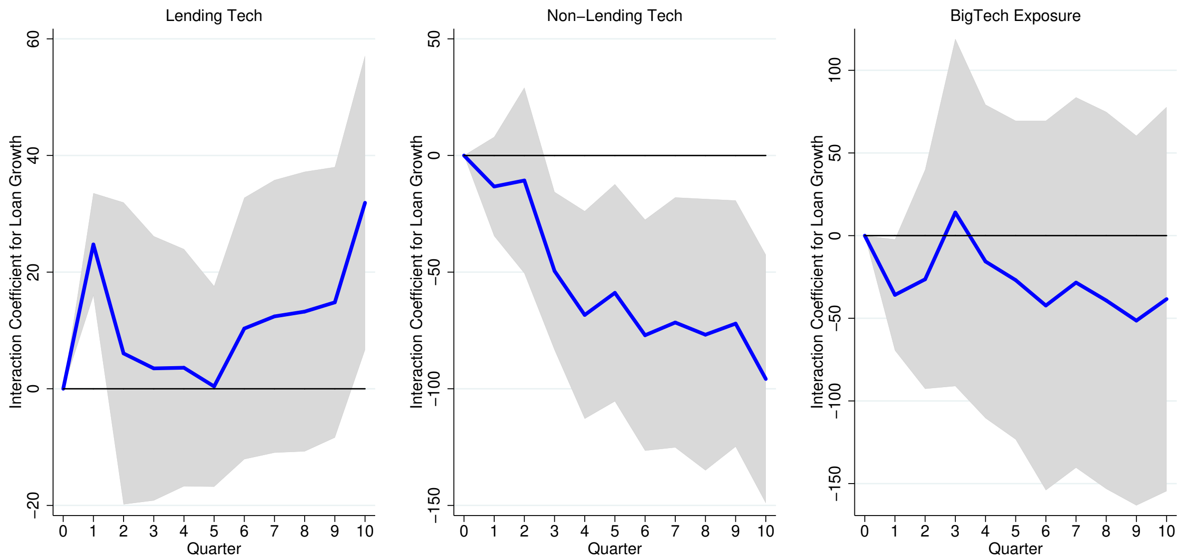

Figure 5: Local Projections of the Role of Technology Adoption: Accounting for Exposure to BigTech Penetration

Notes: This figure presents the estimated coefficients of the interaction term between monetary policy shock and banks' lending-related technology adoption in the left panel, that between monetary policy shock and banks' non-lending-related technology adoption in the middle panel, and that between monetary policy shock and banks' exposure to BigTech competition in the right panel, from a local projection estimation. The outcome variable is the cumulative changes of bank loan growth over the horizon of ten quarters. Note that the lending-related and non-lending-related technology adoption measurements here are orthogonal to BigTech exposure, and the three variables are all standardized to have a mean of zero and a standard deviation of one. The solid lines plot the point estimates and the shades correspond to the 95% confidence interval.

Table 1: Bank Sample List

Bank Name	Bank Nature	Total Assets in 2018Q4 (Trillion RMB)	# of Technology Patents in 2018	# of Technology Patents in 2008-2018
Industrial and Commercial Bank of China	Large state-controlled commercial bank	27.70	36	205
China Construction Bank	Large state-controlled commercial bank	23.22	102	457
Agricultural Bank of China	Large state-controlled commercial bank	22.61	24	100
Bank of China	Large state-controlled commercial bank	21.27	201	397
Bank of Communications	Large state-controlled commercial bank	9.53	13	33
China Merchants Bank	Joint stock commercial bank	6.75	12	35
Industrial Bank	Joint stock commercial bank	6.71	0	2
Shanghai Pudong Development Bank	Joint stock commercial bank	6.29	0	0
China CITIC Bank	Joint stock commercial bank	6.07	0	3
China Minsheng Banking Corporation	Joint stock commercial bank	5.99	2	27
China Everbright Bank	Joint stock commercial bank	4.36	3	11
Ping An Bank	Joint stock commercial bank	3.42	1	14
Hua Xia Bank	Joint stock commercial bank	2.68	0	7
Bank of Nanjing	Urban commercial bank	1.24	0	0
Bank of Ningbo	Urban commercial bank	1.12	0	5
Jiangsu Changshu Rural Commercial Bank	Rural commercial bank	0.17	0	0
Wuxi Rural Commercial Bank	Rural commercial bank	0.15	0	0
Jiangsu Suzhou Rural Commercial Bank	Rural commercial bank	0.12	0	0
Jiangsu Zhangjiagang Rural Commercial Bank	Rural commercial bank	0.11	0	0

Note: This table lists the name, nature, assets in 2019Q4, number of technology patents filed in 2018 and over the period 2008-2018 for each bank used in this study. The 19 banks are all publicly listed banks that have valid quarterly financial statement information.

Table 2: Summary Statistics

	Mean	Standard Deviation	Min	Max	N
MP Shock	-0.001	0.007	-0.017	0.028	612
Loan Growth (%)	4.044	3.258	-3.744	35.628	612
Bank Size	10.368	1.396	6.820	12.550	611
Leverage	0.936	0.011	0.910	0.971	611
Income-Cost Ratio	0.035	0.006	0.021	0.055	612
Loan-to-Deposit Ratio	0.014	0.002	0.009	0.023	608
Tech	8.351	24.095	0.000	201.000	612
Lending Tech	0.941	2.803	0.000	20.000	612
Non-Lending Tech	7.397	21.708	0.000	181.000	612
Tech-AI	0.222	1.122	0.000	11.000	612
Tech-BigData	2.150	6.105	0.000	45.000	612
Tech-Cloud Computing	0.059	0.235	0.000	1.000	612
Tech-Digitalization	4.080	12.372	0.000	106.000	612
Tech-Machine Learning	1.565	4.371	0.000	32.000	612
Tech-Blockchain	0.275	1.291	0.000	10.000	612
$\widetilde{Tech}$	0.000	1.000	-1.700	8.138	575
$\widetilde{LendingTech}$	0.000	1.000	-1.593	7.112	575
$Non-\widetilde{LendingTech}$	0.000	1.000	-1.673	8.065	575
$\widetilde{TechFin\ Exposure}$	0.000	1.000	-2.217	2.761	581
$\widetilde{TechFin\ Exposure\text{-}Payment}$	0.000	1.000	-2.188	2.618	581
$\widetilde{TechFin\ Exposure\text{-}Insurance}$	0.000	1.000	-1.953	3.251	581
$\widetilde{TechFin\ Exposure\text{-}Money\ Fund}$	0.000	1.000	-2.185	2.645	581
$\widetilde{TechFin\ Exposure\text{-}Investment}$	0.000	1.000	-2.227	2.944	581
$\widetilde{TechFin\ Exposure\text{-}Credit}$	0.000	1.000	-2.308	2.524	581
$\widetilde{TechFin\ Exposure\text{-}Credit\ Evaluation}$	0.000	1.000	-1.774	3.867	581

Note: This table presents the summary statistics of all variables used in this study. Detailed explanations of the definition of each variable can be found in Section 3.

Table 3: Baseline Results: Role of Technology Adoption in Monetary Policy Transmission

	DepVar: Loan Growth			
	(1)	(2)	(3)	(4)
MP Shock × L.Tech Adoption	0.146	0.550		
	(1.168)	(1.097)		
MP Shock × L.Lending Tech Adoption			18.414***	16.199***
			(4.283)	(5.322)
MP Shock × L.Non-Lending Tech Adoption			-3.165**	-2.013**
			(1.129)	(0.934)
MP Shock	119.040***	75.542**	117.866***	75.341**
	(18.813)	(27.430)	(27.809)	(36.041)
L.Tech Adoption	-0.008	0.001		
	(0.008)	(0.004)		
L.Lending Tech Adoption			0.029	-0.033
			(0.044)	(0.063)
L.Non-Lending Tech Adoption			-0.019***	-0.000
			(0.004)	(0.009)
L.Bank Size		-1.095***		-1.080**
		(0.279)		(0.443)
L.Leverage		-43.297**		-42.168
		(19.563)		(27.609)
L.Income-to-Cost Ratio		-104.757**		-103.545***
		(40.809)		(30.609)
L.Loan-to-Deposit Ratio		303.631*		289.743**
		(169.555)		(136.415)
Constant	4.206***	55.218**	4.203***	54.161**
	(0.136)	(20.372)	(0.024)	(26.864)
Observations	628	628	628	628
R2-Adjusted	0.114	0.182	0.120	0.184
Bank FE	YES	YES	YES	YES
Controls	NO	YES	NO	YES

Note: This table presents the results of regressing bank loan growth rate on the macro-level monetary policy shock, bank-level technology adoption and their interaction term. Bank fixed effects and other bank-level control variables are specified when indicated. The M2-based monetary policy shock and patent-based technology adoption are used in this table. Columns (1)-(2) show the results using the overall technology adoption and columns (3)-(4) show that distinguishing between lending-related and non-lending related technology adoption. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 4: Role of Technology Adoption: Accounting for Exposure to BigTech Competition

	DepVar: Loan Growth			
	(1)	(2)	(3)	(4)
MP Shock × L.$\widetilde{Tech}$	9.147	10.553		
	(10.813)	(11.969)		
MP Shock × L.$\widetilde{Lending\ Tech}$			27.265***	24.749***
			(5.409)	(5.341)
MP Shock × L.$\widetilde{Non\text{-}Lending\ Tech}$			-19.191*	-13.310
			(11.236)	(12.915)
MP Shock × L.$\widetilde{BigTech\ Exposure}$		-37.945*		-35.867*
		(20.273)		(20.434)
MP Shock	79.905	89.838	78.311	88.383
	(84.706)	(83.515)	(82.568)	(81.307)
L.$\widetilde{BigTech\ Exposure}$		-1.093		-1.128
		(0.780)		(0.785)
L.$\widetilde{Tech}$	-0.024	-0.042		
	(0.089)	(0.082)		
L.$\widetilde{Lending\ Tech}$			-0.071	-0.155
			(0.146)	(0.156)
L.$\widetilde{Non\text{-}Lending\ Tech}$			0.000	0.058
			(0.170)	(0.184)
L.Bank Size	-0.989	-1.596*	-0.989	-1.602*
	(0.704)	(0.934)	(0.708)	(0.936)
L.Leverage	-44.904*	-49.067*	-44.282	-48.313*
	(26.531)	(28.481)	(26.435)	(28.290)
L.Income-Cost Ratio	-105.159**	-105.937**	-105.170**	-107.144**
	(47.938)	(46.098)	(48.340)	(46.877)
L.Loan-to-Deposit Ratio	321.955**	318.502**	313.037*	317.731**
	(157.807)	(156.198)	(156.298)	(157.220)
Constant	55.598**	66.143**	55.125**	65.546**
	(26.177)	(29.649)	(26.179)	(29.483)
Observations	588	588	588	588
R2-Adjusted	0.186	0.194	0.185	0.193
Bank FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Note: This table presents the results of regressing bank loan growth rate on the macro-level monetary policy shock, bank-level exposure to BigTech competition, the non-competition component of bank's technology adoption, and the interaction terms between monetary policy shock and exposure to BigTech competition and between monetary policy shock and the non-competition component of technology adoption. Bank fixed effects and other bank-level control variables are specified when indicated. The M2-based monetary policy shock and patent-based technology adoption are used in this table. Columns (1)-(2) show the results using the overall non-competition component of technology adoption and columns (3)-(4) show that distinguishing between lending-related and non-lending related technology adoption that are also orthogonal to exposures to BigTech competition. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 5: First Stage Results

	$\widetilde{Tech}$		$\widetilde{LendingTech}$		$\widetilde{Non\text{-}Lending\ Tech}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Hangzhou (km)	-0.001**		0.002		-0.002***	
	(0.001)		(0.001)		(0.001)	
Time to Hangzhou (hour)		-0.141		0.336*		-0.198**
		(0.090)		(0.185)		(0.080)
College Enrolled	0.285***	0.273***	0.270***	0.297***	0.278***	0.262***
	(0.061)	(0.064)	(0.055)	(0.067)	(0.061)	(0.063)
L.Bank Size	-2.570***	-2.611***	-1.792***	-1.815***	-2.603***	-2.645***
	(0.548)	(0.563)	(0.421)	(0.434)	(0.553)	(0.569)
L.Leverage	10.957***	10.579**	4.886	6.102*	11.440***	10.869***
	(3.901)	(3.957)	(3.139)	(3.321)	(3.974)	(4.012)
L.Income-Cost Ratio	-0.803	-1.235	-15.912**	-16.490**	0.914	0.505
	(5.689)	(5.629)	(6.250)	(6.395)	(6.079)	(6.003)
L.Loan-to-Deposit Ratio	215.349***	216.432***	230.787***	234.236***	207.608***	208.383***
	(62.495)	(63.355)	(43.015)	(44.024)	(63.890)	(64.715)
Constant	13.646***	14.028***	8.327*	7.166	14.003***	14.571***
	(3.348)	(3.373)	(4.354)	(4.817)	(3.229)	(3.208)
Observations	588	588	588	588	588	588
R2-Adjusted	0.112	0.111	0.030	0.032	0.119	0.118
F-Statistics	12.718	13.235	8.897	8.503	15.746	16.761
Bank FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Note: This table presents the results of regressing the non-competition component of bank's overall, lending-related, and non-lending-related technology adoption on two instrumental variables, i.e., the branch-weighted distance (or hour) to Hangzhou and college enrollment ratio, and other bank-level controls. Bank and quarter fixed effects are specified. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 6: 2SLS IV Regression Results

	IV: Distance to Hangzhou + College Enrolled				IV: Hour to Hangzhou + College Enrolled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MP Shock × $\widetilde{L.Tech(IV)}$	23.368	53.428			22.251	52.196		
	(80.976)	(76.480)			(79.112)	(74.287)		
MP Shock × $\widetilde{L.LendingTech}$			24.006***	22.210***			23.893***	22.048***
			(5.935)	(5.287)			(5.905)	(5.255)
MP Shock × $\widetilde{L.Non\text{-}Lending\ Tech(IV)}$			-2.134	21.949			-2.865	21.141
			(47.308)	(49.024)			(48.451)	(49.952)
MP Shock × $\widetilde{L.BigTech\ Exposure}$		-46.470**		-42.161**		-46.226**		-41.952**
		(22.706)		(20.654)		(22.705)		(20.592)
MP Shock	84.354***	100.105***	83.436	97.188	84.223***	99.872***	83.327	96.985
	(29.396)	(24.369)	(81.431)	(82.856)	(29.335)	(24.194)	(81.315)	(82.659)
$\widetilde{L.BigTech\ Exposure}$		-0.857		-0.931		-0.856		-0.929
		(0.555)		(0.719)		(0.554)		(0.718)
$\widetilde{L.Tech(IV)}$	0.548*	0.529			0.544*	0.522		
	(0.305)	(0.345)			(0.303)	(0.341)		
$\widetilde{L.LendingTech}$			-0.110*	-0.134**			-0.110*	-0.134**
			(0.058)	(0.060)			(0.058)	(0.060)
$\widetilde{L.Non\text{-}Lending\ Tech(IV)}$			0.617	0.597			0.612	0.588
			(0.504)	(0.506)			(0.513)	(0.515)
N	588	588	588	588	588	588	588	588
R2	0.218	0.228	0.221	0.230	0.218	0.228	0.221	0.230
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of two-stage least square (2SLS) estimates of regressing bank loan growth rate on the macro-level monetary policy shock, bank-level exposure to BigTech competition, the non-competition component of bank's technology adoption, and the interaction terms between monetary policy shock and exposure to BigTech competition and between monetary policy shock and the non-competition component of technology adoption. The non-competition component of overall and non-lending related technology adoption is instrumented by the distance (or hour) to Hangzhou and college enrollment ratio, as indicated in the column titles. Bank fixed effects and other bank-level control variables are specified when indicated. The M2-based monetary policy shock and patent-based technology adoption are used in this table. Columns (1)-(2) (5)-(6) show the results using the overall non-competition component of technology adoption and columns (3)-(4) (7)-(8) show that distinguishing between lending-related and non-lending related technology adoption that are also orthogonal to exposures to BigTech competition. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 7: By Categories of Technologies Adopted by Banks

	AI	Bigdata	Cloud Computing	Digitalization	Machine Learning	Blockchain	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP Shock × L.$\widetilde{AI\ Tech}$	6.923						23.973
	(29.526)						(29.848)
MP Shock × L.$\widetilde{Big\ Data\ Tech}$		7.862					-21.996
		(8.646)					(28.936)
MP Shock × L.$\widetilde{Cloud\ Computing\ Tech}$			14.644**				20.031**
			(5.738)				(8.806)
MP Shock × L.$\widetilde{Digitalization\ Tech}$				11.745			47.810
				(11.547)			(32.392)
MP Shock × L.$\widetilde{Machine\ Learning\ Tech}$					9.139		-25.039
					(15.816)		(25.734)
MP Shock × L.$\widetilde{Blockchain\ Tech}$						-13.487	-25.391
						(25.080)	(28.275)
L.$\widetilde{AI\ Tech}$	-0.103						-0.345*
	(0.134)						(0.197)
L.$\widetilde{Big\ Data\ Tech}$		-0.072					-0.598
		(0.058)					(0.371)
L.$\widetilde{Cloud\ Computing\ Tech}$			-0.083				-0.111
			(0.063)				(0.091)
L.$\widetilde{Digitalization\ Tech}$				-0.011			0.647
				(0.082)			(0.400)
L.$\widetilde{Machine\ Learning\ Tech}$					-0.035		0.318
					(0.099)		(0.285)
L.$\widetilde{Blockchain\ Tech}$						-0.143	-0.210
						(0.122)	(0.136)
MP Shock × L.$\widetilde{BigTech\ Exposure}$	-38.124*	-37.479*	-38.405*	-38.114*	-38.244*	-34.769	-39.508
	(21.118)	(19.899)	(20.116)	(20.333)	(20.531)	(21.835)	(24.496)
MP Shock	89.843	89.233	89.752	89.840	90.271	85.337	88.875
	(85.432)	(82.780)	(81.522)	(83.387)	(84.656)	(86.227)	(89.482)
L.$\widetilde{BigTech\ Exposure}$	-1.119	-1.117	-1.090	-1.070	-1.095	-1.121	-1.267
	(0.793)	(0.787)	(0.784)	(0.777)	(0.782)	(0.787)	(0.860)
Observations	588	588	588	588	588	588	588
R2-Adjusted	0.194	0.194	0.195	0.193	0.193	0.194	0.187
Bank FE	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of regressing bank loan growth rate on the macro-level monetary policy shock, bank-level exposure to BigTech competition, the non-competition component of bank's technology adoption (in six categories), and the interaction terms between monetary policy shock and exposure to BigTech competition and between monetary policy shock and the non-competition component of technology adoption. Columns (1)-(6) show the results using each category of technology one at a time and column (7) show that using all six categories at the same time. Bank fixed effects and other bank-level control variables are specified when indicated. The M2-based monetary policy shock and patent-based technology adoption (by categories) are used in this table. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 8: By Categories of Financial Service in BigTech Penetration

	Payment	Insurance	Fund	Investment	Credit	Credit Evaluation
	(1)	(2)	(3)	(4)	(5)	(6)
MP Shock × L.$\widetilde{BigTech\ Exposure}$	-33.972*	-38.781*	-33.940*	-30.425	-36.277*	-56.874*
	(17.722)	(20.227)	(20.025)	(22.082)	(19.624)	(28.238)
L.$\widetilde{BigTech\ Exposure}$	-2.060**	-0.264	-1.080	-1.079	-1.088	-0.717*
	(1.001)	(0.497)	(0.792)	(0.700)	(0.883)	(0.413)
MP Shock × L.$\widetilde{Tech}$	10.867	10.828	10.310	9.055	11.952	11.530
	(12.361)	(11.395)	(11.941)	(11.553)	(12.257)	(11.994)
MP Shock	86.153	91.951	87.525	87.316	88.694	95.186
	(81.407)	(85.857)	(81.941)	(82.405)	(83.763)	(85.246)
L.$\widetilde{Tech}$	-0.056	-0.012	-0.047	-0.052	-0.030	-0.031
	(0.079)	(0.088)	(0.077)	(0.080)	(0.083)	(0.090)
Observations	588	588	588	588	588	588
R2-Adjusted	0.202	0.188	0.194	0.192	0.192	0.201
Bank FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Note: This table presents the results of regressing bank loan growth rate on the macro-level monetary policy shock, bank-level exposure to BigTech competition (in six areas of financial services), the non-competition component of bank's technology adoption, and the interaction terms between monetary policy shock and exposure to BigTech competition and between monetary policy shock and the non-competition component of technology adoption. Columns (1)-(6) show the results using each category of BigTech exposure. Bank fixed effects and other bank-level control variables are specified when indicated. The M2-based monetary policy shock and patent-based technology adoption are used in this table. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 9: Robustness Check: Using Price-based Monetary Policy Measurement

	FR007				Δ FR007			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MP $\times$ L.$\widetilde{\textit{Total Tech}}$	-0.048	0.042			-0.315**	-0.334**		
	(0.154)	(0.191)			(0.124)	(0.138)		
MP $\times$ L.$\widetilde{\textit{Lending Tech}}$			-0.530***	-0.518***			-0.443**	-0.468**
			(0.098)	(0.099)			(0.209)	(0.218)
MP $\times$ L.$\widetilde{\textit{Non-Lending Tech}}$			0.361**	0.458**			0.052	0.049
			(0.140)	(0.170)			(0.248)	(0.253)
MP $\times$ L.$\widetilde{\textit{BigTech Exposure}}$		-0.348		-0.356		-0.025		-0.027
		(0.272)		(0.265)		(0.243)		(0.224)
MP	-1.122**	-1.056*	-1.132**	-1.047*	-0.954	-0.942	-0.963	-0.951
	(0.517)	(0.578)	(0.506)	(0.554)	(0.813)	(0.819)	(0.794)	(0.789)
L.$\widetilde{\textit{BigTech Exposure}}$		1.632		1.588		-1.091		-1.104
		(1.258)		(1.255)		(0.789)		(0.787)
L.$\widetilde{\textit{Total Tech}}$	0.004	-0.224			-0.097	-0.141**		
	(0.468)	(0.584)			(0.062)	(0.064)		
L.$\widetilde{\textit{Lending Tech}}$			1.281***	1.324***			-0.067	-0.123
			(0.250)	(0.250)			(0.151)	(0.151)
L.$\widetilde{\textit{Non-Lending Tech}}$			-1.000**	-1.316**			-0.052	-0.051
			(0.473)	(0.575)			(0.142)	(0.141)
L.Bank Size	-1.002**	-0.619	-0.989*	-0.648	-1.347**	-1.890**	-1.348**	-1.895**
	(0.490)	(0.747)	(0.494)	(0.747)	(0.618)	(0.912)	(0.623)	(0.912)
L.Leverage	-59.585*	-61.368*	-59.678*	-61.134*	-37.202	-36.611	-36.429	-35.836
	(34.822)	(34.336)	(34.597)	(34.030)	(27.078)	(28.405)	(27.025)	(28.365)
L.Income-to-Cost Ratio	-115.608**	-117.717**	-117.019**	-117.876**	-107.927**	-107.639**	-106.317**	-106.574**
	(47.879)	(49.367)	(48.305)	(49.358)	(51.400)	(49.800)	(50.937)	(49.440)
L.Loan-to-Deposit Ratio	522.571**	534.739**	517.476**	525.365**	331.137*	358.143*	319.333*	348.514**
	(220.202)	(221.155)	(213.766)	(214.438)	(168.875)	(177.852)	(163.692)	(172.009)
Constant	70.390**	67.666**	70.463**	67.846**	52.038*	56.956*	51.435*	56.387*
	(33.185)	(30.905)	(32.958)	(30.617)	(27.167)	(29.183)	(27.105)	(29.068)
Observations	588	588	588	588	588	588	588	588
R2-Adjusted	0.238	0.243	0.241	0.245	0.184	0.188	0.183	0.188
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of regressing bank loan growth rate on the macro-level monetary policy shock, bank-level exposure to BigTech competition, the non-competition component of bank's technology adoption, and the interaction terms between monetary policy shock and exposure to BigTech competition and between monetary policy shock and the non-competition component of technology adoption. Bank fixed effects and other bank-level control variables are specified when indicated. The price-based monetary policy shock and patent-based technology adoption are used in this table. Specifically, columns (1)-(4) and columns (5)-(8) show the results when the level and the change of FR007 are used as the monetary policy variable, respectively. Columns (1)-(2) (5)-(6) show the results using the overall non-competition component of technology adoption and columns (3)-(4) (7)-(8) show that distinguishing between lending-related and non-lending related technology adoption that are also orthogonal to exposures to BigTech competition. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 10: Robustness Check: Using Alternative Technology Adoption Measurement

	$\widetilde{Term\ Count}$		Patent Dummy		Term Dummy	
	(1)	(2)	(3)	(4)	(5)	(6)
MP Shock × L.Lending Tech	27.744	6.868	30.295	-2.202	-32.490	-66.945
	(47.281)	(48.533)	(52.089)	(53.559)	(37.138)	(44.595)
MP Shock × L.Non-Lending Tech	-16.143	-8.397	-27.077	-71.220*	-144.819**	-179.853***
	(43.692)	(44.104)	(39.476)	(42.818)	(64.685)	(63.984)
MP Shock × L. $\widetilde{BigTech\ Exposure}$		-37.352*		-61.122**		-68.658**
		(20.653)		(24.350)		(30.120)
MP Shock	80.929***	87.537***	86.534***	128.459***	224.967***	291.805***
	(23.019)	(23.559)	(23.978)	(29.444)	(59.406)	(103.411)
L.Lending Tech	0.288	0.224	-0.219	-0.496	0.459	0.425
	(0.263)	(0.264)	(0.440)	(0.446)	(0.331)	(0.323)
L.Non-Lending Tech	-0.132	-0.145	-0.240	-0.227	-0.478	-0.293
	(0.258)	(0.259)	(0.384)	(0.381)	(0.744)	(1.765)
L.$\widetilde{BigTech\ Exposure}$		-1.064**		-1.231**		-0.875
		(0.500)		(0.506)		(0.742)
Observations	588	588	588	588	588	588
R2-Adjusted	0.184	0.191	0.184	0.197	0.200	0.215
Bank FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Note: This table presents the results of regressing bank loan growth rate on the macro-level monetary policy shock, bank-level exposure to BigTech competition, the bank's technology adoption (by lending-related or not), and the interaction terms between monetary policy shock and exposure to BigTech competition and between monetary policy shock and the technology adoption. Bank fixed effects and other bank-level control variables are specified when indicated. The M2-based monetary policy shock is used throughout this table. Difference technology adoption measures are used across columns, specifically, columns (1)-(2) show the results when it is measured by the count of technological terms in banks' annual reports (derived from the residual approach and thus orthogonal to the exposure to BigTech competition), columns (3)-(4) show that when it is measured by a dummy which takes value of 1 if the bank has at least one technology patent, columns (5)-(6) show that when it is measured by a dummy which takes value of 1 if the bank has mentioned technological terms for at least once in its reports. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 11: Robustness Check: Horse Race with Other Factors

	DepVar: Loan Growth			
	(1)	(2)	(3)	(4)
MP Shock × L.$\widetilde{Tech}$	21.458	8.488		
	(13.192)	(12.076)		
MP Shock × L.$\widetilde{Lending\ Tech}$			17.292*	15.515*
			(9.172)	(8.514)
MP Shock × L.$\widetilde{Non\text{-}Lending\ Tech}$			2.493	-7.871
			(17.843)	(21.213)
MP Shock × L.$\widetilde{TechFin\ Exposure}$		-131.322		-129.782
		(138.972)		(139.382)
MP Shock × L.Bank Size	45.543**	-48.934	42.766**	-50.067
	(18.243)	(99.204)	(18.184)	(101.964)
MP Shock × L.Leverage	27.942**	26.324**	27.932**	26.198**
	(12.107)	(12.811)	(12.057)	(12.711)
MP Shock × L.Income-to-Cost Ratio	-157.194*	-121.685**	-153.103*	-118.375**
	(86.558)	(49.821)	(84.432)	(48.186)
MP Shock × L.Loan-to-Deposit Ratio	27.284	58.549	1.827	36.346
	(133.507)	(147.806)	(142.577)	(153.401)
MP Shock	-2536.895*	-1537.836	-2484.313*	-1493.755
	(1311.374)	(1939.128)	(1328.927)	(1953.240)
L.$\widetilde{TechFin\ Exposure}$		-1.234		-1.248
		(0.828)		(0.833)
L.$\widetilde{Tech}$	-0.019	-0.108		
	(0.077)	(0.068)		
L.$\widetilde{Lending\ Tech}$			-0.026	-0.071
			(0.143)	(0.142)
L.$\widetilde{Non\text{-}Lending\ Tech}$			-0.022	-0.071
			(0.161)	(0.165)
L.Bank Size	-1.212	-1.758*	-1.206	-1.757*
	(0.749)	(0.987)	(0.754)	(0.991)
L.Leverage	-0.539*	-0.497*	-0.534*	-0.493*
	(0.275)	(0.266)	(0.274)	(0.266)
L.Income-to-Cost Ratio	-1.027**	-1.025**	-1.023**	-1.027**
	(0.476)	(0.443)	(0.477)	(0.445)
L.Loan-to-Deposit Ratio	3.423**	3.461**	3.317**	3.385**
	(1.537)	(1.433)	(1.517)	(1.421)
Constant	65.872**	67.769**	65.479**	67.516**
	(27.666)	(28.392)	(27.642)	(28.423)
Observations	588	588	588	588
R2-Adjusted	0.221	0.231	0.219	0.229
Bank FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Note: This table presents the results of regressing bank loan growth rate on the macro-level monetary policy shock, bank-level exposure to BigTech competition, the non-competition component of bank's technology adoption, and the interaction terms between monetary policy shock and every other variable including control variables. Control variables include bank size, leverage, income-to-cost ratio, and loan-to-deposit ratio. Bank fixed effects are specified when indicated. The M2-based monetary policy shock and patent-based technology adoption are used in this table. Columns (1)-(2) show the results using the overall non-competition component of technology adoption and columns (3)-(4) show that distinguishing between lending-related and non-lending related technology adoption that are also orthogonal to exposures to BigTech competition. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Appendix

Technology Adoption and the Bank Lending Channel of Monetary Policy Transmission

Table A1: BigTech Penetration Measurement Structure

Aggregate Usage	Payment	Number of payments per user
		Amount of payments per user
		Share of frequent user (have 50+ activities per year) in total user (have 1+ activities per year)
	Insurance	Number of users with insurance policies purchased in Alipay per ten thousand users
		Number of insurance policies purchased in Alipay per user
		Amount of insurance policies purchased in Alipay per user
	Loan	Number of users that have consumption loans in Alipay per ten thousand users
		Number of consumption loans per user
		Amount of consumption loans per user
		Number of users that have SME business loans in Alipay per ten thousand users
		Number of SME business loans per SME owner
		Amount of SME business loans per SME owner
	Money Market Fund	Number of purchase transaction of Yu'e Bao* per user
		Amount of shares purchased of Yu'e Bao per user
		Number of users that have purchased Yu'e Bao per ten thousand users
	Investment	Number of online investment per user
		Amount of online investment per user
		Number of users that have invested online per ten thousand users
	Credit Evaluation	Number of calls for credit evaluation per user
		Number of users that have used credit score-based services per ten thousand users

Note: (1) The financial services mentioned in the table all refer to that conducted in Alipay; (2) We use the broad measurements of usage, as well as the its first three subcategorical measurements of payment, insurance, and loan within the usage measurement. For the subcategorical measurements of money market fund, investment, and credit evaluation, the time span is much shorter, so we do not use them in the analysis. (3) The measurements are constructed based on nondimensionalization of the 20 root indicators. The original data for these 20 indicators are not publicly available, and we can only access the province-level data for the aggregated FinTech usage, and the subcategorical FinTech usage of payment, insurance, and loan.

*Yu'e Bao is the name of a money market fund. It is the largest fund in China, and also was the largest in the world before falling behind the JPMorgan U.S. Government Money Market Fund in 2020. It lets users of Alipay invest their spare cash for short periods before they spend their money online. Tianhong Asset Management, an affiliate of Ant Financial, is the investment firm which manages the fund. Its assets under management amounted to $157 billion at the end of 2019, down from a peak of $270 billion in March 2018.

Table A2: Top 5 Banks in BigTech Exposure

Bank Name	Aggregated Usage	Payment	Insurance	Money Fund	Investment	Credit	Credit Investigation
			Year 2008				
Bank of Ningbo	1.416	1.901	1.566	1.670	1.311	1.402	1.314
Industrial Bank	1.264	1.607	1.273	1.446	1.186	1.275	1.255
Bank of Nanjing	1.359	1.760	1.385	1.577	1.254	1.324	1.558
China CITIC Bank	1.251	1.547	1.276	1.412	1.194	1.249	1.215
Shanghai Pudong Development Bank	1.259	1.591	1.302	1.441	1.206	1.244	1.231
			Year 2013				
Bank of Ningbo	1.430	1.924	1.581	1.690	1.329	1.407	1.353
Bank of Nanjing	1.366	1.775	1.404	1.590	1.274	1.327	1.512
Industrial Bank	1.249	1.572	1.262	1.425	1.175	1.256	1.241
Ping An Bank	1.287	1.640	1.286	1.455	1.214	1.301	1.256
Shanghai Pudong Development Bank	1.254	1.579	1.298	1.439	1.201	1.238	1.237
			Year 2018				
Bank of Ningbo	1.309	1.607	1.425	1.430	1.214	1.340	1.164
Ping An Bank	1.275	1.522	1.369	1.337	1.198	1.293	1.187
Bank of Nanjing	1.297	1.566	1.404	1.436	1.225	1.313	1.168
Bank of Beijing	1.273	1.491	1.338	1.330	1.240	1.278	1.181
China Merchants Bank	1.233	1.446	1.317	1.288	1.170	1.245	1.158

Table A3: First Stage Results of Original Technology Adoption on IVs

	Total Tech Adoption		Lending Tech Adoption		Non-Lending Tech Adoption	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance to Hangzhou (km)	-0.032***		0.004		-0.035***	
	(0.011)		(0.002)		(0.009)	
Time to Hangzhou (hour)		-3.588**		0.668*		-4.227***
		(1.405)		(0.358)		(1.129)
University Enrolled	5.713***	5.451***	0.658***	0.713***	5.036***	4.722***
	(1.233)	(1.281)	(0.140)	(0.166)	(1.109)	(1.139)
L.Bank Size	-49.781***	-50.383***	-3.959***	-4.013***	-45.770***	-46.324***
	(10.523)	(10.760)	(1.029)	(1.049)	(9.586)	(9.801)
L.Leverage	189.958**	176.242**	7.009	9.260	182.486***	166.612**
	(72.430)	(70.753)	(7.099)	(6.842)	(66.890)	(65.224)
L.Income-Cost Ratio	-71.683	-83.865	-43.892***	-45.464***	-32.643	-43.391
	(106.818)	(105.764)	(15.029)	(15.495)	(102.457)	(101.058)
L.Loan-to-Deposit Ratio	4257.475***	4275.553***	543.477***	551.310***	3710.064***	3720.853***
	(1223.892)	(1238.928)	(99.100)	(101.240)	(1132.225)	(1145.201)
Constant	288.123***	300.044***	22.387**	20.148*	265.823***	279.886***
	(68.297)	(69.007)	(9.520)	(10.390)	(60.335)	(60.399)
Observations	628	628	628	628	628	628
R2-Adjusted	0.409	0.408	0.340	0.340	0.408	0.407
F-Statistics	14.728	16.146	8.572	8.194	19.059	21.889
Bank FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the results of regressing bank's overall, lending-related, and non-lending-related technology adoption on two instrumental variables, i.e., the branch-weighted distance (or hour) to Hangzhou and college enrollment ratio, and other bank-level controls. Bank and quarter fixed effects are specified. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table A4: 2SLS IV Regression Results Using Original Technology Adoption

	IV: Distance to Hangzhou + College Enrolled		IV: Hour to Hangzhou + College Enrolled	
	(1)	(2)	(3)	(4)
MP Shock × L.Tech Adoption (IV)	1.231		1.201	
	(1.421)		(1.399)	
MP Shock × L.Lending Tech Adoption		12.194**		12.179***
		(4.748)		(4.727)
MP Shock × L.Non-Lending Tech Adoption (IV)		-0.426		-0.455
		(1.739)		(1.728)
MP Shock	74.690**	74.431**	74.858**	74.568**
	(30.835)	(31.060)	(30.889)	(31.112)
L.Tech Adoption (IV)	0.031**		0.031**	
	(0.014)		(0.014)	
L.Lending Tech Adoption		-0.041		-0.041
		(0.028)		(0.028)
L.Non-Lending Tech Adoption (IV)		0.037**		0.036**
		(0.016)		(0.015)
N	588	588	588	588
R2	0.220	0.224	0.220	0.224
Bank FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Note: This table presents the results of two-stage least square (2SLS) estimates of regressing bank loan growth rate on the macro-level monetary policy shock, the bank's technology adoption, and the interaction terms between monetary policy shock and the technology adoption. The overall and non-lending related technology adoption is instrumented by the distance (or hour) to Hangzhou and college enrollment ratio, as indicated in the column titles. Bank fixed effects and other bank-level control variables are specified when indicated. The M2-based monetary policy shock and patent-based technology adoption are used in this table. Columns (1) and (3) show the results using the overall technology adoption and columns (2) and (4) show that distinguishing between lending-related and non-lending related technology adoption. Standard errors are clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

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