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Keywords: Innovation; FinTech; Monetary Policy Transmission; Bank Lending Channel
JEL Codes: E52; G21; G23

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1 Introduction

In recent years, financial technologies (FinTech) have been reshaping the landscape of the finance sector and the way financing business is served. What marks the current wave of FinTech differently from the past is the disintermediation and disruption brought by players outside the traditional financial market such as the big technology (BigTech) companies. On one hand, in response to the advancing competition from BigTech's participation in the financing market, banks have become increasingly enthusiastic about developing in-house technologies. Analyzing the effects of banks' use of FinTech innovations is particularly important for understanding the substance of modern finance and its interaction with the real economy (He et al. 2021). On the other hand, as stated in Philippon (2016) and Lagarde (2018), FinTech brings a "brave new world" for monetary policymakers. In the COVID-19 crisis, technology has served an important role in meeting the increased financial services demand and distributing government-guaranteed credit, thus fulfilling the monetary policy.[1] Despite these perceptions, the relationship between FinTech and monetary policy remains a missing link in the literature and little is known about the implications of the use of new technologies in the banking sector on monetary policy transmission.

The research questions in this paper are twofold. First, theoretically speaking, how should banks' technological innovation interact with the lending channel of monetary policy? Second, in the data, what are the patterns of bank-level technology innovation and whether it alters the bank loan growth in response to monetary policy changes? To the best of our knowledge, we are the first to study the heterogeneity in the bank lending channel of monetary policy arising from technological innovation.

We first propose a theoretical model with earnings-based borrowing constraints in the spirit of Holmstrom and Tirole (1997) (see Lian and Ma 2021 for empirical evidence of earnings-based borrowing constraints). In the model, a bank's technological innovation

[1] See Erel and Liebersohn (2022) and Kwan et al. (2023) for evidence from the U.S. Paycheck Protection Program, and Core and De Marco (2023) for evidence from the Italian public guarantee scheme.

relaxes firms' earnings-based borrowing constraints and, consequently, allows the firms to increase their leverage and investments. At the same time, this increased leverage makes the firms' investments more sensitive to changes in the banks' lending interest rates. Therefore, the model predicts that technological innovation amplifies the bank lending channel of monetary policy transmission.

Next, we present empirical investigations of the predictions from theory. First, we construct a new measurement of banks' use of new technologies. To investigate the effects of new technologies in banking, a lack of appropriate bank-level technology data is the biggest challenge. Traditional methods, as documented in the literature, typically rely on IT spending metrics, such as the number of personal computers and expenditures on specific hardware and software (Pierri and Timmer 2022, Kwan et al. 2023, He et al. 2021, Modi et al. 2022). We innovate by using banks' patent applications as a measure. This approach not only identifies the technologies being used but also encompasses recent advancements potentially advantageous to BigTech firms in the finance sector, such as artificial intelligence (AI), big data, and cloud computing. Specifically, we collect the patent application documents of banks, which include a detailed technical description of the invention and its purpose or application scenarios. To account for the variations of the importance across patents, we use the number of forward citations as a weighting factor and aggregate the number of patent applications to the bank-quarter level. Based on careful reading and extraction of the patent files, our patent-based technology measurement has two unique features. First, it can tell whether banks' new technologies are lending-related or not. Second, it classifies the new technologies into the following six categories: AI, big data, cloud computing, digitalization, machine learning, and blockchain.

We examine the validity of our patent-based technology measurement by comparing it with two alternative measurements for gauging banks' FinTech usage. Following Chen and Srinivasan (2023), we employ textual analysis of banks' reports, focusing on the frequency of technology-related terms, to gauge their technology visions. This text-based approach can also classify technologies into lending-related or not and the aforementioned six categories. By definition, the patent-based measurement gives more tangible information about the actual use of technologies in the banking business, while the text-based one accounts more for banks' perceptions and intentions rather than the actual application. As another alternative, we consider the number of customers using mobile and internet banking, which is a key indicator of FinTech lending as defined in recent studies (Buchak et al. 2018, Fuster et al. 2019). We find that the trends in banks' technology development, as revealed by our patent-based measurement, align closely with these alternative measures. Additionally, all these measurements demonstrate significant and positive correlations, reinforcing the validity of our approach.

With the patent-based measurement of banks' technological innovation, we first explore its determinants by analyzing how it correlates with various bank-level characteristics. Next, we examine its role in monetary policy transmission by interacting it with monetary policy shocks, which is constructed following the approach in Chen et al. (2018), and then test whether and how the response in bank loan growth to monetary policy is affected. Local projections (Jordà 2005) are also used to investigate the dynamic impacts of new banking technologies over time. In addition, we provide a battery of robustness checks by running a horse race between technological innovation and other bank characteristics and using alternative monetary policy indicators and restricted samples.

Our main analysis utilizes a dataset comprising quarterly financial data from 42 publicly listed Chinese banks, spanning from 2008Q1 to 2019Q4. This dataset is combined with our bank-level measurement of technological innovation and exposure to BigTech penetration, local economic conditions, and economy-wide monetary policy shocks. The Chinese banking industry provides a good laboratory to study the influence of FinTech on traditional banks because of China's leading role in FinTech innovation, making findings in this study particularly relevant for other countries that are rapidly advancing in FinTech. Besides, different from studies based on data from the 1990s or early 2000s, our analysis captures the impact of the latest and more disruptive financial innovations, reflecting the accelerated and evolving pace of FinTech development in recent years.

Our main findings are the following. First, we document that bank size, cost pressure, and exposure to BigTech demonstrate significant and positive associations with banks' patenting. Second, lending-related technology innovation significantly strengthens the transmission of the bank lending channel, meanwhile, the effects of innovations that are unrelated to lending activities are ambiguous. When faced with an expansionary monetary policy shock, the more advanced the banks' lending technologies, the larger the increase in loan growth. Specifically, a one standard deviation change towards an easing monetary policy brings a 0.07 standard deviation increase in banks' loan growth, and an increase in lending-related technological innovation by one standard deviation enlarges the transmission effect to 0.12 standard deviations. Moreover, the transmission-enhancing effect is persistent and remains strong for ten quarters after the monetary policy shock. The baseline findings are robust when we use alternative measurements of monetary policy and technological innovation, and when we conduct a horse race between innovation and other bank-level characteristics. In addition, we extend discussions to the heterogeneity across the six types of technologies and the role of the pre-COVID technology level in the monetary policy transmission during the COVID-19 period. We show that the transmission-enhancing effect of technological innovation is the most pronounced regarding big data and machine learning technologies and is still present during the pandemic.

To the best of our knowledge, this paper provides the first evidence of the impact of banks' technological innovation on the bank lending channel of monetary policy transmission. While the potential influence of FinTech on the effectiveness of monetary policy is acknowledged in both policy-making and academic discussions (Smets 2016, Philippon 2016), it remains largely unexplored in empirical research. By identifying specific technologies used by banks and determining their relevance to lending activities, we create granular measurements that allow us to uncover the mechanisms by which technological innovation influences the effectiveness of the bank lending channel, thereby testing our theoretical predictions.

The findings of this study have important implications. In the context of FinTech's rapid evolution, it becomes crucial for monetary policymakers to consider the impact of banks' adoption of new lending technologies and their interactions with BigTech lenders when adjusting monetary policy. Furthermore, the relationship between banks' technological innovation and their exposures to BigTech competition aligns with Lagarde (2018) monetary authorities and financial regulators should broaden their focus from solely financial entities to financial activities. In addition, academic explorations of banks' technological innovation should extend beyond mere bank performance, as it bears significant macroeconomic impacts and this area warrants further research.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 provides a theoretical model and testable empirical predictions. Section 4 describes the data and Section 5 presents the empirical results. Section 6 provides further discussions. Section 7 concludes.

2 Literature Review

This paper relates to four branches of literature. First, we add to studies on the macroeconomic impacts of innovation in the banking sector by discussing its influence on the bank lending channel of monetary policy transmission. Second, we relate to factors determining monetary policy transmission and we bring in the new and influencing determinant of FinTech innovation. Third, this paper lies in the expanding literature on the relationship between FinTech and traditional banks, and we contribute by accounting for banks' exposure to BigTech competition in banks' in-house technological innovation. Here, our paper also has a link to the literature on the determinants of financial innovation and patenting.

To begin with, studies of the macroeconomic impacts of technological progress in the banking industry are limited, though the issue has been catching more attention in recent years with the rise of FinTech. 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 of improvements in costs and lending capacities. More recently, Beck et al. (2016) and Pierri and Timmer (2022) examine the effects of IT on financial stability with opposite findings: the latter finds that pre-crisis IT adoption enhances financial stability in the post-crisis years while the former shows that financial innovation increases risk-taking and fragility. He et al. (2021) distinguish between technologies that enhance soft information and link bank IT expenditure with lending. 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 COVID-19 crisis, respectively, Lin et al. (2021), Kwan et al. (2023) and Branzoli et al. (2023) document the importance of information technology as a growth engine for banking.

The relatively scant empirical evidence and somewhat inconclusive findings in the literature are partly due to the difficulty of gauging the operation of multi-dimensional technologies, in particular, FinTech. 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 neither includes in-house inventions nor allows granular classification of technologies. Moreover, the type of technologies employed by commercial banks captured by those measurements, especially when the study period is the early 2000s or earlier, can be different from today's technologies such as AI, big data, and cloud computing. For example, financial patents hardly existed at all in the last millennium (Lerner et al. 2023). Our measurement of banks' use of new technologies 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 invented and their purpose, thus capturing a more detailed and informative landscape of technological progress in the banking industry.

Second, we are the first to provide evidence of technological innovation 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, Gambacorta 2005, Gambacorta and Marques-Ibanez 2011, Brissimis et al. 2014, Drechsler et al. 2017, Gomez et al. 2021). New banking technologies have been documented to affect banks' lending activities by extending credit access, reducing agency costs, and improving hard information processing (Petersen and Rajan 2002, Berger and DeYoung 2006, He et al. 2021), but have not been examined as a factor in the bank lending channel of monetary policy transmission. Buchak et al. (2023), Wang et al. (2022), and Hasan et al. (2020) 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; more recently, De Fiore et al. (2022), Huang et al. (2022), and Erel et al. (2023) compare the responses to monetary policy changes between BigTech lenders or online banks and traditional banks. However, they do not consider the consequences of banks' use of FinTech. Our evidence suggests that technological progress within banks and the technological pressure outside banks are both important factors in explaining 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 the 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. (2022) and

Boot et al. (2021) show that FinTech would make the loan markets more competitive, Buchak et al. (2023) indicate that FinTech lenders substitute for banks in loans that are easily sold, while Erel and Liebersohn (2022) provide an argument of complementarity between them based on the evidence from the U.S. Paycheck Protection Program. However, on one hand, the existing literature does not take into account the strategies adopted by traditional banks such as developing in-house technologies in response to the competition from non-bank FinTech lenders.[2] On the other hand, the current findings rely on the data from the United States or Europe, where the FinTech credit scale is small compared to that of banks, thus its implications on the relationship between the two types of players are limited.[3]

We contribute to this strand of literature by examining the role of exposure to financial services provided by BigTech lenders in banks' in-house innovation, and we account for the effects of both banks' exposure to BigTech competition and their in-house innovation on the bank lending channel simultaneously. Besides, we provide evidence using the bank and BigTech data from China, which is the key 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).

Here, our paper also adds to the literature on the determinants of financial innovation and patenting (see Lerner et al. 2023 for an overview). Initial contributions to that literature, including Lerner (2002, 2006), Hall et al. (2009) and Komulainen and Takalo (2014), were largely inspired by the changes in the legal treatment of financial patents in the United States. More recent contributions such as Chen et al. (2019), Fu and Mishra (2022) and Jiang et al. (2021) provide patent-based evidence of FinTech innovations. However, the literature uses either U.S. or European data and focuses rarely exclusively on the banking sector. Our evidence provides a window into the nature of patenting and

[2] See, e.g., "Big Banks Stake Fintech Claims With Patent Application Surge":`https://www.wsj.com/articles/BL-CIOB-9707`, and "JPMorgan plots 'astonishing' $12bn tech spend to beat fintechs": `https://www.ft.com/content/e543adf0-8c62-4a2c-b2d9-01fdb2f595cc`.

[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.

innovation in the banking sector in China at the frontier of FinTech development.

3 Theoretical Model

Our model borrows central ideas from Holmstrom and Tirole (1997). As in their model, firms' borrowing constraints are earning-based, stemming from the firms' moral hazard problem, and the borrowing constraints can be alleviated if banks engage in costly monitoring.

3.1 Assumptions

We consider a setting in which a *firm* with access to investment projects and a competitive *bank* with access to liquid funds interact. The firm and bank are risk neutral and there is no time preference. For simplicity, we assume that the firm has no liquid funds to be invested in its project. Therefore, the firm must tap into the bank to finance its investment. The firm offers the bank a *repayment* of $\rho \in [0, \infty)$ for the amount $L \in [0, \infty)$ the bank *lends* to the firm. Since the firm's investment is entirely bank-debt financed, we may also denote the firm's *investment* level by L.

Following Holmstrom and Tirole (1997) the firm chooses between two projects and invests an amount of L in the chosen project. A good project succeeds with probability $\sigma \in (0, 1)$ in which case it pays a verifiable return. For simplicity, we work with the standard constant elasticity return function of AL^a in which $A \in (1, \infty)$ and $a \in (0, 1)$. A bad project produces no verifiable returns. Instead, it yields non-verifiable private utility $U \in (0, \infty)$ per unit of investment for the firm's decision maker. Besides the private utility, project choice is non-verifiable; everything else is verifiable to third parties.

The bank can flexibly raise funds at a constant *interest rate* $r \in [0, \infty)$. As an investment in the bad project produces no verifiable income, the bank is not willing to lend if its credit analysis predicts that the firm will choose the bad project. However, as in Holmstrom and Tirole (1997), the bank can eliminate the bad project from the firm's action set by incurring a *monitoring cost* $\mu \in [0, \infty)$ per unit of lending. We assume that the private utility U associated with the bad project is large enough to make the bad project privately attractive to the firm unless the bank monitors. We establish this condition explicitly at the end of the next subsection.

The game describing the interactions of the firm and the bank proceeds in three stages. In stage 1 the firm and bank sign a loan contract: the firm's behavior consists of the set of repayment promises $\rho \in [0, \infty)$ and loan amount proposals $L \in [0, \infty)$, and the bank's strategy consists of a mapping from the set of the firm's loan contract offers $(L, \rho) \in [0, \infty)^2$ into the set of lending and monitoring decisions {lending, no-lending}×{monitoring, no-monitoring}. In stage 2 the firm chooses the project, and makes an investment according to the contract. The firm's project choice in this stage may be described by a mapping from the set of the bank's monitoring decisions into the set of projects {good project, bad project}. In stage 3, the project return is realized, and claims are settled according to the contract.

We seek subgame perfect equilibria in which the bank finances and monitors the firm whenever the bank's expected payoffs to lending and monitoring are larger than from no-lending and no-monitoring and neither finances nor monitors the firm otherwise. The firm offers a loan contract to maximize its expected profits given the bank's behavior, and chooses the good project if the bank monitors, but the bad project otherwise.

3.2 Equilibrium Investment and Lending

The expected payoff of the bank that chooses to finance and monitor the firm when the firm offers a loan contract $(L, \rho) \in [0, \infty)^2$ is given by

$$\Pi(L, \rho) = \sigma \min\{\rho, AL^a\} - (1 + r + \mu)L. \tag{1}$$

The first term on the right-hand side of equation (1) captures the bank's expected gross return for extending a loan of size L to the firm. As it shows, we consider a standard debt contract in which the bank has seniority if the firm cannot honor its promise. The second term captures the bank's cost of making the loan. The payoff to a bank that chooses to lend nothing is 0, whereas the payoff to a bank that chooses to lend but does not monitor is $-(1+r)L < 0$. Therefore, in equilibrium, the firm is either investing in the good project with funds supplied by a monitoring bank or no investment is made.

The expected payoff of the firm investing in the good project and offering a loan contract $(L, \rho) \in [0, \infty)^2$ may be expressed as

$$\Pi^F(L, \rho) = \sigma(AL^a - \min\{\rho, AL^a\}). \tag{2}$$

With probability σ the firm's project succeeds and gives the return of AL^a. If $AL^a \geq \rho$, it is optimal for the firm to make the promised repayment ρ to the bank. If $AL^a < \rho$ or if the project fails (with probability $1-\sigma$) the firm defaults on its loan and receives no payoff. If the firm makes no investment, it receives zero payoff. We proceed under the assumption that $AL^a \geq \rho$ and later verify that it holds in equilibrium.

Since the bank behaves competitively, we can seek a loan contract $(L, \rho) \in [0, \infty)^2$ that maximizes the firm's expected payoff. Letting the bank's expected payoff from funding and monitoring from equation (1) to be equal to zero and solving the resulting equation for ρ yields

$$\rho^*(L) = \frac{(1+r+\mu)L}{\sigma}. \tag{3}$$

Equation (3) identifies the minimal repayment that makes the bank willing to lend the amount L. On the right-hand side, the coefficient $(1+r+\mu)/\sigma$ captures the equilibrium *lending interest rate*.

After inserting equation (3) into equation (2), we can write the firm's investment problem as

$$\max_{L\in[0,\infty)} \Pi^F(L) = \sigma AL^a - (1+r+\mu)L. \tag{4}$$

Solving the problem of equation (4) yields the firm's optimal investment level as

$$L^*(r, \mu, \sigma, A, a) = (\frac{\sigma A a}{1 + r + \mu})^{\frac{1}{1-a}}. \tag{5}$$

By substituting equation (5) for equation (4) we can verify that $\Pi^F(L^*) > 0$. These positive expected equilibrium profits also imply that, in equilibrium, the firm defaults on the loan only if its project fails (see equation (2)). Since the firm's investment is fully debt-financed, equation (5) also determines the bank's equilibrium lending.

To complete the equilibrium analysis we specify the condition under which the firm chooses the bad project unless the bank monitors. Suppose the bank decides to lend but does not monitor. In that subgame the firm's equilibrium loan contract proposal can be obtained from equations (3) and (5) by setting $\mu = 0$. Hence the firm will choose the bad project if $U\tilde{L} \geq \Pi^F(\tilde{L})$ in which $\tilde{L} = [(\sigma A a)/(1 + r)]^{1/(1-a)}$. In words, if the bank shirks in monitoring, the firm will choose the the bad project if the private benefits associated with the bad project are at least as large as the return on investment in the good project. After some algebra, this condition may be rewritten as $U \geq (1 + r)(1/a - 1)$ which we assume to hold.

3.3 Empirical Implications

The bank can make two types of innovations to relax the earning-based constraints of their borrowers. First, the bank's innovations can reduce the lending-related monitoring cost μ. For example, a bank using more advanced lending technologies has smaller monitoring costs. This assumption is consistent with the evidence showing that technological innovations in the banking sector have made the geographical distance less relevant in lending decisions and relations (see Petersen and Rajan 2002). Second, the bank's innovations can improve the average borrower's creditworthiness σ. In sum, we assume that the bank's lending-related technological innovations are inversely related to μ and directly related to σ.

From equation (5) we observe that the two types of lending-related innovations affect bank lending by reducing the equilibrium lending interest rate $(1+r+\mu)/\sigma$. For brevity, we focus on analyzing the effects of μ in what follows, while keeping in mind that the effect of an increase in σ is qualitatively similar as the effect of a decrease in μ.

In equation (5), r captures the bank's cost of funds which is in practice crucially influenced by the central bank's monetary policy, i.e., expansionary (contractionary) monetary policy implies smaller (larger) r. In our empirical context of China where interest rates are only partially liberalized, we may think that r is directly related to the 7-day collateralized interbank repo rate or inversely related to the money supply growth rate (see Section 4.2).

To analyze the effects of monetary policy and technological innovations on bank lending we first take the derivatives of $L^*(r, \mu, \cdot)$ from equation (5) with respect to r and μ. Straightforward differentiation yields

$$\frac{\partial L^*(r, \mu, \cdot)}{\partial r} = \frac{\partial L^*(r, \mu, \cdot)}{\partial \mu} = -\frac{L^*(r, \mu, \cdot)}{(1-a)(1+r+\mu)} < 0. \tag{6}$$

Equation (6) captures two effects. First, there is the bank lending channel of monetary policy: expansionary monetary policy – a decrease in r – increases bank lending (and *vice versa* for contractionary monetary policy). Second, it shows the effect of technological innovations on lending: a bank using more advanced lending technologies – with a smaller μ – should lend more (and *vice versa* for older lending technologies). That changes in r and μ have exactly identical effects on the bank's equilibrium lending interest rate $(1+r+\mu)/\sigma$ and, as a result, on bank lending, is an artefact of our simple model – the effect of σ on L^* is quantitatively different, for example.

We are in particular interested in the interaction of the bank lending channel with lending technologies, i.e., of the sign of $\partial^2 L^*/(\partial r \partial \mu)$. From equation (6) we get that

$$\frac{\partial L^{*2}(r, \mu, \sigma)}{\partial r \partial \mu} = \frac{(2-a)L^*(r, \mu, \cdot)}{[(1-a)(1+r+\mu)]^2} > 0. \tag{7}$$

In words, equation (7) suggests that banks' lending-related technological innovations *amplify* the bank lending channel of monetary policy transmission. The explanation for the result is straightforward: The standard bank lending channel implies that looser monetary policy allows the bank to lend more for a given level of earnings-based borrowing constraints. Lending-related technological innovations relaxing those borrowing constraints in turn allow the bank to lend more for a given level of monetary policy. Therefore monetary policy and lending-related technological innovations unambiguously amplify the effects of each other.

We conclude the theoretical analysis with two remarks. First, the theoretical model lacks a proper innovation stage in which the bank would invest in costly R&D to come up with new lending technologies. As a result, the model is agnostic about whether the new lending technologies affecting μ or σ are developed in-house or adopted from outside. To the extent the costs of the bank's innovation investments would not affect the volume of bank lending directly, our results would not change even if such costs were accounted for. However, if the costs of innovation investments would reduce the volume of bank lending, the effects of innovation on the volume of bank lending might become ambiguous.

Second, an alternative model would use collateral-based borrowing constraints, such as in Kiyotaki and Moore (1997). As is well-known (see, e.g., Bernanke and Gertler 1995) such collateral-based borrowing constraints also create the bank lending channel of monetary policy transmission. However, Lian and Ma (2021) document that the ratio of earnings-based to collateral-based corporate borrowing is four to one in the United States, and Gambacorta et al. (2023) show that credit backed up by FinTech depends less on physical collateral. Moreover, a model based on collateral-based borrowing constraints should yield similar predictions: both looser monetary policy and innovations that relax collateral-based borrowing constraints would allow the bank to lend more for a given level of collateral. Therefore monetary policy and collateral-related banking innovations should amplify the effects of each other, just as in the case of earnings-based borrowing constraints.

4 Data and Variables

To test the predictions from the theoretical model, we compile a dataset including information of monetary policy shocks and banks' balance sheets, income statements, key financial indicators, and technological innovations. We cover 42 publicly listed banks in the period of 2008Q1-2019Q4.[4] Quarterly data is used since China's monetary policy decisions are made quarterly as suggested by the literature and policy practices (details will follow). As shown in Table 1, our sample includes the largest 6 state-controlled commercial banks (the Big6), 9 joint-stock commercial banks, 17 city commercial banks, and 10 rural commercial banks, and they account for 67.4% of the total assets in the Chinese banking industry as of the end of 2019.

4.1 Bank-level Variables

4.1.1 Bank's Technological Innovation

We measure banks' adoption of new technologies through their information technology patent applications, which reflect in-house development and advancements at the technology frontier. Patents are a widely-used measure of innovation outcomes which, in our model, influence the bank's lending activities and the transmission of monetary policy, unlike R&D spending *per se*. Patent data also allows a detailed examination of the nature of these innovations. Consistent with the literature, we focus on patent applications rather than grants since the time taken to prosecute patents can vary significantly, while the delay between patent application and the corresponding R&D expenditure is usually brief. Chen et al. (2019), Fu and Mishra (2022), Jiang et al. (2021), and Caragea et al. (2023) also utilize patent data to identify and categorize FinTech innovations. Moreover, Lerner et al. (2023) document how banks have increasingly sought to protect their innovations through patenting during this millennium, whereas bank-filed patent applications

[4] As of 2020, there are 45 listed banks. The three banks we dropped either went public towards the end of our data period and have less than four consecutive entries of data, or have no valid loan data. There are also 172 non-listed banks that have no quarterly balance sheet and financial statements. These 175 banks with missing financial data are small compared to the 42 banks in our data.

hardly existed in the 20th century (see also Cipher 2018). By analyzing patent application documents, we can pinpoint the specific technology and ascertain its purpose within the bank's operations. Specifically, we can assess whether the technology was developed to enhance the bank's lending business, which allows us to deliberate the implications of innovation for the bank's lending behavior and its transmission of monetary policy.

Our patent documents are sourced from the China National Intellectual Property Administration (CNIPA, the China patent office) and verified against the IncoPat database, which supplements the citation information. We first conduct a search for patent documents filed by Chinese banks, focusing on three specific International Patent Classification (IPC) codes: G06Q20, G06Q30, and G06Q40. These codes broadly define FinTech as digital technologies utilized within financial services (Chen et al. 2019). The higher-level code G06Q covers data processing systems or methods that are specifically adapted for administrative, commercial, financial, managerial, supervisory, or forecasting purposes, and its subcategory of Q20 relates to the granular classification for payment architectures, schemes, or protocols, Q30 for e-commerce, and Q40 for finance, insurance, or tax strategies. Essentially, these three codes encompass digital inventions pertinent to payment, e-commerce, and finance. In this first step, we obtain 1,970 patent applications and collect various details for each of them, including its ID, title, abstract, application date, the applying bank, inventor names, associated IPC codes, forward citations, and a comprehensive description of the technology and its intended use.

Next, based on a careful reading of the descriptions in the patent file, we assign granular categories of technology to each patent. We create a granular classification by assigning the main technologies adopted in each patent into one of the following six categories: (1) AI, if the main technologies employed in the patent are described as "artificial intelligence", "smart [technology]", "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) blockchain, for “blockchain”.

We then evaluate whether the technology described in its patent application is related to banks' lending activities. This assessment is inherently subjective and based on an in-depth examination of the stated primary purpose of the invention. Lending-related technological innovations are closer to the purpose of reducing monitoring costs and increasing the creditworthiness of borrowers as described in the theoretical model. For illustration, consider patent application number 201010272295X, submitted by the China Construction Bank in 2010Q3. Its 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”. Given that the invention purportedly enhances the accuracy and efficiency of lending decisions, we categorize this patent as lending-related, aligning it with the monitoring cost μ in our theoretical framework. Meanwhile, for another patent application by the same bank, numbered 2011101800941 and filed in 2011Q2, the 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...”. Although telephone banking may encompass lending-related services, we assess that the invention's primary utility, as articulated, does not principally serve the bank's lending operations.

We measure the technological innovation of each bank using the number of patent applications in each quarter. Instead of merely counting patents, we follow the literature and account for the significant variation in the value of individual patents by using the citation-weighted number of patents (Harhoff et al. 1999, Hall et al. 2005, Kogan et al. 2017). Specifically, we first calculate the average number of forward citations per patent by the application year and obtain the relative ratios of each patent's forward citations to this average, and then aggregate these ratios at the bank-quarter level.

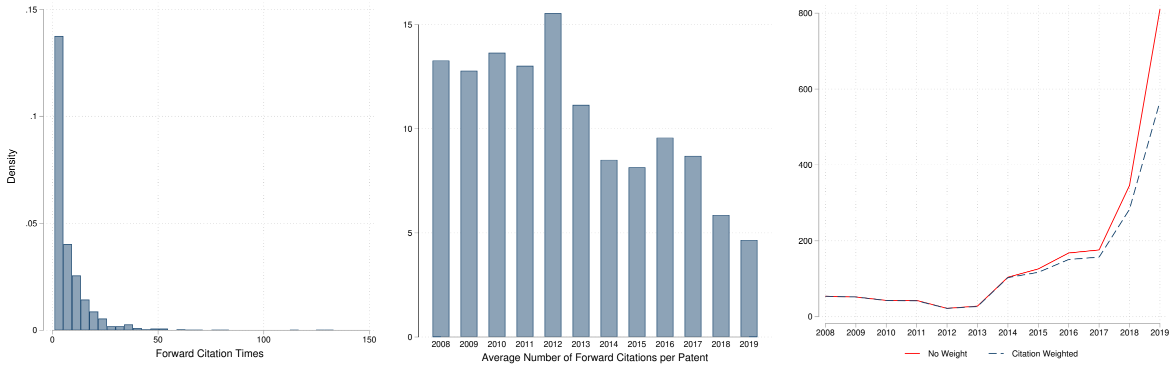

Figure 1: Citation-Weighted Patent Applications

Notes: This figure shows the histogram distribution of the number of forward citations of each patent in the left panel, the average number of forward citations per patent over years in the middle panel, and the comparison of the aggregate trends captured by simple counts and citation-weighted patent measurement in the right panel.

Figure 1 shows the histogram distribution of the number of forward citations at the patent level in the left panel, the average number of citations per patent by application year in the middle panel, and the annual aggregation of patents, both in simple counts and citation-weighted units, in the right panel. Observations indicate that the majority of patents receive fewer than ten citations. In addition, there is a decline in the number of forward citations per patent for the post-2017 periods, which may be attributed to the truncation issue, namely, the time lag between patent applications and subsequent citations resulting in a mechanical tail-off towards the end of the sample (Lerner and Seru 2022). By adjusting the patent applications by time fixed effects for a specific set of technologies, our method has accounted for the truncation issue. Moreover, our main findings remain when employing the pre-2017 subsample.[5]

[5]See Table A2 in the appendix. Furthermore, we have accessed the latest version of patent data as of October 2023 for patent applications submitted between 2008 and 2019, therefore the citations for applications at the end of our sample period may have been largely captured in our data. Another way to address the truncation issue is to use an alternative measure of patent value score rather than the number of citations as the weight. These scores are sourced from the IncoPat database and range from 0 to 10. They are determined based on three dimensions: technical stability, including factors such as the absence of ligation and reexamination requests, technical advancement, including citations by global patents, the number of IPC subgroups, and the members of the R&D team, and scope of protection, including the

Table 1: Bank Sample List

	Bank Name	Type	Asset (Trillion RMB) 2019Q4	# Tech Patents (Count) 2008Q1-2019Q4	# Tech Patents (Citation Weighted) 2008Q1-2019Q4
1	Industrial and Commercial Bank of China	Large State-Controlled Bank	30.11	443	448.23
2	China Construction Bank	Large State-Controlled Bank	25.44	510	413.51
3	Agricultural Bank of China	Large State-Controlled Bank	24.88	111	91.36
4	Bank of China	Large State-Controlled Bank	22.77	663	468.10
5	Postal Savings Bank of China	Large State-Controlled Bank	10.22	6	7.92
6	Bank of Communications	Large State-Controlled Bank	9.91	37	32.03
7	China Merchants Bank	Joint Stock Commercial Bank	7.42	32	36.12
8	Industrial Bank	Joint Stock Commercial Bank	7.15	1	1.26
9	Shanghai Pudong Development Bank	Joint Stock Commercial Bank	7.01	9	6.19
10	China CITIC Bank	Joint Stock Commercial Bank	6.75	14	13.28
11	China Minsheng Bank	Joint Stock Commercial Bank	6.68	27	22.54
12	China Everbright Bank	Joint Stock Commercial Bank	4.73	12	7.10
13	Ping An Bank	Joint Stock Commercial Bank	3.94	74	47.28
14	Huaxia Bank	Joint Stock Commercial Bank	3.02	8	8.07
15	Bank of Beijing	City Commercial Bank	2.74	1	0.84
16	Bank of Shanghai	City Commercial Bank	2.24	3	0.89
17	Bank Of Jiangsu	City Commercial Bank	2.07	1	0.51
18	China Zheshang Bank	Joint Stock Commercial Bank	1.80	6	5.39
19	Bank of Nanjing	City Commercial Bank	1.34	0	0
20	Bank of Ningbo	City Commercial Bank	1.32	3	2.51
21	Chongqing Rural Commercial Bank	Rural Commercial Bank	1.03	0	0
22	Bank Of Hangzhou	City Commercial Bank	1.02	0	0
23	Shanghai Rural Commercial Bank	Rural Commercial Bank	0.93	3	1.32
24	Bank of Changsha	City Commercial Bank	0.60	0	0
25	Bank of Guiyang	City Commercial Bank	0.56	0	0
26	Bank of Chengdu	City Commercial Bank	0.56	0	0
27	Bank Of Chongqing	City Commercial Bank	0.50	0	0
28	Bank of Zhengzhou	City Commercial Bank	0.50	0	0
29	Bank of Qingdao	City Commercial Bank	0.37	0	0
30	Bank of Suzhou	City Commercial Bank	0.34	0	0
31	Qingdao Rural Commercial Bank	Rural Commercial Bank	0.34	3	0.92
32	Bank of Lanzhou	City Commercial Bank	0.34	0	0
33	Qilu Bank	City Commercial Bank	0.31	0	0
34	Bank of Xi'an	City Commercial Bank	0.28	0	0
35	Xiamen Bank	City Commercial Bank	0.25	0	0
36	Jiangsu Zijin Rural Commercial Bank	Rural Commercial Bank	0.20	0	0
37	Jiangsu Changshu Rural Commercial Bank	Rural Commercial Bank	0.18	0	0
38	Wuxi Rural Commercial Bank	Rural Commercial Bank	0.16	0	0
39	Jiangsu Jiangyin Rural Commercial Bank	Rural Commercial Bank	0.13	0	0
40	Jiangsu Suzhou Rural Commercial Bank	Rural Commercial Bank	0.13	3	0.64
41	Jiangsu Zhangjiagang Rural Commercial Bank	Rural Commercial Bank	0.12	0	0
42	Zhejiang Shaoxing Ruifeng Rural Commercial Bank	Rural Commercial Bank	0.11	0	0

Note: This table lists the name, type, assets in 2019Q4, and number of technology patents (in count and weighted by forward citation) filed over the period 2008Q1-2019Q4, for each of the 42 publicly listed banks used in this study.

Table 1 presents the number of technology patents filed by each bank as of 2019Q4. Among the 42 banks in our sample, 22 have filed at least one patent application during the sampling period. Figure 2 provides a time-series summary of our citation-weighted patent

number of claims and diversification of countries and areas in the patent portfolio. Importantly, this score is less affected by the truncation issue and Figure A1 in the appendix indicates no declining trend in these scores over the years. Table A3 in the appendix shows that results using the score-weighted patent measurement are robust.

measurement, categorized into six technology sectors in the left panel and lending-related and non-lending-related technologies in the right panel.[6] Our patent-based technological innovation measurement is used at the quarterly frequency, together with other bank-level variables, for subsequent empirical analysis. However, to simplify the illustration and facilitate comparison with alternative measurements, which are detailed below and available only on an annual basis, we have aggregated the patent data to the annual frequency in the summary figures here.

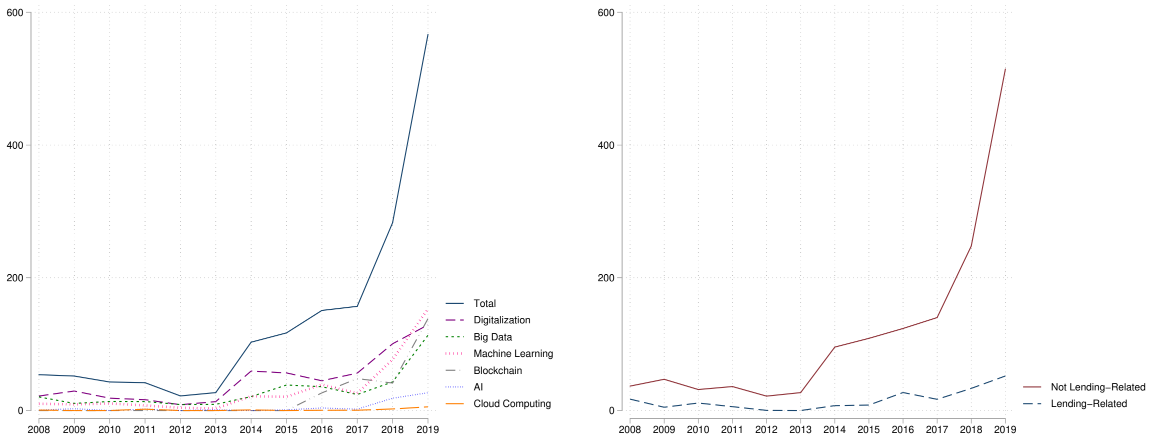

Figure 2: Banks' Technological Innovation: Patent Applications

Notes: This figure shows the yearly variation in the number of citation-weighted patent filings by banks. The left panel shows the total number and its division into six technologies, which are AI, big data, cloud computing, digitalization, machine learning, and blockchain. The right panel shows the number of lending-related and non-lending-related patent applications separately. The categorization of technologies and the determination of whether a patent application is lending-related are based on the descriptions provided in the patent documents.

Three observations stand out. First, a notable increase in patent applications by banks occurred during 2013-2014, predominantly driven by advancements in digitalization and machine learning, as well as technologies not directly related to lending. This period coincides with the advent of the internet financing era in China, exemplified by the launch of Yu'e Bao by Ant Financial in 2013. Ant Financial is one of the world's largest BigTech companies and a dominant force in China. It is the parent company of Alipay, which is the world's largest mobile payment platform and accounted for 55.32% of China's third-party payment market in 2018. Yu'e Bao, the flagship fund of Ant Financial, had a peak of

[6]We present the same figure using the simple count measurement in Figure A2 in the appendix.

$270 billion in assets under management in March 2018. The flexibility and competitive return made Yu'e Bao a strong competitor to bank deposits and thus threatened banks' major source of stable funding. The penetration of BigTech companies in the financial business could motivate traditional banks to catch up in technology; later we will formally test this hypothesis.

Second, the distribution of patent applications among various technologies is markedly uneven. The preponderance of innovations is in digitalization, followed closely by big data and machine learning. Conversely, advancements in blockchain, AI, and cloud computing have seen a rapid increase in recent years. This trend suggests that banks initially concentrated on digitalization and are now progressively pivoting their innovation efforts towards areas like big data, machine learning, and blockchain, where BigTech companies might hold a competitive edge.

Third, a predominant portion of the innovations developed by banks are not directly associated with their lending business. Between 2008 and 2013, the average annual number of lending-related patents was merely 6, in contrast to 33 for non-lending-related patents. Post-2013, there is a noticeable increase, with the average annual numbers rising to 18 for lending-related and 143 for non-lending-related innovations.

While patent documents are a widely used measure of technological innovation, they have some well-known limitations that may be particularly relevant in the context of banking. First, patents only measure the output of banks' in-house innovation and do not measure banks' use of new technologies more broadly. Second, not all banking innovations are patented either because they fail to satisfy the patentability criteria or because banks prefer to resort to secrecy (see, e.g., Komulainen and Takalo 2014 and Lerner et al. 2023). Although patent-based innovation measures conceivably correlate with the banks' innovation efforts and use of new technologies more broadly (see, e.g., Fu and Mishra 2022 for evidence), we validate our patent-based measurement of banks' technological innovation in two ways.

First, we compare our patent-based measure with banks' perception of technology.

There are increasing applications of textual analysis in measuring technology-prone in the recent literature. For instance, Pierri and Timmer (2022) measure bank executives' tech-prone by reading and counting the mentioning of tech-related words in their biographies, Chen and Srinivasan (2023) use textual analysis of the disclosure of digital-related words in corporate financial reports and conference calls to measure to which extent firms go digital, and Modi et al. (2022) classify banks' IT expenses by detecting IT-related keywords from regulatory fillings. In the same vein, we provide a measurement of banks' technology perception by manually collecting the mentioning of specific technological terms in banks' annual reports, and then demonstrate whether the patterns are similar to the patent-based innovation measurement.[7] 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 or not the mentioned technology is related to banks' lending activities depending on the exact contexts in the reports. For example, from 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 the described technology falls into the category of big data and is lending-related because the bank applies the technology to improve its lending decisions and manage credit risk. This technology appears to relate to variable σ in the theoretical model, which captures the borrower's ability to repay its loan.

Figure 3 shows the total number of times that technological terms are mentioned by banks each year. Similarly, we present the pattern by the six categories of technologies in the left panel, and by the binary classification of lending-related or non-lending-related in the right panel. We observe very similar patterns to that of the patent-based measurement. Banks are paying increasing attention to technologies over time. In the beginning, banks barely mentioned the technologies in their reports, while they brought up substan-

[7]For listed banks (and firms) in China, the quarterly reports usually only disclose earnings 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.

tially more technological terms after 2013-2014. Moreover, the perception of technology is mainly unrelated to lending. However, there are some differences regarding the six categories of technologies. For example, AI-related terms are mentioned most frequently in the annual reports, whereas the terms related to digitalization appear most frequently in patent applications. This difference may indicate that banks' recognition is ahead of their actual innovation output efforts in AI technology. It is also conceivable that annual reports use broader language than detailed patent applications and, for example, do not separate machine learning from AI.

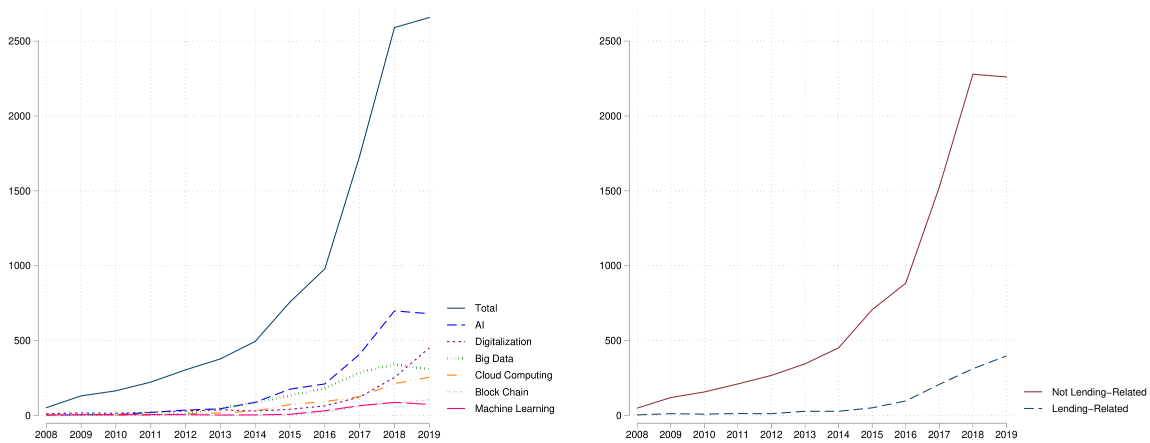

Figure 3: Banks' Technology Adoption: Textual Terms

Notes: This figure shows the total number of technological terms mentioned by banks in their annual reports 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, digitalization, machine learning, and blockchain. The right panel shows the counts of lending-related and non-lending-related mentions separately. We identify the categories of technologies and whether or not the patent is lending-related based on the contexts when mentioning the technological terms.

The second way to justify our technological innovation measurement is to examine whether it is in line with the expansion of mobile and internet banking. We access the number of customers that have mobile and internet banking accounts with the bank from the banks' announcements on websites. Figure 4 shows the expansion of mobile and internet banking across years, together with the technological innovation measurement.[8] Again, these measurements show similar trends over time, indicating that our technological innovation measurement is picking up the diffusion of technology in financial services.

[8]Note that the headcount is for each bank, thus, there could be customers of multiple banks.

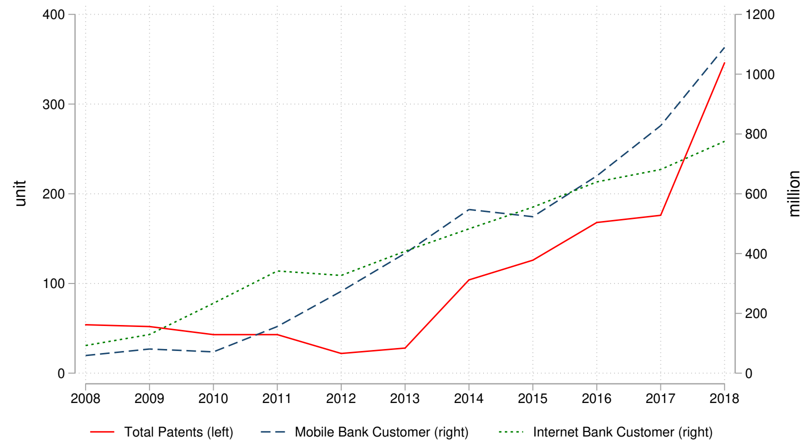

Figure 4: Banks' Technological Innovation, Mobile Banking and Internet Banking

Notes: This figure shows the total number of patents filed by banks by filing year, and the number of bank customers with mobile and internet banking accounts in the same year. We collect the customer numbers from banks' public announcements.

In addition to the similar overall trends among our technological innovation measurements, Table 2 shows that the pairwise correlations are high and statistically significant among them at the bank-year level. The total number of patent filings is highly correlated with the total count of technological terms, the number of mobile banking customers, and the number of internet banking customers, with coefficients of 0.295, 0.344, and 0.442, all significant at the 1% level. Moreover, the correlation between lending patent filings and lending terms is higher than the correlation between lending patent filings and non-lending terms, and the correlation between non-lending patent filings and non-lending terms is also higher than the correlation between non-lending patent filings and lending terms.

Table 2: Pairwise Correlations Between Measurements of Technological Innovation

	Patents-Total	Patents-Lending	Patents-Non Lending	Terms-Total	Terms-Lending	Terms-Non Lending	Mobile Bank Customers	Internet Bank Customers
Patents-Total	1							
Patents-Lending	0.729***	1						
Patents-Non Lending	0.997***	0.676***	1					
Terms-Total	0.295***	0.329***	0.280***	1				
Terms-Lending	0.275***	0.367***	0.254***	0.834***	1			
Terms-Non Lending	0.285***	0.304**	0.272***	0.993***	0.762***	1		
Mobile Bank Customers	0.344***	0.342**	0.329***	0.399***	0.387***	0.381***	1	
Internet Bank Customers	0.442***	0.458***	0.423***	0.434***	0.496***	0.402***	0.983***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

While technological terms in annual reports, and mobile and internet banking customers are helpful in demonstrating the validity of our patent-based measurement of technological innovation, they do not allow as reliable and detailed analysis of those innovations as patent documents. Additionally, these measures are not available at the same quarterly frequency as patent applications. The use of technological terms in annual reports primarily reflects banks' perception of technology, rather than actual technological proficiency. Similarly, the numbers of mobile and internet banking customers might more accurately indicate consumer adoption or the effectiveness of banks' marketing strategies, rather than genuine innovation efforts. Furthermore, the data on mobile and internet banking is limited, encompassing only 26 banks with most observations post-2016. Therefore, we will focus on our patent-based technological innovation measure in what follows.

4.1.2 Bank-level Outcome and Control Variables

We obtain the listed banks' quarterly financial and performance variables from the China Stock Market & Accounting Research (CSMAR) Database and WIND, the Chinese version of Bloomberg. We use loan growth as the main outcome variable to examine banks' response to monetary policy. For control variables, we use the natural logarithm of bank assets (as a measure of bank size), capital ratio, deposit growth rate, loan-to-deposit ratio, and cost-to-income ratio. These characteristics are identified in the literature as main determinants of banks' heterogeneous responses to monetary policy (Kashyap and Stein 2000, Gambacorta 2005, Gomez et al. 2021, Gambacorta and Marques-Ibanez 2011, Brissimis et al. 2014, Drechsler et al. 2017, Acharya et al. 2020). We will also conduct a horse race between these factors and technological innovation in the robustness check.

We also add another variable to capture banks' exposure to BigTech competition. Due to the rapidly rising BigTech financial services in China and worldwide (Cornelli et al. 2020), the relationship between BigTech and traditional banks could be an important driver for banks to engage in technology development to either compete or cooperate with BigTech companies, and at the same time it could be a factor affecting the bank loan growth on its own (Modi et al. 2022). Thus, it is necessary to control banks' exposure to BigTech competition in our analysis. Specifically, we use the branch-weighted BigTech penetration across regions:

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

where c and t denote city and time, and $BigTech_{ct}$ is the penetration of BigTech financial services in city c at time t.[9] For bank branch distribution, we collect data on the exact location of bank branches from the China Banking and Insurance Regulatory Commission (CBIRC). Then we assign them to cities based on the address and merge them with the city-level BigTech penetration. For BigTech penetration $BigTech_{ct}$, we use an index constructed from individuals' usage of various financial services provided by Ant Financial. More specifically, this index 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, which is constructed based on the nondimensionalization of 20 individual-level indicators covering the services of payment, insurance, money fund, investment, credit, and credit evaluation service in the BigTech platform, and we report them in Table A1 in the appendix. A higher value indicates more extensive penetration of BigTech in providing financial services in the city. The same regional BigTech penetration variable is also used in Hong et al. (2023), Hasan et al. (2020) and Ding et al. (2022).

The raw BigTech indicators display a clear time trend, with an annual growth rate of more than 25% for the aggregate 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 penetration indicators across cities. Therefore, a value larger than 1 indicates that the city's BigTech penetration is more advanced than the national average, and a value smaller than 1 indicates that the city is

[9] For example, if bank i has 2 branches in city c_1 and 3 branches in city 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.

lagging behind in BigTech penetration. In this way, we are able to erase the strong time trend meanwhile preserving the relative rank.[10]

Lastly, we control for local economic conditions to account for, at least partially, the credit demand. Specifically, we take the city where the bank's headquarter is located, and obtain quarterly city-level GDP growth, inflation, and loan growth from the CEIC database.

4.2 Monetary Policy Shock

The specification of the monetary policy rule and the identification of its shocks are crucial for examining the transmission of monetary policy within the economy. While modeling China's monetary policy framework has been subject to debate, recent research, such as Chen et al. (2018) and Kamber and Mohanty (2018), compares the effectiveness of monetary policy transmission in China with that in advanced economies, revealing similarities in the impulse response mechanisms. Based on these analyses, we posit that the findings on monetary policy transmission in this study may have broader implications.

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, 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 following year. Chen et al. (2018) capture the monetary policy decision process in

[10]There are 338 cities 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 are the same as in 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.

China as the People's Bank of China (PBC) adjusts M2 growth rates on a quarterly basis in response to inflation and GDP growth in the previous quarter.[11] 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:

$$g_{m,t} = \gamma_0 + \gamma_m g_{m,t-1} + \gamma_\pi(\pi_{t-1} - \pi^*) + \gamma_{x,t}(g_{x,t-1} - g^*_{x,t-1}) + \epsilon_{m,t} \tag{8}$$

where g_m is the M2 growth rate, π is the CPI inflation rate, g_x is the GDP growth, and π^* and g^*_x are the targets for inflation and GDP growth set by the State Council, respectively.[12] The GDP growth target serves as a lower bound for monetary policy; the output coefficient $\gamma_{x,t}$ is thus time-varying. Then the estimated M2 growth rate ($\hat{g_{m,t}}$) is the endogenous M2 growth, and the monetary policy shock is calculated as the difference between the actual and endogenous M2 growth. Employing this methodology, we estimate the monetary policy rules and extend the indicators of monetary policy shocks up to 2019Q4. This expansion goes beyond the original indicators in Chen et al. (2018), which conclude in 2016Q2.

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.[13]

[11]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.

[12]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 next spring.

[13]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

By definition, $\Delta FR007$, the quarterly change in FR007, is based on the interest rate instead of M2 growth, and we use it 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. In addition to FR007, we also use a similar 7-day interbank rate R007, which is the weighted average 7-day repo rate for the whole market, and report the results in the appendix.

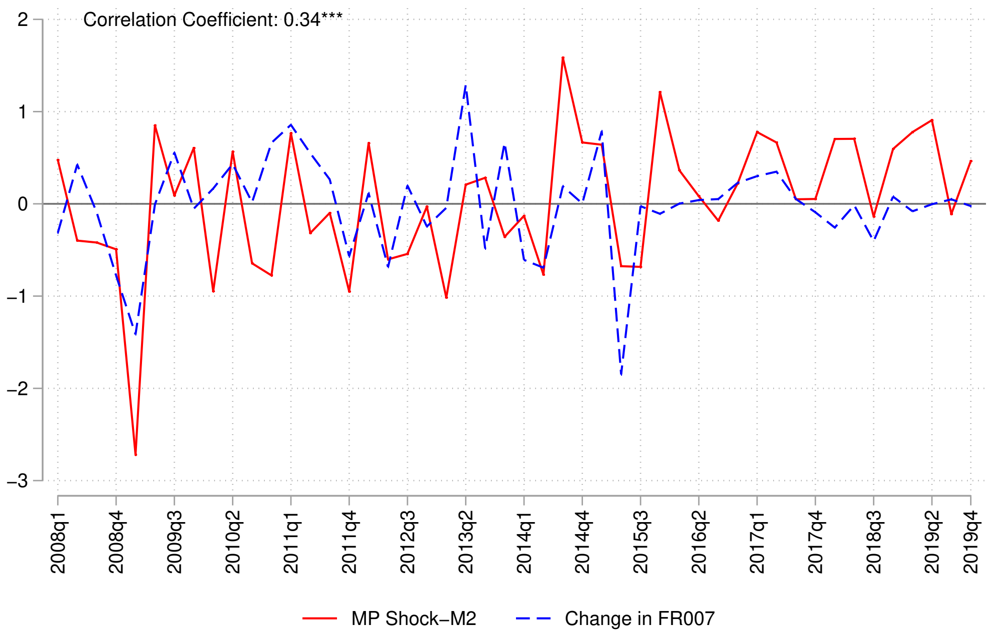

Figure 5: Monetary Policy Shocks

Notes: The red solid line indicates the M2-based measurement of monetary policy shocks (in percentage points), 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 value of both measurements indicates tighter monetary policy.

We reverse the sign of the M2-based monetary policy shock measurement to ease the interpretation of the results and rescale the units to percentage points change in the M2 growth rates. Thus a higher value in both the M2-based shock measurement and $\Delta FR007$ indicates contractionary monetary policy, and a lower value indicates expansionary monetary policy. Figure 5 presents the time series of the two monetary policy shock indicators. We observe large variations of monetary policy shocks in our sample pe-

DR007 have a correlation coefficient of 0.83.

riod of 2008Q1-2019Q4. Moreover, the price-based and quantity-based monetary policy shock measurements comove with each other, with a correlation coefficient of 0.34 and significance at 1%, suggesting that they are consistent with each other. Furthermore, in Figure A3 in the appendix, we demonstrate the impulse responses of key aggregate macroeconomic variables, such as real GDP, inflation, employment, and bank loans, to our M2-based monetary policy shocks using local projections (Jordà 2005). Results show that monetary policy tightening shocks lead to significant declines in these macroeconomic indicators, suggesting a conventional transmission of monetary policy within the Chinese economy.

Finally, Table 3 shows the summary statistics of all variables used in this paper.

Table 3: Summary Statistics

	Mean	Standard Deviation	Min	Max	N
Panel A: Bank Technological Innovation Variables					
Tech	1.268	7.171	0.000	166.583	1268
Lending Tech	0.145	0.840	0.000	11.252	1268
Non-Lending Tech	1.122	6.643	0.000	156.721	1268
Tech-AI	0.047	0.445	0.000	8.790	1268
Tech-Big Data	0.277	1.694	0.000	34.946	1268
Tech-Cloud Computing	0.010	0.146	0.000	3.645	1268
Tech-Digitalization	0.432	2.168	0.000	30.658	1268
Tech-Machine Learning	0.302	1.881	0.000	40.735	1268
Tech-Blockchain	0.201	2.260	0.000	47.810	1268
Panel B: Bank Outcome and Control Variables					
Loan Growth (%)	4.277	3.156	-6.834	35.766	1268
Total Asset (Billion RMB)	3999.910	6006.743	19.351	30426.381	1268
Bank Size	7.107	1.710	2.963	10.323	1268
Capital Ratio	11.362	3.062	2.173	25.590	1268
Deposit Growth	3.761	4.310	-12.530	33.282	1268
Loan-to-Deposit Ratio	68.241	11.644	25.932	109.448	1268
Cost-to-Income Ratio	30.255	6.450	15.600	64.810	1268
BigTech Exposure	1.237	0.146	0.800	1.706	1268
Panel C: Macroeconomic Variables					
MP Shock	0.113	0.670	-2.719	1.586	1268
Δ FR007 Rate	-0.012	0.494	-1.849	1.290	1268
City GDP Growth	11.494	4.584	0.400	38.353	1268
City Inflation	2.530	1.603	-4.700	8.800	1268
City Loan Growth	2.947	2.353	-10.634	19.265	1268

5 Empirical Results

5.1 Factors of Banks' Technological Innovation

We start by analyzing the determinants of banks' technological innovation captured by patenting activities. To do that, we estimate the following specification:

$$Tech_{it} = \alpha + \Gamma Control_{it} + \delta_i + \epsilon_{it} \tag{9}$$

where i and t refer to bank and quarter, respectively. The dependent variable $Tech_{it}$ is the total number of patent filings by the bank, or its components of lending-related and non-lending-related patent filings. Concerning that the number of patent applications is skewed, we adopt Poisson regression for this estimation. $Control_{it}$ consists of an array of bank characteristics including size, capital ratio, deposit growth rate, loan-to-deposit ratio, cost-to-income ratio, and BigTech exposure, and an array of local economic conditions including GDP growth, inflation, and loan growth in the city where the bank's headquarter lies.

We first estimate the specification as a pooled regression without fixed effects, and then specify a bank type or bank fixed effect. There are four types of banks in our sample: (1) Big6, which are large state-controlled banks; (2) joint stock commercial banks; (3) city commercial banks; and (4) rural commercial banks. The specification of bank type fixed effect can help absorb the difference in developing in-house technologies across different types of banks, and the specification of bank fixed effect yields the within-bank effects of changes in bank characteristics on technological innovation. We cluster the standard errors at the bank level in all estimations.

Table 4 presents the results. First, larger banks tend to be more active innovators as the coefficients of bank size are significantly positive across all specifications. Second, banks that are more exposed to BigTech penetration in financial services are more likely to innovate. Specifically, based on column (3), if the bank moved its branch from regions that have the average level of BigTech penetration to regions where the BigTech penetration is twice the average, the expected increase in log count of total patent applications would be 12.71, a substantial increase. Third, capital ratio is a significant driver of banks' innovation in lending-related technologies, but it plays a larger role cross-sectionally than within-bank. In addition, higher cost-to-income ratios are significantly associated with more patent applications, especially for non-lending-related innovations, suggesting the pressure to leverage technology to enhance operational efficiency. These findings are consistent with the factors explaining banks' investment in IT and FinTech innovations in Modi et al. (2022) and Caragea et al. (2023).

Table 4: Factors of Banks' Technological Innovation

DepVar:#Patents	Total Tech			Lending Tech			Non-Lending Tech		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank Size	3.316***	3.428***	5.082***	2.509***	2.650***	4.088**	3.442***	3.544***	5.218***
	(0.755)	(1.051)	(1.636)	(0.547)	(1.001)	(2.013)	(0.791)	(1.065)	(1.586)
Capital Ratio	0.171	0.161	0.199	0.225**	0.220*	0.182	0.160	0.151	0.199
	(0.112)	(0.124)	(0.146)	(0.113)	(0.131)	(0.251)	(0.112)	(0.123)	(0.128)
Deposit Growth	-0.036	-0.033	-0.053**	-0.006	-0.006	-0.008	-0.040	-0.037	-0.060**
	(0.042)	(0.043)	(0.025)	(0.030)	(0.033)	(0.023)	(0.045)	(0.046)	(0.027)
Loan-to-Deposit Ratio	0.057*	0.059*	-0.046	0.037	0.034	-0.020	0.061*	0.063*	-0.049
	(0.032)	(0.032)	(0.037)	(0.025)	(0.025)	(0.044)	(0.033)	(0.033)	(0.036)
Cost-to-Income Ratio	0.090**	0.095*	0.126	0.074***	0.077**	0.141**	0.092**	0.097*	0.125
	(0.041)	(0.050)	(0.082)	(0.028)	(0.038)	(0.067)	(0.043)	(0.052)	(0.085)
BigTech Exposure	15.770***	15.601***	12.711***	10.710***	11.076***	9.922***	16.498***	16.223***	13.024***
	(2.378)	(2.504)	(2.680)	(2.629)	(2.838)	(3.066)	(2.439)	(2.541)	(2.949)
City GDP Growth	-0.012	-0.011	-0.008	-0.006	-0.006	-0.006	-0.013	-0.013	-0.009
	(0.008)	(0.008)	(0.008)	(0.019)	(0.019)	(0.022)	(0.009)	(0.009)	(0.008)
City Inflation	-0.064	-0.062	-0.057	0.086	0.084	0.096	-0.084	-0.082	-0.079
	(0.057)	(0.058)	(0.056)	(0.063)	(0.061)	(0.072)	(0.061)	(0.062)	(0.061)
City Loan Growth	0.006	0.010	0.021	0.068	0.068*	0.082**	-0.003	0.002	0.014
	(0.041)	(0.040)	(0.031)	(0.043)	(0.038)	(0.038)	(0.044)	(0.043)	(0.036)
Observations	1268	1268	1268	1268	1268	1268	1268	1268	1268
R2-Pseudo	0.653	0.654	0.709	0.452	0.453	0.509	0.657	0.659	0.714
Bank Type FE	NO	YES	-	NO	YES	-	NO	YES	-
Bank FE	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note: This table presents the results of Poisson regression of the number of banks' patent applications on bank characteristics. The dependent variable is the total number of patent applications in columns (1)-(3), the lending-related patent applications in columns (4)-(6), and non-lending-related patent applications in columns (7)-(9). Bank type fixed effect and bank fixed effect are specified when indicated. Standard errors at clustered at bank-level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

5.2 Baseline Results

Now we move to examine the role of banks' technological innovation in monetary policy transmission. The baseline regression specification is the following:

$$Loan\ Growth_{it} = \alpha + \beta_1 MP_t \times Tech_{it-1} + \beta_2 MP_t + \beta_3 Tech_{it-1} + \Gamma Control_{it-1} + \delta_i + \epsilon_{it} \quad (10)$$

where $Loan\ Growth_{it}$ is the bank's loan growth rate, MP_t is the monetary policy shock, and $Tech_{it-1}$ is the lagged banks' technological innovation. We use the total patent filings or the lending- and non-lending-related patent filings as $Tech_{it-1}$ separately, and also show the results when lending- and non-lending-related technological innovations are specified simultaneously. These measurements are weighted by the number of forward citations to account for the various importance across patents. $Control_{it-1}$ is an array of lagged control variables, including bank size, capital ratio, deposit growth, loan-to-deposit ratio, cost-to-income ratio, BigTech exposure, and city-level GDP growth, inflation, and loan growth, which can help account for credit demand and at the same time capture cyclical movements. We use the lagged terms of technological innovation and other control variables to mitigate the concern about reverse causality.[14]

We add controls and fixed effects gradually: we first show the results without control variables and fixed effects, and then with controls, bank type fixed effect, and bank fixed effect. Time fixed effect is not specified 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' technological innovation. Specifically, as higher MP_t indicates a tighter monetary policy, a negative β_2 shows the smooth transmission of the bank lending channel, i.e., more contractionary monetary policy is associated with less lending. A β_1 with the same sign of β_2 implies that the higher the bank's technological innovation, the more enhanced impact of monetary policy transmission, *vice versa*. Our theoretical model predicts the same, negative signs for β_1 and β_2, and a positive sign for β_3.

[14] Ma and Zimmermann (2023) find a negative impact of monetary policy tightening on innovation activities, and this impact only becomes significant about two years after the monetary policy shock. Thus, the endogeneity concern on our measurement of banks' technological innovation, especially when lagged by one period, and monetary policy shocks, could be mitigated.

Table 5 shows the results. Several findings stand out. First, the conventional monetary policy transmission to bank lending works. The coefficients of the monetary policy shock variable alone are significantly negative, indicating that a tightening (easing) monetary policy shock induces slower (higher) loan growth. More specifically, based on estimates shown in the fourth row of column (16), a one standard deviation change towards an easing monetary policy brings a 0.07 standard deviation increase in banks' loan growth.

Table 5: Baseline Results: Role of Technological Innovation in Monetary Policy Transmission

DepVar: Loan Growth	All Patents				Lending-related				Not Lending-related				Together			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
MP Shock × L.Tech	0.007	0.013	-0.000	-0.005												
	(0.042)	(0.037)	(0.040)	(0.041)												
MP Shock × L.Lending Tech					-0.375***	-0.168**	-0.188**	-0.212***					-0.487***	-0.250***	-0.264***	-0.286***
					(0.078)	(0.075)	(0.079)	(0.073)					(0.055)	(0.050)	(0.049)	(0.046)
MP Shock × L.Non-Lending Tech									0.057	0.043	0.028	0.024	0.139***	0.085**	0.073**	0.071*
									(0.040)	(0.038)	(0.041)	(0.042)	(0.021)	(0.032)	(0.034)	(0.036)
MP Shock	-0.805***	-0.321*	-0.285	-0.341*	-0.733***	-0.274	-0.245	-0.300*	-0.835***	-0.338*	-0.303*	-0.363**	-0.786***	-0.312*	-0.275	-0.333*
	(0.176)	(0.169)	(0.180)	(0.178)	(0.174)	(0.163)	(0.173)	(0.170)	(0.175)	(0.168)	(0.180)	(0.177)	(0.176)	(0.169)	(0.179)	(0.177)
L.Tech	-0.044*	-0.019	-0.007	-0.004												
	(0.024)	(0.016)	(0.016)	(0.016)												
L.Lending Tech					-0.153***	-0.016	0.031	0.035					0.015	0.046	0.066	0.060
					(0.054)	(0.053)	(0.056)	(0.053)					(0.080)	(0.056)	(0.062)	(0.061)
L.Non-Lending Tech									-0.069***	-0.034*	-0.020	-0.019	-0.091***	-0.048***	-0.037***	-0.035**
									(0.024)	(0.017)	(0.017)	(0.017)	(0.020)	(0.015)	(0.013)	(0.015)
L.Exposure to BigTech Credit		2.935***	2.482***	1.912		2.959***	2.488***	1.932		2.920***	2.470***	1.902		2.917***	2.465***	1.930
		(0.671)	(0.471)	(1.398)		(0.674)	(0.474)	(1.400)		(0.671)	(0.472)	(1.396)		(0.673)	(0.473)	(1.397)
L.Bank Size		-0.143**	-0.335**	-0.325		-0.154**	-0.340**	-0.333		-0.141**	-0.333**	-0.319		-0.142**	-0.335**	-0.319
		(0.064)	(0.139)	(0.323)		(0.066)	(0.139)	(0.321)		(0.063)	(0.139)	(0.323)		(0.065)	(0.139)	(0.322)
L.Capital Ratio		0.046	0.078***	0.110***		0.044	0.077***	0.110***		0.046	0.078***	0.110***		0.046	0.078***	0.111***
		(0.035)	(0.028)	(0.025)		(0.035)	(0.028)	(0.025)		(0.034)	(0.028)	(0.025)		(0.035)	(0.028)	(0.025)
L.Deposit Growth		0.034	0.020	0.014		0.034	0.020	0.014		0.033	0.019	0.014		0.034	0.020	0.014
		(0.021)	(0.020)	(0.021)		(0.020)	(0.020)	(0.021)		(0.021)	(0.020)	(0.021)		(0.020)	(0.020)	(0.021)
L.Loan-to-Deposit Ratio		-0.026***	-0.030***	-0.026**		-0.025***	-0.030***	-0.026**		-0.026***	-0.031***	-0.026**		-0.026***	-0.030***	-0.025**
		(0.009)	(0.009)	(0.012)		(0.009)	(0.009)	(0.012)		(0.009)	(0.009)	(0.012)		(0.009)	(0.009)	(0.012)
L.Cost-to-Income Ratio		0.018	0.020	0.023		0.019	0.021	0.024		0.017	0.020	0.023		0.017	0.020	0.023
		(0.016)	(0.018)	(0.027)		(0.016)	(0.018)	(0.027)		(0.016)	(0.018)	(0.027)		(0.016)	(0.018)	(0.027)
City GDP Growth		0.057***	0.035*	0.041**		0.057***	0.036*	0.041**		0.057***	0.035*	0.041**		0.057***	0.036*	0.041**
		(0.019)	(0.019)	(0.019)		(0.019)	(0.019)	(0.019)		(0.019)	(0.019)	(0.019)		(0.019)	(0.019)	(0.019)
City Inflation		-0.267***	-0.257***	-0.259***		-0.262***	-0.252***	-0.253***		-0.266***	-0.257***	-0.259***		-0.258***	-0.249***	-0.250***
		(0.065)	(0.067)	(0.066)		(0.067)	(0.069)	(0.068)		(0.065)	(0.067)	(0.066)		(0.067)	(0.069)	(0.068)
City Loan Growth		0.509***	0.478***	0.477***		0.505***	0.473***	0.472***		0.510***	0.480***	0.479***		0.505***	0.474***	0.473***
		(0.061)	(0.059)	(0.060)		(0.061)	(0.059)	(0.060)		(0.060)	(0.058)	(0.059)		(0.062)	(0.060)	(0.061)
Observations	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268
R2-Adjusted	0.035	0.278	0.298	0.304	0.037	0.279	0.299	0.306	0.036	0.279	0.298	0.305	0.043	0.280	0.300	0.307
Bank Type FE	NO	NO	YES	-	NO	NO	YES	-	NO	NO	YES	-	NO	NO	YES	-
Bank FE	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES

Note: This table presents the results of regressing bank loan growth rate on the monetary policy shock, bank-level technological innovation, and their interaction term. Bank type and bank fixed effects are used as indicated. The M2-based monetary policy shock and patent-based technological innovation are used in this table. Columns (1)-(4) show the results using the overall innovation and columns (5)-(16) show that when we distinguish between lending-related and non-lending-related technologies. Standard errors are clustered at the bank level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Second, banks' technological innovation plays a role in monetary policy transmission but the role depends on whether the technology is lending-relevant or not. Results in columns (1)-(4) suggest that overall technological innovation is insignificantly associated with the bank's response to monetary policy, however, results in columns (5)-(16) show that lending-related technologies significantly strengthen the monetary policy transmission while non-lending-related technologies show no significant impact or even dampen the transmission. More precisely, based on column (8), one standard deviation increase in the use of lending-related technologies tends to enlarge the response of banks' loan growth to the same one standard deviation of monetary policy shock from 0.07 to 0.10 standard deviations. When the two types of technologies are specified together, results from column (16) show that one standard deviation increase in the use of lending-related technologies tends to enlarge the response of banks' loan growth to the same one standard deviation of monetary policy shock from 0.07 to 0.12 standard deviations, meanwhile increasing the use of non-lending-related technologies by one standard deviation would mitigate the transmission from 0.07 to 0.03. In other words, there is a strengthening effect of over 70% from lending-related technologies and a weakening effect of over 50% from the use of non-lending-related technologies, together resulting in an ambiguous effect of overall technological innovation. In comparing these findings with the predictions of the theory it is reasonable to assume that lending-related technologies are more likely to relax the earning-based borrowing constraints by reducing monitoring costs and thus more likely to amplify monetary policy transmission than non-lending-related technologies.

In contrast to the predictions of the theory, technological innovation on its own appears to have an ambiguous association with loan growth. The role of technological innovations is insignificant or even negative when fixed effects are not specified. To reconcile the empirical findings with the model prediction, it is worth noticing that our theoretical model does not take into account the costs of a bank's innovation. If a bank's innovation expenses would either increase the cost of the bank's funds or reduce the amount it can lend to the firms, the bank's innovations would no longer necessarily have a direct positive effect on lending, while they could still have the indirect impact via the lending channel of monetary policy transmission. Also, the results concerning the sign of β_3 are more in line with the theoretical prediction in the long run when we do not consider monetary policy and examine the role of technological innovation alone (see Figure A4 in the appendix).

The relations of other control variables with bank loan growth are intuitive. Results show that banks with smaller sizes, higher capital ratios, and lower loan-to-deposit ratios tend to have higher loan growth rates. More exposure to BigTech is also associated with higher loan growth cross-sectionally but not within the bank. It indicates that for a given bank the role of competition from the BigTech is ambiguous, but when we compare banks facing tight competition and weak competition, the former tend to have higher loan growth. In addition, stronger economic and loan growths and lower inflation in the local region are associated with higher bank loan growth.

Then we examine the dynamic impact using the Jordà (2005)-style local projection, which is specified as follows:

$$\begin{aligned} Loan_{it+h-1} - Loan_{it-1} = \alpha + \beta_{1h} MP_t \times Tech_{it-1} + \beta_{2h} MP_t + \beta_3 Tech_{it-1} \\ + \Sigma_{k=1}^{3} \gamma_{h,k} MP_{t-k} + \Gamma_h Control_{it-1} + \delta_{ih} + \epsilon_{ith} \end{aligned} \tag{11}$$

where $h = 0, 1, 2, ..., 10$ indexes the forecast horizon. We use the cumulative change in bank loan from $t-1$ to $t+h-1$ on the left-hand side, and add three lags of the monetary policy shock on the right-hand side to mitigate the concern on autocorrelation of the shock series. The coefficient β_{1h} measures how the cumulative response of bank loan growth in quarter $t+h$ to a monetary policy shock in quarter t depends on the bank's technology adoption in quarter $t-1$.

Figure 6 shows the estimates of β_{1h}. The left panel shows no significant role in the total technological innovation throughout the horizon of ten quarters. The two middle panels, which analyze lending and non-lending-related technologies separately, reveal an interesting pattern. Specifically, we find that the adoption of lending-related technologies enhances a bank's responsiveness to monetary policy shocks. This transmission-boosting effect not only becomes more pronounced over time but also remains significant for as long as eight quarters post-shock. Notably, however, this effect appears subdued during the initial one to six quarters following the shock. In contrast, non-lending-related technological innovations are insignificantly associated with the response to the monetary policy shock throughout ten quarters. On the right panel, when we specify the two types of technological innovations together, the transmission-enhancing role of lending-related technologies displays larger and more persistent effects over time. Non-lending-related technologies display a role in mitigating banks' responses to monetary policy two quarters after the shock, but the magnitudes do not increase over time and are smaller than those of lending-related technologies.

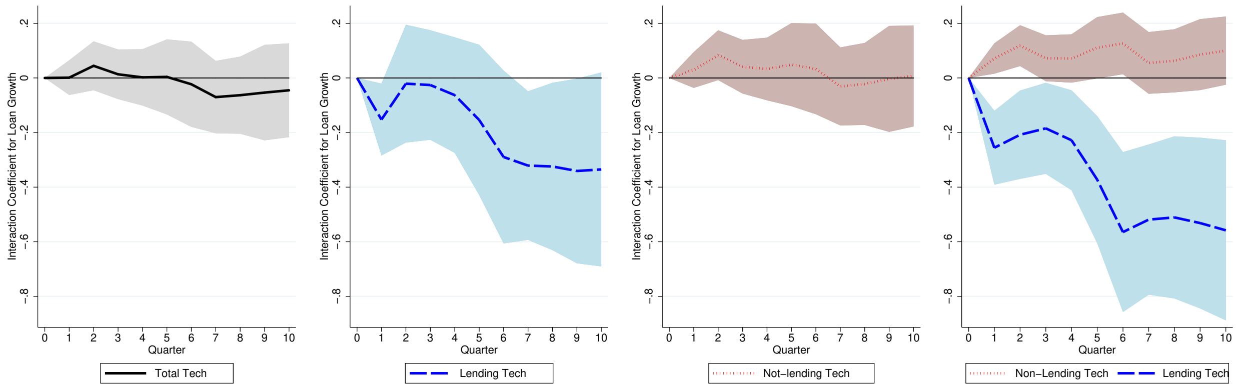

Figure 6: Local Projections of the Role of Technological Innovation

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

5.3 Robustness Checks

We next conduct various robustness checks. First, we conduct a horse race between technological innovation and other factors that could affect banks' responses to monetary policy. Specifically, in addition to using them as control variables, we also interact bank size, capital ratio, cost-to-income ratio, loan-to-deposit ratio, and exposure to BigTech with monetary policy shocks, and examine whether the role of technological innovation still holds in this horse race with alternative factors. Results in Table 6 show that the transmission-enhancing role of lending-related technological innovation is still significantly present in this horse race. Moreover, banks with a higher capital ratio tend to show an enhanced lending channel transmission when faced with monetary policy shocks, which is consistent with Fungáčová et al. (2016) using Chinese data, while the roles of size, deposit growth, loan-to-deposit ratio, cost-to-income ratio, and BigTech exposure are ambiguous in affecting banks' response to monetary policy shocks.

Table 6: Robustness Check: Horse Race with Other Characteristics

DepVar: Loan Growth	All Patents			Lending-related			Not Lending-related			Together		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MP Shock × L.Tech	0.033	0.025	0.019									
	(0.039)	(0.041)	(0.042)									
MP Shock × L.Lending Tech				-0.147**	-0.149**	-0.182**				-0.233***	-0.236***	-0.269***
				(0.069)	(0.066)	(0.087)				(0.067)	(0.068)	(0.062)
MP Shock × L.Non-Lending Tech							0.068*	0.060	0.056	0.102***	0.094**	0.094**
							(0.036)	(0.039)	(0.040)	(0.034)	(0.036)	(0.039)
MP Shock × L.Bank Size	-0.099	-0.129	-0.129	-0.049	-0.083	-0.081	-0.110	-0.141	-0.144	-0.082	-0.113	-0.111
	(0.101)	(0.101)	(0.097)	(0.095)	(0.094)	(0.093)	(0.098)	(0.098)	(0.094)	(0.098)	(0.099)	(0.094)
MP Shock × L.Capital Ratio	-0.129**	-0.112*	-0.101	-0.127*	-0.110	-0.099	-0.131**	-0.114*	-0.104	-0.131**	-0.114*	-0.104
	(0.063)	(0.066)	(0.069)	(0.073)	(0.076)	(0.069)	(0.063)	(0.066)	(0.069)	(0.063)	(0.066)	(0.069)
MP Shock × L.Deposit Growth	0.006	0.012	0.013	0.005	0.012	0.013	0.006	0.013	0.014	0.007	0.013	0.015
	(0.047)	(0.047)	(0.047)	(0.055)	(0.057)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
MP Shock × L.Loan-to-Deposit Ratio	0.007	0.010	0.005	0.001	0.004	-0.001	0.007	0.010	0.005	0.001	0.004	-0.002
	(0.015)	(0.016)	(0.016)	(0.014)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.016)
MP Shock × L.Cost-to-Income Ratio	-0.028	-0.019	-0.026	-0.029	-0.020	-0.027	-0.028	-0.018	-0.026	-0.028	-0.018	-0.026
	(0.024)	(0.024)	(0.023)	(0.025)	(0.026)	(0.023)	(0.024)	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)
MP Shock × L.Exposure to BigTech Credit	-0.638	-0.871	-0.648	-0.656	-0.882	-0.660	-0.602	-0.837	-0.603	-0.557	-0.789	-0.545
	(1.222)	(1.205)	(1.207)	(1.473)	(1.460)	(1.207)	(1.219)	(1.202)	(1.203)	(1.212)	(1.195)	(1.201)
Observations	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268
R2-Adjusted	0.286	0.303	0.309	0.286	0.304	0.310	0.286	0.304	0.309	0.287	0.305	0.311
Bank Type FE	NO	YES	-	NO	YES	-	NO	YES	-	NO	YES	-
Bank FE	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of regressing bank loan growth rate on the monetary policy shock, bank-level technological innovation, and the interaction terms between each bank-level characteristics and monetary policy shock. Bank type and bank fixed effects are specified when indicated. The M2-based monetary policy shock and patent-based technological innovation are used in this table. Columns (1)-(3) show the results using the overall innovation and columns (4)-(12) show that when we distinguish between lending-related and non-lending-related technologies. Standard errors are clustered at the bank level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 7: Robustness: Interest Rate as MP

DepVar: Loan Growth	All Patents			Lending-related			Not Lending-related			Together		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Rate × L.Tech	0.011	0.006	0.005									
	(0.018)	(0.018)	(0.017)									
Δ Rate × L.Lending Tech				-0.213*	-0.219*	-0.228**				-0.338**	-0.338**	-0.349**
				(0.109)	(0.115)	(0.111)				(0.134)	(0.137)	(0.133)
Δ Rate × L.Non-Lending Tech							0.036	0.029	0.030	0.088**	0.081**	0.084**
							(0.024)	(0.023)	(0.022)	(0.033)	(0.033)	(0.032)
Δ Rate	-0.510***	-0.516***	-0.521***	-0.472***	-0.481***	-0.485***	-0.522***	-0.529***	-0.534***	-0.504***	-0.510***	-0.516***
	(0.158)	(0.156)	(0.150)	(0.154)	(0.153)	(0.147)	(0.158)	(0.157)	(0.150)	(0.158)	(0.157)	(0.150)
L.Tech	-0.014***	-0.008**	-0.007**									
	(0.005)	(0.004)	(0.003)									
L.Lending Tech				-0.049	-0.008	-0.009				0.008	0.028	0.027
				(0.055)	(0.058)	(0.057)				(0.082)	(0.086)	(0.087)
L.Non-Lending Tech							-0.015***	-0.009**	-0.009**	-0.016**	-0.011	-0.011
							(0.005)	(0.004)	(0.003)	(0.007)	(0.007)	(0.007)
Observations	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268
R2-Adjusted	0.280	0.301	0.306	0.280	0.302	0.307	0.281	0.301	0.306	0.281	0.302	0.307
Bank Type FE	NO	YES	-	NO	YES	-	NO	YES	-	NO	YES	-
Bank FE	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of regressing bank loan growth rate on the $\Delta FR007$, bank-level technological innovation, and their interaction term. Bank type and bank fixed effects are specified when indicated. The price-based monetary policy shock and patent-based technological innovation are used in this table. Columns (1)-(3) show the results using the overall innovation and columns (4)-(12) show that when we distinguish between lending-related and non-lending-related technologies. Standard errors are clustered at the bank level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Second, we show the results using the price-based instead of the M2-based monetary policy measure. Specifically, Table 7 presents the baseline estimates using the change in the interbank seven-day repo rate of FR007 as MP_{t-1}. Again, the bank lending channel of monetary policy works as an increase in this rate-based rate is significantly associated with a decrease in loan growth. Based on estimates shown in column (12), a one standard deviation increase in $\Delta FR007$ is associated with a 0.08 standard deviation decrease in bank loan growth, the magnitude of which is similar to that in the baseline. Moreover, the coefficients of the interaction term between $\Delta FR007$ and lending-related technological innovation are significantly negative, in both the specifications when the lending-related technological innovation is used alone or together with non-lending-related technological innovation. A one standard deviation increase in the pace of lending-related technological innovation almost doubles the effect of monetary policy change by one standard deviation on loan growth. These results suggest that the baseline finding of the transmission-enhancing role of new lending-related technologies holds.

Table 8: Robustness Check: Alternative Measurement of Technological Innovation

DepVar: Loan Growth	All Patents			Lending-related			Not Lending-related			Together		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MP Shock × L.Ln(1+Tech)	-0.071	-0.122	-0.144									
	(0.185)	(0.188)	(0.185)									
MP Shock × L.Ln(1+Lending Tech)				-0.512**	-0.565**	-0.650***				-0.732***	-0.754***	-0.862***
				(0.216)	(0.222)	(0.203)				(0.151)	(0.155)	(0.128)
MP Shock × L.Ln(1+Non-Lending Tech)							-0.001	-0.061	-0.075	0.289*	0.237	0.257
							(0.203)	(0.208)	(0.206)	(0.165)	(0.166)	(0.161)
MP Shock	-0.295	-0.250	-0.305	-0.269	-0.239	-0.293*	-0.313*	-0.267	-0.325*	-0.317*	-0.271	-0.331*
	(0.177)	(0.188)	(0.186)	(0.164)	(0.174)	(0.172)	(0.177)	(0.189)	(0.186)	(0.178)	(0.190)	(0.187)
L.Ln(1+Tech)	-0.323***	-0.178**	-0.159**									
	(0.084)	(0.071)	(0.077)									
L.Ln(1+Lending Tech)				-0.157	0.022	0.003				0.323*	0.321*	0.217
				(0.165)	(0.151)	(0.141)				(0.175)	(0.170)	(0.170)
L.Ln(1+Non-Lending Tech)							-0.370***	-0.220***	-0.191**	-0.488***	-0.339***	-0.280***
							(0.090)	(0.074)	(0.080)	(0.097)	(0.082)	(0.092)
Observations	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268
R2-Adjusted	0.281	0.299	0.306	0.279	0.300	0.307	0.282	0.299	0.305	0.283	0.301	0.307
Bank Type FE	NO	YES	-	NO	YES	-	NO	YES	-	NO	YES	-
Bank FE	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note: This table presents the results of regressing bank loan growth rate on the monetary policy shock, bank-level technological innovation specified as log(1+tech patents), and their interaction term. Bank type and bank fixed effects are specified when indicated. The M2-based monetary policy shock and patent-based technological innovation are used in this table. Columns (1)-(3) show the results using the overall innovation and columns (4)-(12) show that when we distinguish between lending-related and non-lending-related technologies. Standard errors are clustered at the bank level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Third, we use a transformation of the technological innovation measurement and a restricted sample to re-estimate the baseline specification. Specifically, we use the natural logarithm of one plus the number of technological patents to mitigate the concern of the skewness of the patenting activities, and we restrict the sample to the 22 banks who had at least one technology patent to mitigate the concern that there are many zeros in the patenting measurement. Here we use the M2-based monetary policy shock as in the baseline. Results are shown in Tables 8 and 9. Again, the coefficients of the interaction term between the monetary policy shock and the lending-related technological innovation are significantly negative in both alternative settings, implying that lending-related technologies strengthen the bank lending channel.

Table 9: Robustness Check: Restricting to Banks with At Least One Patent

DepVar: Loan Growth	All Patents			Lending-related			Not Lending-related			Together		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MP Shock × L.Tech	0.006	-0.001	-0.003									
	(0.039)	(0.041)	(0.041)									
MP Shock × L.Lending Tech				-0.171**	-0.175**	-0.187**				-0.247***	-0.250***	-0.261***
				(0.080)	(0.082)	(0.077)				(0.051)	(0.049)	(0.049)
MP Shock × L.Non-Lending Tech							0.034	0.027	0.025	0.075**	0.068*	0.068*
							(0.040)	(0.042)	(0.042)	(0.036)	(0.036)	(0.037)
MP Shock	-0.379*	-0.324	-0.373	-0.326	-0.275	-0.323	-0.402*	-0.348	-0.400*	-0.369	-0.314	-0.365
	(0.218)	(0.237)	(0.220)	(0.208)	(0.225)	(0.208)	(0.218)	(0.237)	(0.220)	(0.218)	(0.236)	(0.219)
L.Tech	-0.010	-0.002	-0.001									
	(0.016)	(0.016)	(0.016)									
L.Lending Tech				0.024	0.054	0.049				0.061	0.074	0.060
				(0.057)	(0.057)	(0.051)				(0.061)	(0.063)	(0.058)
L.Non-Lending Tech							-0.023	-0.015	-0.015	-0.038**	-0.031**	-0.030*
							(0.017)	(0.017)	(0.017)	(0.015)	(0.014)	(0.015)
Observations	848	848	848	848	848	848	848	848	848	848	848	848
R2-Adjusted	0.324	0.331	0.347	0.326	0.333	0.350	0.325	0.331	0.348	0.326	0.333	0.350
Bank Type FE	NO	YES	-	NO	YES	-	NO	YES	-	NO	YES	-
Bank FE	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Note: This table presents the results of regressing bank loan growth rate on the monetary policy shock, bank-level technological innovation, and their interaction term. The sample is restricted to the banks that had at least one technological patent across the period. Bank type and bank fixed effects are specified when indicated. The M2-based monetary policy shock and patent-based technological innovation are used in this table. Columns (1)-(3) show the results using the overall innovation and columns (4)-(12) show that when we distinguish between lending-related and non-lending-related technologies. Standard errors are clustered at the bank level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

6 Discussion

6.1 Different Categories of Technology

With the granularity of our data, we can have a look at the heterogeneity across six categories of technology adopted by the bank. We first simply use the three categories from the broad IPC codes, G06Q20, G06Q30, and G06Q40, which correspond to technologies in payment, e-commerce, and finance, respectively. Then we use the six granular types of technologies identified through textual analysis: AI, big data, cloud computing, digitization, machine learning, and blockchain. We use the citation-weighted number of patent applications in each type of technology and interact it with the monetary policy shock.

Results are shown in Tables 10 and 11, where we first examine each type of technology separately and then consider them all together. They show that the transmission-strengthening role of e-commerce, big data, and machine learning technologies stands out compared to the rest. First, in comparison with payment and finance technologies in which traditional banks may have an advantage over BigTech and FinTech players, banks' innovation in e-commerce technologies, in which banks are at a disadvantage, is the driver of the transmission-enhancing effect. This finding relates to the increasing need for banks to capture customers' digital footprint in terms of online shopping, thereby better assessing their cash flows and creditworthiness. Second, big data and machine learning technologies could help banks depict borrower images and catch up with BigTech in the data collection and large models of credit evaluation. Moreover, the opposite findings regarding blockchain align with Cheng et al. (2022) who document that cloud computing shows a substitutive effect on profit efficiency from blockchain. Overall, these results suggest that new technologies enhance transmission via increased data access to digital footprints and enhanced computing and storing capacities, which may be used to reduce earning-based borrowing constraints as shown in the theory.

Table 10: Heterogeneity by Three Broad Categories of Technology

DepVar: Loan Growth	Payment	E-Commerce	Finance	All
	(1)	(2)	(3)	(4)
MP Shock × L.Payment Tech	0.039			0.078
	(0.065)			(0.056)
MP Shock × L.E-Commerce Tech		-0.257		-0.323**
		(0.181)		(0.142)
MP Shock × L.Finance Tech			-0.008	0.000
			(0.054)	(0.055)
L.Payment Tech	-0.069**			-0.119***
	(0.034)			(0.022)
L.E-Commerce Tech		0.129**		0.250**
		(0.058)		(0.098)
L.Finance Tech			-0.003	-0.000
			(0.020)	(0.017)
MP Shock	-0.355**	-0.322*	-0.342*	-0.337*
	(0.173)	(0.170)	(0.177)	(0.178)
Observations	1268	1268	1268	1268
R2-Adjusted	0.305	0.305	0.304	0.305
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, different categories of bank-level technological innovation, and their interaction term. Bank fixed effects and other bank-level and macro-level control variables are specified when indicated. The M2-based monetary policy shock and patent-based innovation measures are used in this table. Columns (1)-(3) show the results using different categories of bank-level innovations on their own and columns (4) show the results when they are specified together. Standard errors are clustered at the bank level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 11: Heterogeneity by Six Granular Categories of Technology

DepVar: Loan Growth	AI	Bigdata	Cloud Computing	Digitalization	Machine Learning	Blockchain	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MP Shock × L.AI Tech	0.010						0.105
	(0.221)						(0.133)
MP Shock × L.Big Data Tech		-0.104*					-0.124***
		(0.037)					(0.021)
MP Shock × L.Cloud Computing Tech			-0.050				-0.400
			(0.325)				(0.256)
MP Shock × L.Digitalization Tech				0.062			0.129**
				(0.063)			(0.024)
MP Shock × L.Machine Learning Tech					-0.055		-0.069**
					(0.103)		(0.017)
MP Shock × L.Blockchain Tech						0.054	0.096***
						(0.066)	(0.004)
L.AI Tech	-0.120						-0.082**
	(0.091)						(0.021)
L.Big Data Tech		0.032**					0.100*
		(0.007)					(0.042)
L.Cloud Computing Tech			-0.339**				-0.372**
			(0.136)				(0.078)
L.Digitalization Tech				-0.065**			-0.110*
				(0.030)			(0.036)
L.Machine Learning Tech					-0.003		0.032***
					(0.042)		(0.005)
L.Blockchain Tech						-0.025	-0.018*
						(0.018)	(0.006)
MP Shock	-0.347**	-0.316	-0.345**	-0.363**	-0.334*	-0.351**	-0.332
	(0.169)	(0.178)	(0.169)	(0.177)	(0.171)	(0.169)	(0.194)
Observations	1268	1268	1268	1268	1268	1268	1268
R2-Adjusted	0.305	0.305	0.305	0.305	0.305	0.304	0.301
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, different categories of bank-level technological innovation, and their interaction term. Bank fixed effects and other bank-level and macro-level control variables are specified when indicated. The M2-based monetary policy shock and patent-based innovation measures are used in this table. Columns (1)-(6) show the results using different categories of bank-level innovations on their own and columns (7) show the results when they are specified together. Standard errors are clustered at the bank level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

6.2 COVID-19 Episodes

The COVID-19 pandemic is an interesting period to test the role of technology in banking, as there was a shock for digital banking services due to mobility restrictions, and some studies have shown that technological savviness is associated with banks' performance during the pandemic (Kwan et al. 2023, Dadoukis et al. 2021, Berger and Demirgüç-Kunt 2021). Here we discuss the role of banks' technological innovation in the monetary policy transmission during the COVID-19 episode.

We re-estimate the baseline specification but replace the sample period with 2020Q1-2021Q4 and use banks' patenting activities at the end of 2019Q4 to measure technological innovation, therefore it is exogenous as well as time-invariant. In this way, we can also mitigate the concern that technological innovation is endogenous to bank lending. As explained in Section 4.2, the quantity-based monetary policy framework has gradually been replaced by the price-based one in most recent years and the government did not specify the M2 growth target after 2018, thus, it is more reasonable to use the price-based monetary policy measurement, i.e., $\Delta FR007$, in the estimation based on COVID-19 episodes.

Table 12: Pre-COVID technological innovation and bank lending channel in COVID-19 period

DepVar: Loan Growth	All Patents			Lending-related			Not Lending-related			Together		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ Rate $\times$ Tech (2019)	-0.003*	-0.003**	-0.003**									
	(0.001)	(0.001)	(0.001)									
Δ Rate $\times$ L.Lending Tech (2019)				-0.028**	-0.029**	-0.030**				-0.016	-0.018	-0.025
				(0.014)	(0.013)	(0.012)				(0.031)	(0.029)	(0.025)
Δ Rate $\times$ L.Non-Lending Tech (2019)							-0.003*	-0.003**	-0.003*	-0.002	-0.001	-0.001
							(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Δ Rate	-1.250***	-1.186***	-1.045***	-1.239***	-1.177***	-1.026***	-1.255***	-1.190***	-1.051***	-1.241***	-1.175***	-1.025***
	(0.364)	(0.365)	(0.363)	(0.366)	(0.366)	(0.361)	(0.363)	(0.364)	(0.362)	(0.367)	(0.368)	(0.362)
Observations	312	312	312	312	312	312	312	312	312	312	312	312
R2	0.373	0.397	0.556	0.373	0.397	0.556	0.373	0.397	0.556	0.373	0.397	0.556
Bank Type FE	NO	YES	-	NO	YES	YES	NO	YES	YES	NO	YES	-
Bank FE	NO	NO	YES	NO	NO	NO	NO	NO	NO	NO	NO	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of regressing bank loan growth rate on $\Delta FR007$, bank-level technological innovation as of 2019Q4, and their interaction term. The sample period is 2020Q1-2021Q4. Bank type and bank fixed effects are specified when indicated. Columns (1)-(3) show the results using the overall innovation and columns (4)-(12) show that when we distinguish between lending-related and non-lending-related technologies. Standard errors are clustered at the bank level and they are shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 12 shows the results. First, an increase (decrease) in the monetary policy rate is significantly associated with reduced (increased) loan growth in this period. Second, results in columns (1)-(9) indicate that a more advanced level of pre-COVID technological innovation is significantly associated with larger responses of bank lending to monetary policy during the COVID episode, though the last three columns show an insignificant effect when they are specified together. Regarding magnitudes, the transmission-strengthening effect of lending-related technologies is more pronounced than that of non-lending-related ones.

7 Conclusion

This study examines the effects of bank-level technological innovation on the lending channel of monetary policy transmission. We first construct a theoretical model in which technological innovation relaxes the earnings-based borrowing constraints. We show how this lending-related technological innovation amplifies the response of banks' lending to monetary policy shock. Then we provide empirical evidence that is consistent with this theoretical prediction. Specifically, we construct a patent-based measurement of bank-level technological innovation, and test whether its interaction term with monetary policy shocks shows significant effects on bank loan growth. Results demonstrate that if banks' technological innovation is lending-related it is significantly associated with strengthened responses to monetary policy shocks. Similar patterns are not found for other, non-lending banking innovations. These findings hold in a battery of robustness checks.

These findings are important to understanding 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. There should be a stronger focus on monitoring these new factors that are likely to influence the functioning of the monetary policy transmission mechanism. The impact of financial innovation also calls for more intensive financial supervision and wider prudential regulation, and the effects of various types of technological innovation and exposures to the BigTech competition imply that the regulation will have to further expand the focus from financial entities to financial activities in the future.

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Appendix

Technological Innovation and the Bank Lending Channel of Monetary Policy Transmission

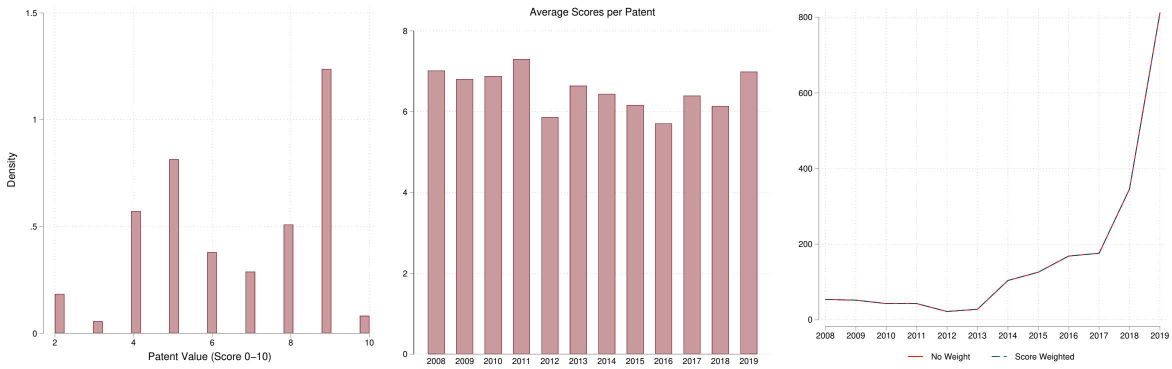

Figure A1: Score-Weighted Patent Applications

Notes: This figure shows the histogram distribution of the value scores of each patent in the left panel, the average score per patent over years in the middle panel, and the comparison of the aggregate trends captured by simple counts and score-weighted patent measurement in the right panel.

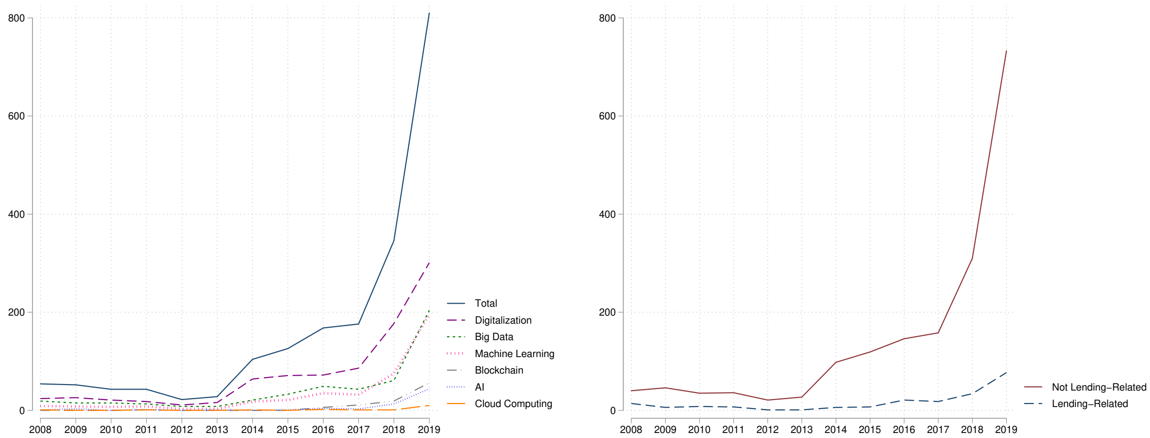

Figure A2: Banks' Technological Innovation: Patent Applications (Not-Weighted)

Notes: This figure shows various numbers of patent filings by banks by filing year. The left panel shows the total number and its division into six technologies, which are AI, big data, cloud computing, digitalization, machine learning, and blockchain. The right panel shows the number of lending-related and non-lending-related patent applications separately. We identify the categories of technologies and whether or not the patent application is lending-related based on the descriptions in the patent document.

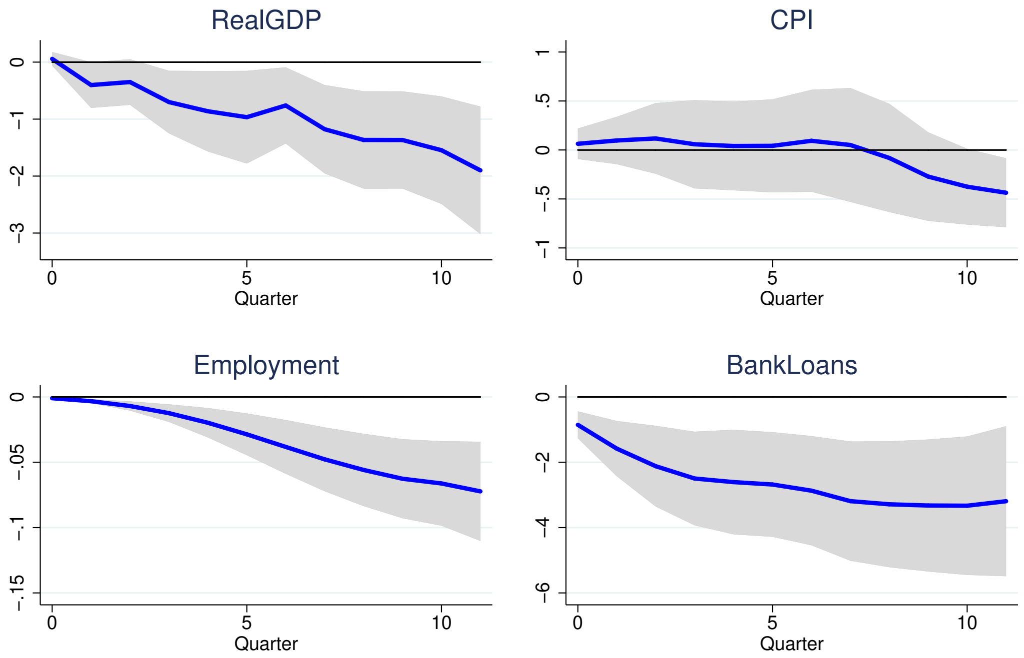

Figure A3: Local Projection: Monetary Policy Transmission

Notes: This figure shows the impulse responses of real GDP, inflation, employment, and bank loans to the M2-based monetary policy shock indicator. The estimations are conducted using the local projection methodologies (Jordà 2005) and the aggregate macroeconomic variables are obtained from the Center for Quantitative Economic Research in the Federal Reserve Bank of Atlanta.

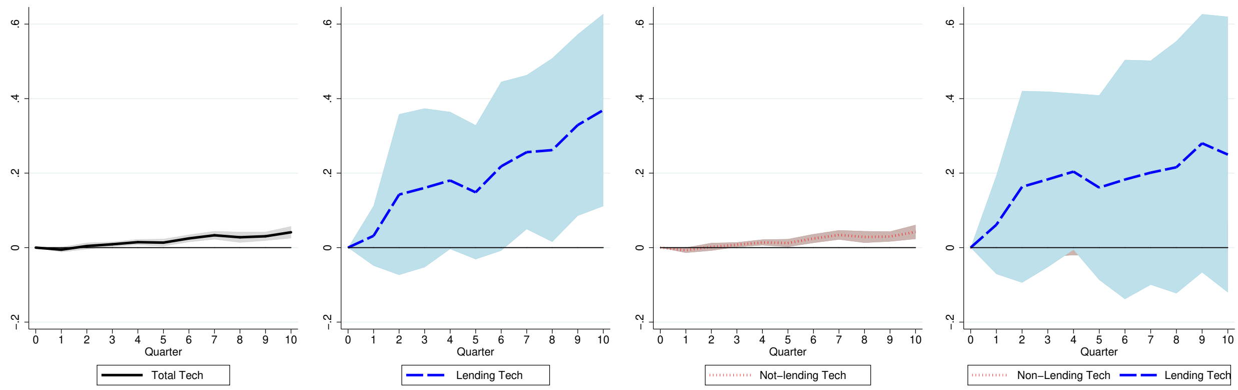

Figure A4: Technological Innovation and Loan Growth: No Consideration of Monetary Policy

Table A1: BigTech Penetration Measurement

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: The financial services mentioned in the table all refer to those conducted in Alipay. We use the broad measurements of usage in the analysis. The measurement is constructed based on nondimensionalization of the 20 root indicators. The original data for these 20 indicators are not publicly available.

*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 that 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: Baseline Results Using Pre-2017 Sample

DepVar: Loan Growth	All Patents				Lending-related				Not Lending-related				Together			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
MP Shock × L.Tech Adoption	-0.033	-0.012	-0.022	-0.029												
	(0.039)	(0.037)	(0.037)	(0.034)												
MP Shock × L.Lending Tech Adoption					-0.489***	-0.173**	-0.174**	-0.145**					-0.699***	-0.268***	-0.265**	-0.227**
					(0.049)	(0.065)	(0.065)	(0.065)					(0.124)	(0.098)	(0.098)	(0.089)
MP Shock × L.Non-Lending Tech Adoption									0.068	0.036	0.020	0.006	0.274***	0.127***	0.110***	0.087**
									(0.067)	(0.048)	(0.048)	(0.043)	(0.048)	(0.039)	(0.039)	(0.035)
MP Shock	-0.982***	-0.488**	-0.484**	-0.431**	-0.921***	-0.460**	-0.463**	-0.417**	-1.045***	-0.518**	-0.513**	-0.457**	-1.014***	-0.506**	-0.502**	-0.449**
	(0.199)	(0.212)	(0.207)	(0.205)	(0.195)	(0.202)	(0.198)	(0.196)	(0.201)	(0.214)	(0.210)	(0.209)	(0.202)	(0.214)	(0.209)	(0.208)
L.Tech Adoption	-0.048	-0.012	0.003	0.020												
	(0.043)	(0.027)	(0.026)	(0.020)												
L.Lending Tech Adoption					-0.264**	0.012	0.062	0.152**					-0.011	0.125	0.129	0.170
					(0.104)	(0.096)	(0.088)	(0.059)					(0.164)	(0.138)	(0.135)	(0.118)
L.Non-Lending Tech Adoption									-0.090	-0.034	-0.016	0.003	-0.148**	-0.073*	-0.055	-0.035
									(0.058)	(0.036)	(0.035)	(0.029)	(0.060)	(0.036)	(0.035)	(0.028)
Observations	820	820	820	820	820	820	820	820	820	820	820	820	820	820	820	820
R2-Adjusted	0.044	0.325	0.344	0.344	0.049	0.326	0.345	0.345	0.045	0.325	0.344	0.343	0.056	0.326	0.345	0.344
Bank Type FE	NO	NO	YES	-	NO	NO	YES	-	NO	NO	YES	-	NO	NO	YES	-
Bank FE	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES

Table A3: Baseline Results Using Score-Weighted Patent Measurement

DepVar: Loan Growth	All Patents				Lending-related				Not Lending-related				Together			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
MP Shock × L.Tech Adoption	0.024	0.022	0.008	0.002												
	(0.038)	(0.031)	(0.033)	(0.034)												
MP Shock × L.Lending Tech Adoption					-0.505***	-0.228**	-0.255**	-0.287***					-0.777***	-0.421***	-0.445***	-0.473***
					(0.093)	(0.107)	(0.113)	(0.104)					(0.053)	(0.070)	(0.067)	(0.069)
MP Shock × L.Non-Lending Tech Adoption									0.060	0.044	0.028	0.023	0.158***	0.098***	0.085***	0.082***
									(0.045)	(0.033)	(0.034)	(0.035)	(0.031)	(0.022)	(0.023)	(0.024)
MP Shock	-0.818***	-0.328*	-0.292	-0.349*	-0.733***	-0.276*	-0.246	-0.302*	-0.838***	-0.340*	-0.305*	-0.363**	-0.792***	-0.316*	-0.279	-0.337*
	(0.174)	(0.169)	(0.179)	(0.177)	(0.173)	(0.164)	(0.174)	(0.171)	(0.174)	(0.169)	(0.180)	(0.178)	(0.174)	(0.170)	(0.180)	(0.178)
L.Tech Adoption	-0.050**	-0.021	-0.009	-0.007												
	(0.019)	(0.013)	(0.013)	(0.013)												
L.Lending Tech Adoption					-0.269***	-0.056	0.006	0.010					-0.065	0.009	0.015	-0.000
					(0.084)	(0.060)	(0.053)	(0.054)					(0.108)	(0.052)	(0.055)	(0.062)
L.Non-Lending Tech Adoption									-0.070***	-0.032**	-0.019	-0.017	-0.084***	-0.044***	-0.032***	-0.029**
									(0.022)	(0.015)	(0.014)	(0.015)	(0.021)	(0.012)	(0.011)	(0.013)
L.Exposure to BigTech Credit		2.926***	2.475***	1.903		2.955***	2.489***	1.962		2.913***	2.466***	1.892		2.903***	2.450***	1.931
		(0.672)	(0.472)	(1.396)		(0.674)	(0.473)	(1.400)		(0.673)	(0.473)	(1.395)		(0.675)	(0.475)	(1.395)
L.Bank Size		-0.143**	-0.334**	-0.323		-0.150**	-0.338**	-0.324		-0.140**	-0.333**	-0.320		-0.142**	-0.334**	-0.318
		(0.063)	(0.139)	(0.323)		(0.065)	(0.139)	(0.322)		(0.062)	(0.140)	(0.323)		(0.064)	(0.139)	(0.322)
L.Capital Ratio		0.046	0.077***	0.110***		0.045	0.078***	0.111***		0.046	0.077***	0.110***		0.046	0.078***	0.110***
		(0.035)	(0.028)	(0.025)		(0.035)	(0.028)	(0.025)		(0.034)	(0.028)	(0.025)		(0.035)	(0.028)	(0.025)
L.Deposit Growth		0.034	0.020	0.014		0.034	0.020	0.014		0.034	0.020	0.014		0.034	0.020	0.015
		(0.021)	(0.021)	(0.021)		(0.020)	(0.020)	(0.021)		(0.021)	(0.021)	(0.021)		(0.021)	(0.021)	(0.021)
L.Loan-to-Deposit Ratio		-0.026***	-0.030***	-0.026**		-0.025***	-0.030***	-0.025**		-0.026***	-0.031***	-0.026**		-0.025***	-0.030***	-0.025**
		(0.009)	(0.009)	(0.012)		(0.009)	(0.009)	(0.012)		(0.009)	(0.009)	(0.012)		(0.009)	(0.009)	(0.012)
L.Cost-to-Income Ratio		0.018	0.020	0.023		0.019	0.021	0.024		0.017	0.020	0.023		0.017	0.020	0.023
		(0.016)	(0.018)	(0.027)		(0.016)	(0.018)	(0.027)		(0.015)	(0.018)	(0.027)		(0.016)	(0.018)	(0.027)
City GDP Growth		0.057***	0.035*	0.041**		0.058***	0.036*	0.042**		0.056***	0.035*	0.041**		0.057***	0.036*	0.042**
		(0.018)	(0.019)	(0.019)		(0.019)	(0.019)	(0.019)		(0.018)	(0.019)	(0.019)		(0.018)	(0.019)	(0.019)
City Inflation		-0.267***	-0.257***	-0.259***		-0.264***	-0.254***	-0.255***		-0.266***	-0.257***	-0.259***		-0.259***	-0.249***	-0.250***
		(0.065)	(0.067)	(0.066)		(0.066)	(0.068)	(0.067)		(0.065)	(0.067)	(0.066)		(0.067)	(0.069)	(0.068)
City Loan Growth		0.510***	0.479***	0.478***		0.504***	0.473***	0.471***		0.510***	0.480***	0.479***		0.505***	0.473***	0.472***
		(0.060)	(0.059)	(0.059)		(0.061)	(0.059)	(0.060)		(0.060)	(0.058)	(0.059)		(0.062)	(0.060)	(0.061)
Observations	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268	1268
R2-Adjusted	0.036	0.278	0.298	0.304	0.040	0.279	0.300	0.306	0.037	0.279	0.298	0.305	0.045	0.281	0.300	0.307
Bank Type FE	NO	NO	YES	-	NO	NO	YES	-	NO	NO	YES	-	NO	NO	YES	-
Bank FE	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES