BigTech Credit, Small Business, and Monetary Policy Transmission: Theory and Evidence

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Abstract

This paper provides both theoretical and empirical analyses of the differences between BigTech lenders and traditional banks in response to monetary policy changes. Our model integrates Knightian uncertainty into portfolio selection and posits that BigTech lenders possess a diminishing informational advantage with increasing firm size, resulting in reduced ambiguity when lending to smaller firms. The model suggests that the key distinction between BigTech lenders and traditional banks in response to shifts in funding costs, triggered by monetary policy changes, is more evident at the extensive margin rather than the intensive margin, particularly during periods of easing monetary policy. Using a micro-level dataset of small business loans from both types of lenders, we provide empirical support for our theoretical propositions. Our results show that BigTech lenders are more responsive in establishing new lending relationships in an easing monetary policy environment, while the differences in loan amounts are not statistically significant. We also discuss other loan terms and the implications of regulatory policies.

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

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1 Introduction

The recent use of technology in providing financial services has significantly disrupted the financial sector, with big technology companies – referred to as BigTech, such as Alibaba, Amazon, and Mercado Libre – emerging as key players in the credit market.[1] By leveraging advancements in information technology and credit-scoring techniques, which utilize vast amounts of transaction and payment data within their digital ecosystems, BigTech lenders are able to extend credit to borrowers that have been unserved or underserved by traditional financial institutions (Petersen and Rajan 1994, Berger and Udell 1995, Cornelli et al. 2022, Gambacorta et al. 2023, Beck et al. 2022, BIS 2019). Consequently, BigTech credit has become particularly important for micro, small, and medium-sized enterprises (MSMEs), which are crucial to entrepreneurship and economic growth. This shift places BigTech lending at the forefront of economic policy concerns (Carstens et al. 2021, Adrian 2021). Understanding the interactions between these new credit providers and traditional financial institutions, particularly in response to monetary policy changes, provides critical insights into the challenges and opportunities of the "brave new world" in the FinTech era (Philippon 2016, Lagarde 2018).

Despite the growing body of research on BigTech credit, its implications for monetary policy transmission remain largely unexplored. This study aims to bridge this gap by providing both theoretical and empirical analyses of the differences between BigTech lenders and traditional banks in lending to small businesses, particularly in the context of monetary policy transmission. Theoretically, we develop a model that highlights the key differences between BigTech and traditional banks based on their understanding of the risks associated with lending to businesses of various sizes, a concept known as Knightian uncertainty. BigTech lenders, with their abundance of data and advanced analytic capabilities, are posited

[1] Figures A1-A2 in the appendix show that BigTech credit has recently surpassed credit issued by decentralized platforms and accounts for 2%-3% of the GDP in leading countries such as China.

to have an information advantage over traditional banks when lending to smaller firms. This advantage reduces the ambiguity in lending, which affects the complexity of the perceived and actual returns. Monetary policy shocks, by directly influencing funding costs and the gap between perceived returns and funding costs, generate a larger differential impact on the scope of lending (i.e., extensive margin) rather than the intensity of lending (i.e., the intensive margin) between BigTech and traditional banks. Empirically, to test the predictions from the theory, we employ a unique dataset that covers the complete borrowing history of sampled MSMEs from both a major BigTech lender and traditional banks in China. This dataset comprises monthly observations of both BigTech and bank credit extended to a sample of 340,000 small businesses from January 2017 to December 2019. Combined with variations in monetary policy, our dataset serves as an ideal laboratory to compare the effects of monetary policy transmission between BigTech lenders and traditional banks.

Specifically, our model is founded on principles of optimal portfolio selection, where investment decisions are based on the balance between excess expected returns and volatility. However, the presence of lending ambiguity, characterized by a divergence between perceived and actual returns, introduces complexity. Financial intermediaries, faced with this uncertainty, adjust their expected returns downward. The extent of this adjustment depends on their informational disadvantage regarding specific types of firms. When BigTech has an informational advantage over traditional banks in the context of small and micro firms, it perceives higher expected returns from lending to these businesses compared to what banks perceive.[2] This leads to a market equilibrium where banks and BigTech allocate their lending efforts toward different segments of the market based on a clear cutoff strategy: banks focus on larger firms above a certain size threshold, while BigTech targets smaller firms below a threshold. These thresholds are defined by the point at which perceived returns align with the required return, which is determined by both the cost of funding through deposits

[2]Conversely, if banks hold an informational edge over BigTech for larger, mega firms, they would perceive higher expected returns from these loans than BigTech.

(directly influenced by monetary policy changes) and a predetermined profitability margin. Therefore, monetary policy affects the extensive and intensive lending margins of the two types of lenders differently, depending on their relative information advantages.

Our model highlights two key implications regarding the behavior of BigTech lenders and traditional banks in response to changes in monetary policy. First, the distinction between these two types of financial intermediaries is more evident in their strategic decisions to enter or exit particular lending markets (extensive margin) rather than in the amount they lend within those markets (intensive margin). Although the two types of lenders choose significantly different sectors at the extensive margin because each of them possesses a comparative information advantage over specific segments of the market, their methodologies for determining loan amounts at the intensive margin are quite similar for their selected firm sizes. Second, BigTech lenders demonstrate a notably asymmetrical response to monetary policy changes, with a more pronounced responsiveness during periods of monetary easing compared to tightening. This asymmetry is largely due to BigTech's pronounced information advantage with smaller firms. During periods of monetary tightening, the impact of increased funding costs on BigTech is lessened by their rapidly growing informational advantage within their niche market. Conversely, in times of monetary easing when funding costs decrease, BigTech expands its lending to include larger firms, where they must downgrade expectations due to a smaller informational advantage, leading to a more pronounced response to changes in funding costs.

To empirically test the above implications, we utilize a dataset at the firm-lender-month level in the Chinese context. This dataset includes both BigTech and traditional banks, focusing on small businesses that have borrowed from either type of lender. We begin with a comprehensive description of the institutional background, the construction of the sample, and summary statistics of the dataset, before proceeding to regression analyses and results. The extensive margin in our analysis refers to the establishment of new lending

relationships, defined as the first time a firm obtains a loan from a lender. The intensive margin, on the other hand, measures the scale of credit granted by the lender once the lending relationship is established, represented by the logarithmic amount of newly issued loans. Then we regress them on the interaction between monetary policy changes and a dummy variable representing BigTech lenders. Thus, the coefficient of the interaction term indicates the relative responsiveness of BigTech lenders to monetary policy changes compared to traditional banks. Following Khwaja and Mian (2008) and Jiménez et al. (2014), we specify firm-month fixed effects to control for any time-varying firm-level confounding factors, such as credit demand. This ensures that our estimates capture the impact stemming from credit supply variations.

Our findings are as follows. First, the BigTech lender demonstrates significantly greater responsiveness to changes in monetary policy than traditional banks at the extensive margin, while differences at the intensive margin are insignificant. Specifically, when the monetary policy rate decreases by one standard deviation, the probability of a BigTech lender establishing a new lending relationship with a firm is 0.25 percentage points higher than that of a traditional bank. Given that the average probability of lending is 3.4%, this represents a substantial economic impact. Second, the responsiveness of BigTech lenders to monetary policy changes at the extensive margin varies asymmetrically between easing and tightening environments. Specifically, the transmission-enhancing role of the BigTech lender manifests primarily during periods of monetary easing, with significant magnitude: when the monetary policy rate decreases by one standard deviation, the probability of a BigTech company initiating a new lending relationship is 0.97 percentage point higher than that of a traditional bank, nearly four times the magnitude in the symmetric specification. Third, compared to traditional banks, BigTech lending reacts more significantly to monetary policy changes for larger firms. These findings are consistent with our theoretical predictions and support the argument that BigTech lenders possess an informational advantage with small businesses and

exhibit a more pronounced response to monetary policy changes at the extensive margin, especially when monetary policy eases.

Finally, we discuss the impact of monetary policy on other terms of BigTech lending, such as interest rates and maturity, using an extended dataset. We show that an increase in monetary policy rates is associated with a decrease in BigTech credit amount, an increase in interest rates, and a reduction in loan maturity. The opposing effects on the quantity and price of BigTech loans suggest that these outcomes are driven by changes in credit supply. In addition, we develop a measure of BigTech regulation policy stringency and examine its impact on various terms of BigTech loans. This additional evidence not only strengthens our main findings but also helps alleviate concerns related to regulatory policies. These insights contribute to a deeper understanding of how monetary and regulatory environments influence BigTech lending practices.

Our study sheds light on the intricate interplay between BigTech lenders and traditional banks, focusing on their strategic responses to shifts in monetary policy and highlighting the crucial role of informational advantages associated with firm sizes in shaping the lending landscape. We observe an asymmetrical reaction from BigTech lenders, which has the potential to significantly influence the distribution of credit across firm sizes. This responsiveness varies during different phases of monetary policy, underlining a dynamic influence on the credit market. Monetary policymakers need to recognize the unique role of BigTech lenders in transmitting policy changes to small businesses. Furthermore, there is a necessity for coordination between macroeconomic policies and BigTech regulation to enhance the use of BigTech credit in supporting small businesses and contributing to the real economy.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and highlights the contribution of our study. Section 3 presents the theoretical model and outlines the testable predictions. Section 4 details the institutional background and the construction of the dataset used in this study, and then presents the main empirical findings.

Section 5 provides further discussions. Finally, Section 6 concludes.

2 Related Literature

This study mainly relates to three branches of literature. First, we contribute to the literature on monetary policy transmission by focusing on BigTech lenders as a new participant and examining their reactions to monetary policy changes compared to traditional banks. The literature has documented various dimensions of the cross-sectional heterogeneity in the bank lending channel of monetary policy (Bernanke and Blinder 1988, 1992, Kashyap and Stein 1995), including liquidity, size, income gap, leverage, market power, and risk tolerance of the financial intermediaries (Kashyap and Stein 2000, Brissimis et al. 2014, Drechsler et al. 2017, Gomez et al. 2021, Wang et al. 2021, Coimbra et al. 2022, Di Tella and Kurlat 2021). Nonetheless, the literature lacks a comprehensive examination of the technological characteristics and informational advantages of lenders.[3]

Recent studies by Hasan et al. (2024) and Hasan et al. (2022) examine the role of regional FinTech penetration and banks' in-house technological advancements on the effectiveness of monetary policy. Zhou (2022) emphasizes the role of social networks in enabling FinTech to enhance the monetary policy transmission to the mortgage market. None of them, however, explore the role of BigTech in transmitting monetary policy compared to traditional banks. Such questions remain theoretically underexplored and empirically limited due to data constraints. Our paper addresses this gap in the literature. A closely related study is by De Fiore et al. (2022), which examines BigTech's response to monetary policy and models BigTech's role as facilitating the matching between sellers and buyers. The key innovation

[3]See Allen et al. (2021) for a survey of research and policy discussion. While some studies address technology adoption and its interaction with monetary policy, they are limited to non-financial firms. For instance, Consolo et al. (2021) find that firms' information technology investment weakens the credit channel of monetary policy transmission, and Fornaro and Wolf (2021) study the impact of monetary policy on firms' technology adoption decisions.

of our study is our focus on the relative information advantages and lower lending ambiguities that BigTech lenders possess over traditional banks, particularly for small firms. We underscore the significant difference in lending capabilities between BigTech and traditional banks across various firm types, attributing this to asymmetric information advantages and degrees of Knightian uncertainty. These factors are crucial for understanding the asymmetric responses to monetary policies during periods of easing and tightening. Furthermore, we use a unique microlevel dataset of small firms' borrowing from both BigTech and traditional banks to empirically test the theoretical implications.

Relatedly, as the popularity of digital payment methods increases, central banks worldwide are actively investigating the implications of issuing central bank digital currencies (CBDCs).[4] Concerns are growing about the impact of CBDCs on the banking system and monetary policy transmission. CBDCs may disintermediate banks by competing for deposits (Whited et al. 2022, Infante et al. 2022, Keister and Sanches 2023), and their effects on the bank lending channel of monetary policy are inconclusive, depending on the specific designs of CBDCs and the extent to which banks rely on deposit funding (Meaning et al. 2018, Burlon et al. 2022). In contrast, BigTech's lending model, which is technologically distinct from CBDCs, tends to disrupt banks more on the asset side rather than the funding side. This disruption has a significant and direct impact on the lending channel.

Second, the theory part of our study is deeply integrated into the discussions surrounding Knightian uncertainty, which diverges from the traditional risk-based uncertainty frameworks. (e.g., Di Tella 2017, Alfaro et al. 2024, Wu and Suardi 2021, Berger et al. 2022). This line of research views uncertainty not merely as measurable risk but as the potential ignorance of the true data generation processes, leading to decisions based on possibly incorrect models.[5] Our paper is grounded in the literature on portfolio selection under ambiguity, for

[4]See Duffie et al. (2021) for an overview and Cong and Mayer (2022), Minesso et al. (2022), and Kumhof et al. (2023) for frameworks to analyze the macroeconomic properties of CBDCs.

[5]Prominent works foundational to this discourse include Epstein and Wang (1994), Chen and Epstein (2002), Anderson et al. (2000), Hansen et al. (1999), and Hansen and Sargent (2001), among others.

instance, Maenhout (2004) and Uppal and Wang (2003) which investigate how ambiguity affects diversification strategies by extending the conventional portfolio model of Merton (1973). We apply this conceptual framework to analyze how financial intermediaries with varying degrees of ambiguity respond to changes in monetary policy. Our study is innovative in the way of modeling BigTech and in explaining the asymmetric responses during monetary policy easing and tightening periods.[6]

Third, our study contributes to the expanding body of research that explores the fundamental distinctions and relationships between BigTech firms and traditional banks in the financial sector. As summarized in Stulz (2019), Boot et al. (2021), Thakor (2020) and Berg et al. (2022), the recent wave of financial technologies is disruptive and has brought an abundance of data and codification of soft information. Theoretically, different studies present varied models of the data and information advantages held by BigTech lenders. For example, De Fiore et al. (2022), highlight the distinction in the consequences of loan defaults: defaulting on a bank loan typically results in the loss of collateral for firms, whereas defaulting on a BigTech loan may threaten future profits due to potential exclusion from BigTech's e-commerce ecosystems. In a similar way, Li and Pegoraro (2022) model the competition between banks and BigTechs, characterizing BigTech as mitigating financing frictions by enforcing partial loan repayments through control over marketplace access, thus reducing the risk of strategic default. In addition, Su (2021) examines the macroeconomic implications of BigTech and focuses on the nature of borrowing constraints: banks and BigTech primarily rely on collateral-based and earning-based borrowing constraints, respectively. In contrast, our paper posits that the main difference between BigTech and banks lies in their respective degrees of model misspecifications, particularly when lending to different types of firms. The advantage of our Knightian uncertainty approach is that it can explain the different effects of monetary policy on intensive and extensive margins of lending decisions, which is also

[6]For more recent advances in this literature, see Pritsker (2013), Nishimura and Ozaki (2007), Gerba and Żochowski (2017), Nishimura and Ozaki (2004), Lopomo et al. (2011) and Amoroso et al. (2017).

consistent with our empirical findings.

Empirically, many studies demonstrated that BigTech and FinTech lenders possess superior information, more advanced monitoring, and risk management capabilities compared to traditional banks (see Buchak et al. 2018, Berg et al. 2020, Di Maggio and Yao 2021, Jagtiani and Lemieux 2018, Dolson and Jagtiani 2024, Hughes et al. 2022, Suri et al. 2021, Erel and Liebersohn 2022, Liu et al. 2022).[7] However, the evidence regarding whether FinTech represents a complementary or substitutive relationship with traditional banks is mixed. For instance, Gopal and Schnabl (2022) document that FinTech lenders substituted for the reduction in bank lending to small businesses after the 2008 financial crisis. Tang (2019) and Beaumont et al. (2022) show that while FinTech lending substitutes bank lending for inframarginal bank borrowers, it complements bank lending for small loans. Buchak et al. (2021) demonstrate that FinTech facilitates interest rate liberalization in banks through competition in deposit-like products. Our empirical innovation does not merely show the difference between BigTech and banks using another dataset, but documents their varying responses to monetary policy at both the extensive and intensive margins when lending to the same small firms.

To summarize, our study contributes to the literature by first theoretically modeling the differences between BigTech and traditional banks from the perspectives of Knightian uncertainty and lending ambiguities across various firm sizes and monetary policy environments. We then empirically demonstrate their differing reactions to monetary policy using a microlevel dataset that allows us to distinguish between the extensive and intensive margins and disentangle the effects of credit demand and credit supply.

[7] Other studies, such as Pierri and Timmer (2022), Lin et al. (2021), Kwan et al. (2021), He et al. (2021), Hasan et al. (2022), and Modi et al. (2022), focus on technology adoption by banks and its impact on lending, but do not compare this with FinTech or BigTech lenders.

3 Theoretical Model

In this section, we introduce a partial-equilibrium model to elucidate the differential responses of BigTech lenders and traditional banks to monetary policy shocks. To emphasize the innovative aspect of our model's mechanism, we focus on a singular distinction between the two types of financial intermediaries, namely, the level of ambiguity they confront when extending credit to various kinds of firms. This unique approach allows us to isolate the effect of ambiguity on lending practices and observe how each entity navigates the uncertainties associated with monetary policy shocks.

3.1 Model Setup

Consider an infinite-horizon continuous-time economy with a representative bank ($\mathcal{B}$) and also a representative BigTech lender ($\mathcal{F}$). Both types of financial intermediaries need to consume a homogeneous good c. In addition, they have the same utility function $u(c)$ and rate of time preference ρ. These two financial intermediaries operate by investing in N risky business loans and are funded through deposits. The interest rates on these deposits, denoted by $r_t = r(X_t)$, are influenced by an M-dimensional vector of economic fundamentals, X_t, which captures the variables that can affect monetary policy changes and, consequently, the funding costs for these intermediaries. We assume that X_t follows a general random process:

$$dX_t = \mu_X(X_t)\,dt + \sigma_X(X_t)\,d\mathcal{Z}_t \tag{1}$$

where μ_X and σ_X are the drift and volatility components, meanwhile, $\mathcal{Z}_t$ denotes the $(N+M)$-dimension random Brownian motion process. For the sake of brevity and focused analysis, we do not delve into modeling the government's optimal monetary policy decision-making process. Instead, we directly interpret monetary policy shocks as changes in the real interest rate r. This approach allows us to concentrate on the core dynamics of how financial

intermediaries, specifically BigTech lenders and traditional banks, respond to fluctuations in monetary policy without the complexity of government policy formulation.

In our exploration, beyond their consumption requirements and deposit funding, the two financial intermediaries face decisions on whether and how much to allocate towards investments in N different types of risky business loans. We assume, without loss of generality, that $n \in \{1, 2, \ldots, N\}$ is increasing in firm size or market valuation. In other words, $n = 1$ denotes the category of the smallest micro firms, while $n = N$ indicates the group of mega firms. As we will see later, BigTech lenders and traditional banks possess varying degrees of information advantages over firms of different sizes.

The return processes of lending to the N groups of firms are given by the following random process:

$$dR_t = \mu_R \left(R_t, X_t\right) dt + \sigma_R \left(R_t, X_t\right) d\mathcal{Z}_t \tag{2}$$

where μ_R and σ_R are the usual drift and volatility components. The equation above can be viewed as the reference model. However, a crucial aspect of our analysis is acknowledging that these two types of financial intermediaries exhibit varying degrees of ambiguity towards this reference model. This differentiation in ambiguity levels directly relates to the information advantage or disadvantage that BigTech firms and banks have when assessing and deciding on investments in risky business loans across a spectrum of firm sizes, from micro to mega firms.

To streamline the analysis and derive a straightforward closed-form solution for the investment decisions of each financial intermediary, we introduce the following two simplifying assumptions. First, we assume that the drift component μ_R is the same for different types of business loans, i.e., $\mu_{R,i} = \mu_{R,j}$, $\forall i, j \in \{1, 2, \ldots, N\}$. This means that, within the confines of our reference model, lending to the smallest micro firms is expected to yield the same return as lending to the largest mega firms. This assumption is primarily introduced to simplify the

mathematical analysis and facilitate the derivation of a clear cutoff strategy for the investment decisions of financial intermediaries. The cutoff strategy will help to delineate under what conditions and to what extent an intermediary should invest in risky business loans, given the same expected return across different firm sizes. It's important to note that while this simplifying assumption eases the analysis, it doesn't compromise the broader applicability of our model. In fact, our model's mechanism could be enhanced by assuming that μ_R is higher for lending to micro firms, acknowledging the higher risk and potentially higher returns associated with smaller, less established businesses. Such an assumption would align with the reality that smaller firms often incur higher borrowing costs due to perceived higher risks, thus translating into higher returns for lenders prepared to bear these risks.

Second, we introduce the profitability criteria for lending to different types of firms. Specifically, we stipulate that the expected return on any given loan, after adjusting for the potential impact of model misspecification, must be greater than or equal to the sum of the funding cost, r, and a non-negative parameter, $\underline{\mu} \geq 0$, which serves as a proxy for the minimum profitability requirement. This assumption ensures that both BigTech lenders and traditional banks aim for a baseline level of profitability in their lending activities, reflecting a common threshold for investment viability across different types of business loans. Importantly, our model's key mechanism does not hinge on the differences in funding costs or profitability requirements between banks and BigTech firms. Thus, we maintain the assumption that both types of financial intermediaries face the same profitability requirement, which simplifies the analysis by focusing attention on the differences in responses to model uncertainty and monetary policy shocks rather than on variations in operational costs or return expectations.

We now address a crucial assumption within our model: the two types of financial intermediaries, BigTech firms and traditional banks, not only possess distinct informational advantages but also encounter varying levels of ambiguity in their lending practices across

different firms. To formalize these concepts, we introduce:

- Γ: represents the degree of model misspecification encountered by an intermediary, with a higher number indicating less ambiguity and higher information advantage
- Λ: denotes the relative ratio between $\Gamma_{\mathcal{F}}$ for BigTech firms and $\Gamma_{\mathcal{B}}$ for banks, capturing the comparative information accuracy between the two.

Both Γ and Λ are $N \times N$ diagonal matrices, with γ_n and λ_n being the corresponding n-th element, respectively. Our pivotal assumption asserts that BigTech firms, relative to traditional banks, possess an information advantage that decreases and becomes convex as firm size, denoted by n, increases. This indicates a pronounced advantage for BigTech in dealing with micro and small firms, with this advantage tapering off for larger entities. Mathematically, this relationship is described by a decreasing and convex function of firm size: $\frac{\partial \lambda_n}{\partial n} < 0, \frac{\partial^2 \lambda_n}{\partial n^2} < 0$, indicating that BigTech's information advantage diminishes at a decreasing rate as firm size grows. This assumption is essential for explaining the varying responsiveness of BigTech lenders to monetary policy changes, particularly their heightened sensitivity to easing conditions due to their superior ability to minimize model misspecification for smaller firms.[8] We also summarize this key assumption as follows:

Assumption 1 *BigTech firms and traditional banks encounter varying levels of ambiguity in their lending practices across different firms. More specifically,*

- *Bank's information advantage is linearly increasing in firm size, i.e.,* $\frac{\partial \gamma_n^{\mathcal{B}}}{\partial n} > 0, \frac{\partial^2 \gamma_n^{\mathcal{B}}}{\partial n^2} = 0$
- *BigTech's information advantage is decreasing in firm size, i.e.,* $\frac{\partial \gamma_n^{\mathcal{F}}}{\partial n} < 0$
- *The relative information advantage of BigTech compared to banks is a convex and decreasing function of firm size, i.e.,* $\frac{\partial \lambda_n}{\partial n} < 0, \frac{\partial^2 \lambda_n}{\partial n^2} < 0$

[8] We show one illustration of this assumption in Figure A3 in the appendix, where BigTech information advantage grows faster when lending to smaller firms.

- $\gamma_1^{\mathcal{B}} = \gamma_N^{\mathcal{F}}$ *and* $\gamma_N^{\mathcal{B}} = \gamma_1^{\mathcal{F}}$

This premise posits that BigTech has a decreasing and convex information advantage as firm size increases, which significantly influences its lending behaviors in response to monetary policy shocks. This assumption is pivotal to the conclusions drawn in our model and here we provide support by leveraging the real-world dynamics and findings from the literature. In practice, BigTech lenders, leveraging their technological capabilities and data analytics, may possess a distinct advantage in reducing or managing this ambiguity, especially when dealing with smaller businesses that have a significant digital footprint (Berg et al. 2020, Di Maggio and Yao 2021, Liu et al. 2022, Beaumont et al. 2022, Huang et al. 2020). Traditional banks, on the other hand, might rely on more established, albeit less flexible, risk assessment models that could either exacerbate or mitigate their perception of ambiguity depending on the firm's profile (Jagtiani and Lemieux 2018, Hughes et al. 2022). By setting the degree of ambiguity as the primary variable, our model offers insights into how each type of lender adjusts its lending strategy in response to economic policies and how these adaptations impact their lending behavior to different sectors of the economy. This novel perspective not only contributes to our understanding of financial intermediation in a modern economy but also informs policy discussions on the regulatory and macroeconomic implications of the growing presence of technology-driven financial services.

Generally speaking, each financial intermediary wishes to maximize his/her intertemporal lifetime utility, subject to the budget constraint, while taking into account model misspecification when making decisions. If we use ω to denote the wealth of each financial intermediation, and π_n to represent the share of the intermediary's wealth invested in the n-th risky business loans, then the dynamics of financial intermediation's wealth, for a given investment decision π and the consumption decision c, can be written as follows:

$$d\omega_t = \omega_t \left[r_t + \pi_t \left(\mu_R - r_t \right) - \frac{c_t}{\omega_t} \right] dt + \omega_t \pi_t \sigma_R d\mathcal{Z}_t \tag{3}$$

3.2 Equilibrium Characterization

Building on the established model setups, we can now delineate the optimal decision-making processes of the two financial intermediaries. To begin with, we rewrite the investor's indirect utility function as $\mathcal{J}(t;\omega_t, R_t, X_t)$. Based on the continuous-time ambiguity literature, when faced with possible model misspecificaiton, financial intermediation i simply downward adjust their perceived returns by Δ_R^i. In this way, the essential equilibrium outcome of our analysis is described in Proposition 1, which provides a structured summary of how BigTech lenders and traditional banks navigate their lending strategies in response to the varying levels of ambiguity and information asymmetry identified earlier.

Proposition 1 *The optimal investment portfolio for the traditional bank is* $[n_{\mathcal{B}}^*, N]$*, where* $n_{\mathcal{B}}^*$ *satisfies the condition that* $\mu_{R,n_{\mathcal{B}}^*} - r - \Delta_{R,n_{\mathcal{B}}^*}^{\mathcal{B}} = \underline{\mu}$*. Meanwhile, the optimal investment portfolio for the BigTech is* $[1, n_{\mathcal{F}}^*]$*, where* $n_{\mathcal{F}}^*$ *satisfies the condition that* $\mu_{R,n_{\mathcal{F}}^*} - r - \Delta_{R,n_{\mathcal{F}}^*}^{\mathcal{F}} = \underline{\mu}$*. Within their optimal portfolio, the weight of their wealth invested in each group of firms can be computed as follows:*

$$\pi^i = -\frac{1}{\omega \mathcal{J}_{\omega\omega}} \left[\sigma_R \sigma_R^T\right]^{-1} \left[\mathcal{J}_\omega \left(\mu_R - r - \Delta_R^i\right) + \sigma_R \sigma_X^T \mathcal{J}_{\omega X} + \sigma_R \sigma_R^T \mathcal{J}_{\omega R}\right] \tag{4}$$

where $i = \{\mathcal{B}, \mathcal{F}\}$ *and*

$$\begin{bmatrix} \Delta_R^i \\ \Delta_X^i \end{bmatrix} = \frac{1}{\psi(\mathcal{J})} \Gamma_i^{-1} \begin{bmatrix} \mathcal{J}_\omega \omega_\pi + \mathcal{J}_R \\ \mathcal{J}_X \end{bmatrix} \tag{5}$$

where ψ *is a usual penalty normalization term.*

The detailed proof can be found in the appendix. Here we explain the intuitions behind this proposition, which are threefold. First, both BigTech firms and traditional banks strategically select the subset of firms they extend credit to, guided by a cutoff strategy. This strategy emerges from the varying levels of information advantage and ambiguity they encounter across different firm sizes. In addition, the model highlights BigTech's propensity

to lend to smaller and micro firms, a preference rooted in our key assumption that BigTech possesses a relative informational advantage in assessing and managing risks associated with these smaller entities. The advanced analytics and data processing capabilities of BigTech lenders allow them to effectively reduce ambiguity and mitigate model misspecification risks in this segment. On the contrary, traditional banks predominantly lend to larger firms. This is because banks, lacking BigTech's informational edge for smaller firms, find it more efficient and less ambiguous to lend to larger, more established firms. These firms typically have more transparent financial histories and lower perceived default risks, making them more attractive to traditional banking models.

The second key insight from Proposition 1 concerns the investment behaviors of BigTech firms and traditional banks regarding the intensity of their investment, or the intensive margin, within their chosen lending segments. This is captured by π, the proportion of the financial intermediary's resources allocated to lending. Proposition 1 uncovers a significant symmetry in the intensive margin of portfolio weight between the two types of financial intermediaries following their target firm selection for lending. This symmetry in the intensive margin stems naturally from the initial selection process at the extensive margin. Once BigTech and banks have identified their respective market segments – smaller firms for BigTech and larger ones for banks – criteria guiding their investment amounts align. Specifically, the optimal portfolio weight, π, for each group of firms they invest in is determined by common financial metrics, like volatility and expected investment returns. This underscores a fundamental financial principle: once a lender commits to a particular market segment, investment decisions are primarily driven by universal risk and return considerations. Despite their initial target market differences, BigTech lenders and traditional banks eventually adhere to a unified financial rationale at the intensive margin.

The final aspect of Proposition 1 delves into the critical role of information advantage on both the extensive and intensive margins of lending decisions by financial intermediaries,

revealing how ambiguity and information asymmetry intricately shape investment strategies. Within our model, ambiguity serves as an adjustment mechanism for expected returns; a higher level of ambiguity regarding a firm leads investors to lower their return expectations. This adjustment mechanism is pivotal in our model, as the information advantage significantly influences the financial intermediary's perception of expected returns. If the adjusted expected return falls below the profitability threshold, the intermediary may opt not to invest in the firm, illustrating how ambiguity significantly influences the extensive margin by dictating the selection of investment-worthy firms. At the same time, once a subset of firms has been selected for investment, the degree of ambiguity remains influential at the intensive margin, that is, in determining the optimal weight allocated to each investment. This allocation is optimized based on factors such as the Sharpe ratio, which depends on expected returns. Thus, the information advantage and the associated adjustments for ambiguity also indirectly influence the decision at the intensive margin. Interestingly, while BigTech and banks differ in their extensive margin choices—namely, the types of firms they opt to invest in—their strategies at the intensive margin, or their within-selection allocation strategies, demonstrate a notable similarity. This parallel arises from the equivalent levels of information advantage each holds over their selected firm sizes; BigTech's information advantage over smaller firms mirrors that of banks over larger firms. Therefore, the decision calculus for the portfolio weight or the intensive margin aligns closely between BigTech and banks, despite the divergent selection of firms for investment.

3.3 Model Implication

We now turn to discuss the strategic responses by BigTech lenders and traditional banks to changes in monetary conditions, as outlined in Proposition 2. This proposition delves into the nuanced effects of monetary policy shocks on financial intermediaries, particularly examining how these impacts vary with the degree of ambiguity the intermediaries hold

towards different types of firms.

Proposition 2 *The difference of the impact of monetary policy shocks on the intensive margin is negligible between banks and BigTech, i.e.,* $\frac{\partial \pi_{\mathcal{B},n_{\mathcal{B}}}}{\partial r} \approx \frac{\partial \pi_{\mathcal{F},n_{\mathcal{F}}}}{\partial r}$ *for* $n_{\mathcal{B}} \in [n^*_{\mathcal{B}}, N]$ *and* $n_{\mathcal{F}} \in [1, n^*_{\mathcal{F}}]$*. However, the extensive margin shows significant differences in responses to monetary policy shocks between banks and BigTech. More importantly, the differences are asymmetric: BigTech lenders are more sensitive to monetary easing but less so to tightening, compared to banks. That is,* $|\frac{\partial n^*_{\mathcal{B}}}{\partial r}| > |\frac{\partial n^*_{\mathcal{F}}}{\partial r}|$ *for* $r > r^*$ *and* $|\frac{\partial n^*_{\mathcal{B}}}{\partial r}| < |\frac{\partial n^*_{\mathcal{F}}}{\partial r}|$ *for* $r < r^*$*.*

Similarly, the detailed proof can be found in the appendix. In essence, this proposition implies that the main distinction in how these financial intermediaries respond to monetary policy changes lies in their decision-making about which markets to engage in (extensive margin), rather than the amount they choose to lend within those markets (intensive margin).

The underlying mechanisms are quite intuitive. To begin with, the negligible difference in the intensive margin responses is attributed to the parallel nature of their information advantages over their chosen subsets of firms, which results in similar reactions to monetary policy changes. Additionally, the varying effects on the broader market are due to their distinct informational edges regarding different firm types. The cutoff strategy formula indicates that an exogenous shift in monetary policy directly alters the left-hand side of the equation, with the derivative of the interest rate with respect to itself being one. To maintain profitability, financial intermediaries need to recalibrate their portfolios to offset the impact of monetary policy fluctuations. Thus, the availability and precision of information across different groups become crucial for this recalibration. When the informational advantage is distinct and varies significantly between groups, the broader market adjustment will be minimal, as intermediaries can more easily adapt by selecting firms within their well-understood sectors. Conversely, if the informational edge is relatively consistent across groups, a more substantial recalibration is necessary.

This dynamic also explains why monetary policy shocks have asymmetric effects. In our simplified model, banks have a linearly increasing informational advantage, which implies a constant adjustment elasticity. However, for tech giants, the elasticity is higher for smaller firms. Therefore, when monetary policy eases or funding costs decrease, these giants begin extending credit to larger entities or those requiring downward adjustments in expectations. Given their reduced informational advantage and minimal variation across firm types, their response to reductions in funding costs is more pronounced. Conversely, during periods of monetary tightening, when higher expected returns coincide with rapidly escalating informational advantages, their reaction to increased funding costs is less significant. This varied response illustrates the strategic agility of tech giants, who use favorable economic conditions to expand their lending, particularly to smaller and micro enterprises where their informational leverage is strongest.

3.4 Summary of Empirical Predictions

Based on the assumptions and framework outlined above, we can forecast two key predictions regarding the responses of BigTech lenders and traditional banks to monetary policy changes. These predictions highlight the distinct strategies these financial intermediaries employ under varying economic conditions.

Prediction 1 *The primary distinction between how BigTech lenders and traditional banks react to monetary policy shocks is observed at the extensive margin, rather than the intensive margin.*

Prediction 2 *The difference responses in the extensive margin are asymmetric. Specifically, compared to traditional banks, BigTech firms are more responsive to easing monetary policy shocks at the extensive margin but exhibit less sensitivity to tightening monetary policy shocks.*

4 Empirical Analyses

Now we turn to the empirical examination of the theoretical implications. Data availability is the primary challenge in testing the role of BigTech and its interactions with traditional banks in monetary policy transmission, as we need simultaneous observations of credit from both types of lenders to the same entities. We address this challenge by utilizing a micro-level dataset from China, which includes data on small firms' borrowing from both a representative BigTech lender and traditional banks, matched with changes in monetary policy. We will first outline the institutional background of BigTech credit in China, establishing it as an effective laboratory for our empirical tests. Then we will describe the construction of our sample and the key variables. Finally, we present our identification strategy and discuss the main findings and the mechanisms suggested by our theoretical model.

4.1 Institutional Background

China has emerged as a prominent player in the BigTech credit market, surpassing other nations in both absolute and per capita terms since 2017.[9] Several factors contribute to this rapid growth. On the one hand, by leveraging their inherent advantages in information, technology, and monitoring within their ecosystems, BigTech companies can efficiently serve millions of credit users, particularly MSMEs, who are otherwise unserved or underserved by traditional banks, at a significantly lower cost (Hua and Huang 2021). This also explains why BigTech credit in China primarily targets business lending rather than mortgage lending, unlike the trends observed in the U.S. and other advanced economies. On the other hand, the government's regulatory leniency during the early stage has significantly facilitated the rapid expansion of BigTech credit (Chui 2021).

[9]See Figure A2 in the appendix. In contrast, BigTech credit in the U.S. remains relatively modest: Amazon issued $1 billion USD in 2018, and Apple $7 billion USD in 2019, whereas the four largest Chinese BigTech lenders disbursed $363 billion USD and $516 billion USD in 2018 and 2019, respectively (Cornelli et al. 2020).

Our dataset originates from one of the biggest BigTech lenders in China, MYBank, a virtual bank launched in 2015 without any physical branches. MYBank has become an important data source for studying BigTech credit in the recent literature (see Huang et al. 2020, Hong et al. 2020, Hau et al. 2021, Gambacorta et al. 2023, Liu et al. 2022). Operating on a general banking model, it attracts deposits and extends loans to borrowers. Owned by Ant Group (formerly known as Ant Financial), an affiliate of the Alibaba Group, MYBank is part of a larger conglomerate that engages in various FinTech sectors including payments, wealth management, insurance, and credit scoring.[10] Notably, it owns Alipay, the world's largest digital payment platform. MYBank primarily serves small businesses that use Alipay for transactions, thereby generating valuable digital footprints. With access to extensive data and sophisticated risk management models, MYBank offers loans through a "contact-free feature" that ensures speed and convenience without the need for physical branch visits.[11]

Besides MYBank, two other major BigTech lenders in China are WeBank, backed by Tencent, and XWBank, backed by Mi. The primary distinction of MYBank, as compared to these, lies in its focus on business loans for MSMEs, whereas WeBank and XWBank predominantly provide consumer loans to individual households. Table A2 in the appendix details the outstanding loan amounts and customer bases for each as of 2019; however, it does not provide a breakdown by types of loans due to data limitations. Although MYBank does not boast the largest customer base among the three, it maintains the highest per capita loan balance due to its concentration on small businesses rather than individual borrowers.

In terms of regulatory compliance, MYBank adheres to the same rules and policies of the China Banking and Insurance Regulatory Commission (CBIRC) as traditional banks regarding deposit-to-loan ratios, capital ratios, and credit quality.[12] However, MYBank's

[10]Figure A4 in the appendix illustrates the business subsidiaries of Ant Group.

[11]MYBank operates under a "3-1-0" model, which guarantees user registration and loan application completion within 3 minutes, money transfer to an Alipay account in 1 second, and zero human intervention.

[12]Previously, the China Banking Regulatory Commission (CBRC) was the agency that managed banking regulations. In April 2018, it merged with the China Insurance Regulatory Commission (CIRC) to form the CBIRC.

parent company, Ant Group, may be subject to different regulations, potentially influencing MYBank's lending activities. We will explore the implications of these regulatory differences further in Section 5.2.

The lending model of MYBank, like that of other BigTech lenders, differs from traditional banks. Specifically, MYBank specializes in providing credit services to very small, privately owned firms rather than state-owned enterprises. While these MSMEs can also borrow from traditional banks, large and state-owned companies exclusively utilize traditional banking services.[13] This segmentation also aligns with our theoretical assumption. Consequently, while we underscore the significant role of MSMEs, particularly those in the retail sector, in driving employment and economic growth in the Chinese economy, it is crucial to acknowledge that our findings are applicable primarily to small firms and may not extend to larger enterprises.[14] Some of these firms conduct sales through an e-commerce platform, while others operate exclusively from physical stores and do not engage in digital commerce. We label them as online and offline firms, respectively. Both types of firms process transactions via Alipay, with offline merchants utilizing QR codes to collect payments, thus leaving digital footprints within the Ant Group ecosystem.[15] Moreover, the business activities of online merchants on digital platforms operated by the Alibaba Group furnish MYBank with extra data to assess their risks.

To illustrate the differences between MYBank and traditional banks, Figure 1 presents key financial indicators for them from 2015 to 2021, including the deposit-to-asset ratio, profitability (net income to assets ratio), capital adequacy (capital to risk-weighted assets ratio), and the non-performing loans (NPLs) to assets ratio.[16] Three observations stand

[13]Specifically, we examine the listed Chinese firms' bank loans and find no instances of borrowing from BigTech banks.

[14]As of 2018, MSMEs represent 99.8% of business establishments, account for 79.4% of employment, and contribute to 68.2% of sales in the Chinese economy. The retail sector comprises 29.8% of business establishments, employs 10.5% of the workforce, and makes up 29.9% of sales. See Table A4 in the appendix.

[15]For more details on the QR code payment system, see Beck et al. (2022).

[16]The year 2015 was an exception as MYBank was launched mid-year, requiring some time to achieve

out. First, following its launch in 2015, MYBank exhibited greater volatility across all indicators compared to traditional banks, reflecting its focus on serving MSMEs versus the larger firms typically served by traditional banks. Second, MYBank is less reliant on deposits and displays slightly lower capital adequacy and profitability, alongside a lower NPL ratio. The lower profitability could be attributed to heightened competition in the credit market, while the lower NPL ratio suggests potentially superior risk management through the use of comprehensive data and advanced technologies. Third, a structural shift in 2020 indicates that the COVID-19 pandemic reversed previous trends in MYBank's increasing deposit ratio, profitability, and capital adequacy. The NPL ratio also surged, contrasting with the declining trend in traditional banks. This underscores the critical role of online banking during the pandemic, when physical contact was minimized, and highlights the vulnerability of small businesses during the crisis.

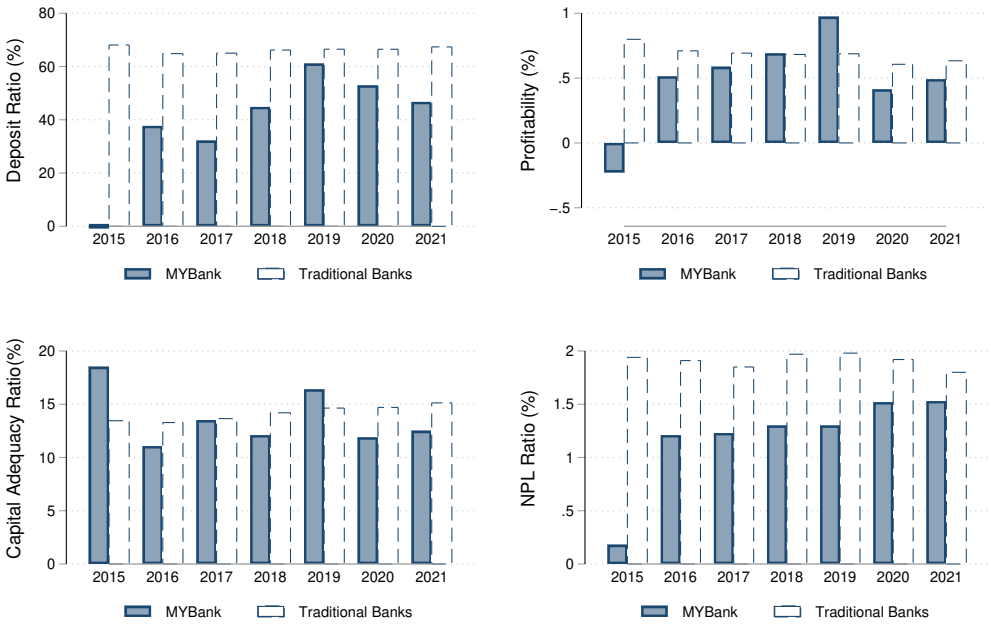


Figure 1: Main Indicators for MYBank and Traditional Banks

Sources: Annual Report of MYBank; CBIRC.

operational stability.

4.2 Sample Construction

4.2.1 BigTech Credit and Bank Credit

The sample construction begins with the firms listed in the MYBank database, which includes firm characteristics. We then obtain these firms' histories of bank credits and BigTech credits separately. After appending the data, the unit of observation is firm-lender type-month. This means we include two observations for each firm in each month: one indicating bank loans and the other indicating BigTech loans.

Specifically, we first obtained a 10% random sample of MYBank's MSME customers covering the period from January 2017 to December 2019.[17] Specifically, before sampling, we impose the following criteria to exclude inactive firms from the full pool of MSMEs: (i) the firm must have been registered before 2019; (ii) the firm's owner must be younger than 60 years; and (iii) the firm must have conducted more than five transactions per month for at least 70% of its operational lifespan. We then randomly draw a 10% sample from the remaining firms, employing stratified sampling by province and sector to ensure the sample distribution mirrored the overall population in terms of geographical and industry representation. As a result, the sample comprises approximately 340,000 firms. Table A3 in the appendix presents the sector distribution of these firms, with a significant number operating in the retail industry. Table A4 further indicates that the retail sector accounts for nearly one-third of all establishments and sales in the economy.

The dataset includes key characteristics of each firm, such as business location, the age and gender of the business owner, and monthly sales figures. In addition, we observe a network score for each firm, which reflects the firm's centrality within the Ant Group network based on its sales and payment history.[18] A higher score indicates greater activity and a

[17]Full access to MYBank's MSME customer data is restricted due to its data regulation policy. The 10% random selection is a conventional approach in the literature, for instance, Gambacorta et al. (2023), Beck et al. (2022) and Huang et al. (2020) are all based on the same sampling method.

[18]The network score is determined using a PageRank algorithm, originally developed by Larry Page, a

more significant impact by the firm within the platform's ecosystem.

The MYBank database provides comprehensive details on each firm's borrowing history. First, we track the monthly issuance of new loans from MYBank, which is termed BigTech credit in our study. All BigTech credits are non-secured loans, that is, they are not backed by collateral, which aligns with the depiction of earnings-based lending by BigTech firms as described in Gambacorta et al. (2023) and Su (2021). Then we retrieve data on traditional bank credits issued to each firm monthly from the central bank's credit information system. For traditional bank credits, we can further distinguish between secured and unsecured loans. By combining these data, we observe each firm's access to both BigTech and traditional bank credit, whether it uses any credit, the type of credit utilized, and the extent of its use. Our dataset thus spans the firm-lender-month level, focusing on two types of lenders: the BigTech lender (MYBank) and traditional banks.[19] Firms may borrow exclusively from MYBank, solely from traditional banks, or from both.[20] These varying borrowing patterns allow us to examine the impacts on both the extensive and intensive margins of credit usage. We will later detail the empirical specifications and provide summary statistics for each of the three firm types.

Combined with monetary policy variables, to be detailed in Section 4.2.2, our dataset uniquely addresses the challenges of testing theoretical implications and examining the role of BigTech in monetary policy transmission. Specifically, the simultaneous observation of BigTech and traditional bank credits to the same firms allows for granular analysis of how BigTech credit influences monetary policy transmission, distinct from traditional banks. Nevertheless, there are some limitations which warrant clarification. First, we cannot dif-

founder of Google, to assess the importance of web pages. It uses webgraphs where web pages are nodes and hyperlinks are edges, with each hyperlink to a page acting as a vote of support. In the Ant Group context, customers and merchants are treated as interconnected nodes and payment flows are the edges.

[19]It is possible for a firm to originate multiple loans in a month. For our analysis, we aggregate all new loan originations per firm each month to the firm-month-lender level.

[20]Meanwhile, firms that have not borrowed from either BigTechs or traditional banks are excluded from our data and any other credit registration datasets.

ferentiate among traditional bank loans, as these are aggregated. This aggregation prevents comparison between different types of traditional banks, such as state-owned versus non-state-owned, in their response to monetary policy compared to BigTech lenders.[21] Second, our data is limited to a single BigTech lender—MYBank. Access to loan data from other BigTech lenders like WeBank and XW Bank could provide additional insights into variations among BigTech lenders, but this is not feasible due to data anonymization and the impossibility of matching firms across platforms. It is reassuring that MYBank is the dominant BigTech lender in business lending and the other two big players are more focused on household credit. Despite this, we acknowledge that limiting our analysis to one lender might underrepresent the broader impact of BigTech credits on monetary policy responses.

Table 1 presents the summary statistics of the full sample used in this study, with variable definitions provided in Table A1 in the appendix. Panel A shows that in any given month, the average shares of firms utilizing BigTech and bank credit are 5.5% and 1.2%, respectively. Only 0.3% of firms obtained secured loans, and 1.1% accessed unsecured loans from traditional banks. The average credit amount from the BigTech lender is approximately 21,841 Chinese yuan (about $3,120), with the 90th percentile reaching 51,000 yuan. In contrast, the average amounts for secured and unsecured bank credits are 536,947 yuan (approximately $76,707) and 118,833 yuan (approximately $16,976), respectively, with the 90th percentile of bank credit reaching 499,400 yuan. This significant variance in loan sizes suggests that BigTech lending complements traditional bank credits for the small firms in our sample. Panel B indicates that the majority of firms are offline, with only 1.5% being online sellers. The average monthly sales for these firms are 10,415 yuan (about $1,488), highlighting that our sample predominantly consists of micro and small enterprises. The average age of business owners is 38 years, with a nearly balanced gender distribution. These statistics show

[21] As shown in Figure A5 in the appendix, as of 2019, when SMEs borrow from traditional banks, roughly 40% are from rural banks and credit cooperatives, 30% from large commercial banks (state-owned), and the remaining 30% from joint stock and city commercial banks.

that Bigtech credit primarily targets MSMEs, which is consistent with the role of FinTech in small business lending as documented by Beaumont et al. (2022) and Gopal and Schnabl (2022), and aligns with our theoretical model's assumption.

Table 1: Summary Statistics: Full Sample

Variables	N	Mean	St. Dev	P10	P25	Median	P75	P90
			Panel A: Credit					
Credit use -All	15,139,162	0.034	0.181	0	0	0	0	0
Credit use -BigTech	7,569,581	0.055	0.229	0	0	0	0	0
Credit use -Bank	7,569,581	0.012	0.110	0	0	0	0	0
Credit use -Bank unsecured	7,569,581	0.011	0.104	0	0	0	0	0
Credit use -Bank secured	7,569,581	0.003	0.051	0	0	0	0	0
Loan amount -All	173,484	38,852.846	168,685.817	1,500	4,166	11,000	30,000	75,000
Loan amount -BigTech	158,795	21,841.588	38,277.228	1,300	3,900	10,000	25,000	51,000
Loan amount -Bank credit	14,689	216,895.731	525,568.777	10,000	39,000	100,000	200,000	499,400
Loan amount -Bank secured credit	2,389	536,947.291	718,637.589	50,000	140,000	300,000	651,250	1,232,712
Loan amount -Bank unsecured credit	12,438	118,832.744	426,258.515	7,100	20,000	50,000	132,000	299,000
			Panel B: Firm Characteristics					
Network Centrality	15,139,162	37.501	20.997	13.838	22.251	33.974	48.673	66.001
Sales	15,139,162	10,414.674	68,203.854	262	876	2,732	7,794	19,663
Online	15,139,162	0.015	0.123	0	0	0	0	0
Owner Age	15,139,162	38.328	8.866	27	31	38	45	50
Owner Gender-Male	15,139,162	0.511	0.500	0	0	1	1	1
			Panel C: Macroeconomic Conditions					
DR007	15,139,162	2.688	0.166	2.470	2.582	2.649	2.845	2.888
ΔDR007	15,139,162	-0.005	0.096	-0.146	-0.064	0.001	0.044	0.135
GDP-city (bn)	15,139,162	195.182	210.853	33.011	54.733	109.423	267.907	496.540

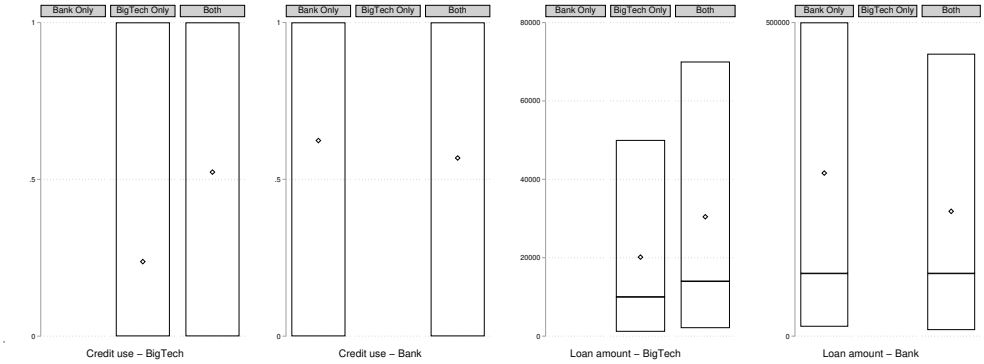
Note: (1) The unit of observation is firm-lender type-month, as we include two observations for each firm in each month: one indicating bank loans and the other indicating BigTech loans.(2) The loan amounts and sales are denominated in Chinese yuan. (3) Due to the principles of anonymization and privacy protection, we are unable to report the minimum and maximum values of the variables obtained from MYBank.

We benchmark our sample against existing literature in the FinTech market. Specifically, Beck et al. (2022) adopt a selection approach similar to ours for sampling from MYBank, with loan characteristics that closely match those in our study: 4.8% and 1.0% of firms in their sample utilized BigTech credit and bank credit, respectively, and the average loan amounts were 18,295 and 166,749 Chinese yuan for BigTech credit and bank loans, respectively. Additionally, the average age of firm owners in their study was 38.9 years, with 50.9% being male. These similarities suggest comparable methods and sample selections from two independent studies. We can also compare our loan sizes with those in Liu et al. (2022),

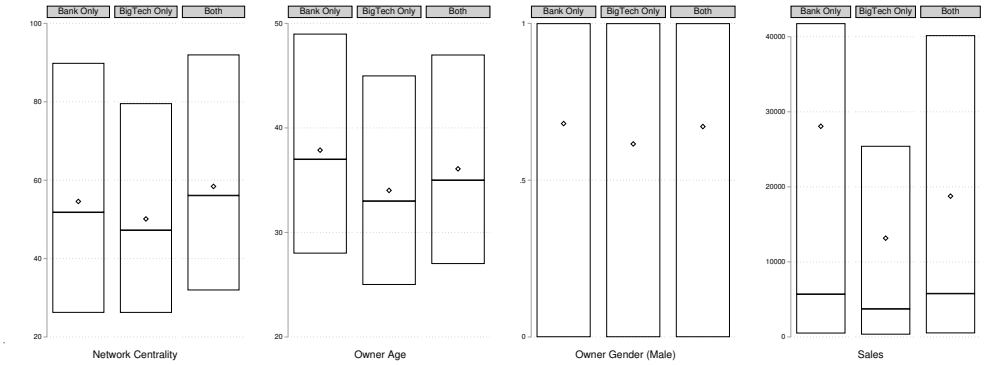
who analyzed MYBank as a representative of BigTech credit and an unnamed traditional bank for traditional bank credit. Their data show average BigTech and traditional bank credits of 36,099 and 159,087 yuan, respectively, with an average borrower age of 32.8 years and 68% male representation among BigTech borrowers. These figures are also reasonably comparable to ours. Further, we can compare firm characteristics with those reported by Cong et al. (2021), who examined a representative survey of SMEs comprised of private enterprise owners and self-employed entrepreneurs, regardless of their access to BigTech platforms. Their average firm owner age was 32.4 years. A notable difference is in the gender distribution, where only 17.3% of firm owners were female, compared to 49% in our sample. This discrepancy may suggest that female-owned small firms are more inclined to use FinTech in their businesses. Additionally, 82.4% of the SMEs in their sample belonged to the service sector (broadly defined as non-agriculture and non-construction sectors), which aligns closely with our sector distribution as shown in Table A3.

Furthermore, as previously described, firms can be categorized into three types based on their borrowing history: (1) the firm is a customer of MYBank but has never borrowed from traditional banks; (2) the firm has borrowed only from banks, not from BigTech lenders; (3) the firm has borrowed from both banks and BigTech lenders. Figure 2 illustrates the loan and firm characteristics for each category, where the diamond mark represents the mean, the lower and upper bounds indicate the 10th and 90th percentiles, respectively, and the middle line indicates the median value. We observe that MYBank extends larger credits to firms with relationships with both lender types than those borrowing solely from MYBank. Conversely, traditional banks issue more credit to firms that exclusively borrow from them. Firms that borrow only from traditional banks typically show higher network scores and sales, and are more likely to have older and male business owners compared to firms that only borrow from the BigTech lender.[22]

[22]In addition, we differentiate between online and offline firms. Figure A6 in the appendix presents the summary statistics for these two firm types separately. It reveals that online firms obtain more BigTech



(a) Loan Characteristics



(b) Firm Characteristics

Figure 2: Loan and Firm Characteristics by Borrowing History

Note: The diamond mark represents the mean, while the lower and upper bounds indicate the 10th and 90th percentiles, and the middle line denotes the median value. "Bank Only" refers to the group of firms that have borrowed solely from traditional banks. "BigTech Only" describes the group of firms that have only borrowed from MYBank. "Both" categorizes firms that have borrowed from both traditional banks and MYBank.

4.2.2 Monetary Policy Variable

To assess the relative responses of BigTech lenders to monetary policy, we need to integrate both loan and firm characteristics with monetary policy variables. Selecting an appropriate monetary policy variable in the Chinese context is challenging. The People's Bank of China (PBC) traditionally focuses on two intermediate targets: quantity-based money supply and priced-based market interest rates (McMahon et al. 2018, Huang et al. 2019, Chen et al.

credit and bank credit than offline firms, and they exhibit higher centrality, younger owner age, and larger sales.

2018). Recently, however, the emphasis has shifted from quantity to price targets. This shift is evident in several ways. First, the disappearance of M2 or credit aggregate targets since 2018 from the State Council's Annual Report on the Work of Government, which still outlines GDP growth targets, indicates a reduced focus on quantity-based targets. Second, the liberalization of interest rates, which began with money market rates and included the removal of the ceiling on bank deposit rates in 2015, marks significant steps towards adopting a modern, price-based monetary policy framework. Third, as detailed in the appendix, the explanatory power of output and inflation gaps for M2 growth has diminished, while the influence of interbank rates has increased and now surpasses M2 growth rates in more recent periods.[23] In summary, while quantity-based rules dominated in earlier years (up to 2016, as noted by Chen et al., 2018), for the recent period covered in our sample (2017-2019), price-based interest rates are more relevant as intermediate targets.

Among various interest rate variables, we use the seven-day interbank pledged repo rate (DR007) in this paper for several reasons. According to the Monetary Policy Executive Report issued in the third quarter of 2016, "DR007 aligns with the open market operation 7-day reverse repo rate and effectively reflects the liquidity conditions in the banking system, playing a crucial role in establishing the market base rate".[24] This suggests that the PBC considers DR007 as a *de facto* intermediate target (McMahon et al. 2018), and it is a closely monitored rate in the market. Furthermore, DR007 is preferable for matching the monthly frequency of our data, unlike other measures such as the required reserve ratio, which changes much less frequently. Moreover, as illustrated in Figure A7 in the appendix, when compared with other interbank rates like Shibor and R007, DR007 shows a greater relevance to the output and inflation gaps.

[23]Though the Taylor rule's applicability to China's monetary policy remains debatable, empirical analysis as presented in the appendix supports the relative effectiveness of price over quantity rules. See Figure A7 for details.

[24]The Monetary Policy Executive Report, a key communication tool of the central bank, has been issued quarterly by the PBC since 2001 (McMahon et al. 2018).

Following Jiménez et al. (2014), we use the monthly change in the DR007 rate ($\Delta DR007$) to measure changes in monetary policy, where a positive change signifies a tightening of policy and a negative change indicates an expansion. Recent studies, such as Fernald et al. (2014), Chen et al. (2018), Kamber and Mohanty (2018), and Das and Song (2023), have shown that the impulse responses of monetary policy transmission in China are comparable to those in advanced economies. Thus, although China has a unique institutional framework, the findings on monetary policy transmission in our study could provide insights applicable to other economies as well.

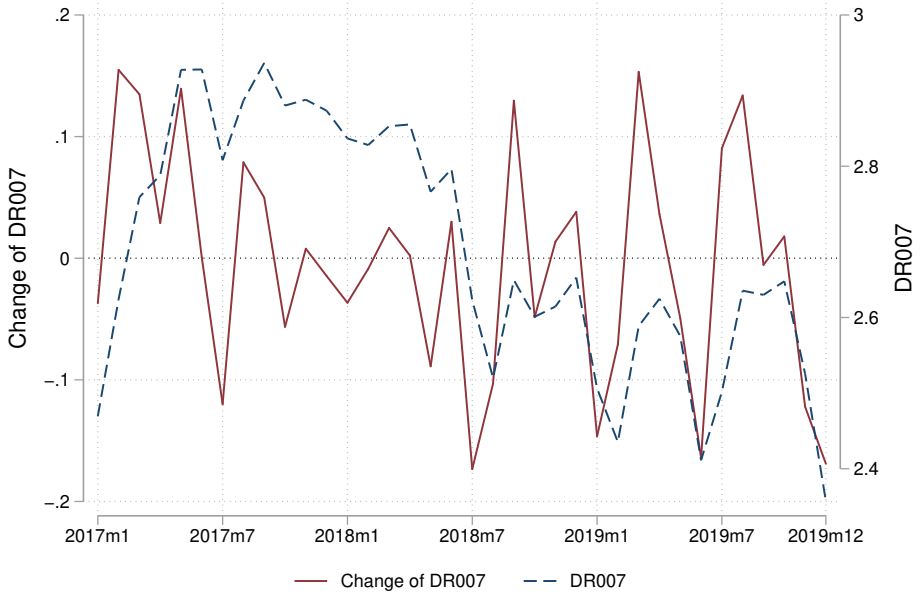


Figure 3: Monetary Policy Rate

Figure 3 presents the time series of both the level and change in the monetary policy rate. During our sample period, the rates exhibit significant variability. Both tightening and easing cycles occurred alternately, with neither trend dominating the entire period. This variation aids in our identification process and in examining the theoretical implications concerning the asymmetric effects of tightening versus easing. Additionally, we control for the logarithm of GDP at the city level, aligned with the locations of the firms, to address

potential concerns about regional economic fluctuations and credit demand. However, the selection of macroeconomic control variables is not critical, as their effects will be accounted for by the firm×month fixed effects in our empirical analysis. These variables are summarized in Panel C of Table 1.

4.3 Main Findings

4.3.1 Extensive and Intensive Margin

We now examine the first empirical implication, which posits that the primary difference between BigTech lenders and traditional banks in their response to monetary policy is observed at the extensive margin rather than the intensive margin. To do this, we employ the following specification:

$$Credit_{ibt} = \alpha + \beta MP_t \times D(BigTech)_b + \delta_b + \theta_{it} + \epsilon_{ibt} \tag{6}$$

where i, b and t indicate firm, lender, and month, respectively. Our dataset includes two types of lenders: the BigTech lender MYBank and a group of traditional banks. The dummy variable $D(BigTech)_b$ is set to one for the BigTech lender. The variable MP_t captures changes in monetary policy, represented by $\Delta DR007$. A positive $\Delta DR007$ indicates a tightening of monetary policy, while a negative value indicates easing. The lender fixed effect, δ_b, captures the time-invariant differences between traditional banks and BigTech lenders. Following Khwaja and Mian (2008), we specify the firm-month fixed effect, θ_{it}, which absorbs any confounding aggregate macroeconomic factors and firm-time variant factors, including firms' credit demand. This specification allows us to compare lending by the two types of lenders to the same firm at the same time, thus isolating the credit supply side response to monetary policy through β. Additionally, we will present results using separate firm and time fixed effects, controlling for a set of firm characteristics, including the logarithm of sales, the network centrality score, and the logarithm of the city's GDP. All these control

variables are specified in lagged terms to mitigate concerns about reverse causality. Later, we also perform a robustness check by interacting the BigTech dummy variable with each of the control variables, confirming that the findings related to the monetary policy variable interaction remain valid.

In our model, the dependent variable, $Credit_{ibt}$, examines the impact of monetary policy on both the extensive and intensive margins, drawing on methodologies from Khwaja and Mian (2008) and Bittner (2022). Our theoretical framework suggests that the differences between the two types of lenders are more pronounced at the extensive margin. For both margins, we focus on the coefficient of β. As a higher MP_t indicates a tightening of monetary policy, a significant and negative β suggests that BigTech lenders are more responsive to changes in monetary policy compared to traditional banks, and *vice versa*.

For the extensive margin, we define a dummy variable, $D(\textit{New Lending Relationship})_{ibt}$, which is set to one if firm i starts to obtain credit from lender b at time t. This indicates that prior to time t, firm i was not a client of lender b, but establishes a relationship at t and continues thereafter. This variable tracks the initiation of new lending relationships between firm i and bank b. We adopt a linear probability model for this dichotomous dependent variable to simplify the interpretation of the interaction term in our estimation. For the intensive margin, our focus shifts to the logarithm of the credit amount, $Ln(Loan)_{ibt}$, a conventional measure for analyzing the credit channel of monetary policy. Here the sample is conditional upon each firm having an existing lending relationship with the lender and the loan amount being positive. Essentially, we perform a quasi-loan-level regression, and our strategy is to compare the amounts lent to the same firm by different lenders in response to monetary policy changes. Consequently, the number of observations available for investigating the intensive margin is significantly reduced compared to the extensive margin.

Table 2 presents the results. The key finding from comparing columns (1)-(2) with columns (3)-(4) is that the interaction term between monetary policy and the BigTech

Table 2: Baseline Results

DepVar	D(New Lending Relationship)		Ln(Loan)	
	(1)	(2)	(3)	(4)
Δ DR007 × D(BigTech)	-0.026***	-0.026***	-0.080	-0.020
	(0.0003)	(0.0005)	(0.134)	(2.553)
L.Ln(Sales)	0.001***		0.012***	
	(0.00005)		(0.003)	
L.Network Centrality	0.001***		-0.001	
	(0.00002)		(0.001)	
L.Ln(Regional GDP)	0.001***		0.048**	
	(0.0003)		(0.023)	
Obs	15,139,162	15,139,162	173,484	173,484
Adj R-Square	0.405	0.166	0.676	0.490
Bank FE	YES	YES	YES	YES
Firm FE	YES	-	YES	-
Month FE	YES	-	YES	-
Firm × Month FE	NO	YES	NO	YES

Note: The unit of observation is firm-lender type-month, as we include two observations for each firm in each month: one indicating bank loans and the other indicating BigTech loans. *D(New Lending Relationship)* is a dummy variable indicating the first time the firm borrows from traditional banks or the BigTech lender. $Ln(Loan)$ is the logarithm of loan amounts issued to the firm. $\Delta DR007$ is the monthly change in the 7-day repo rates in the inter-bank market. $D(BigTech)$ is a dummy variable indicating the BigTech lender. $Ln(Sales)$ is the logarithm of the monthly sales of the firm. *Network Centrality* is a measurement of centrality based on the firms' payments connections. *Ln(Regional GDP)* is the logarithm of the city-level GDP where the firm is located. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the lender level and are shown in parentheses.

dummy is negative and statistically significant for the extensive margin, but insignificant for the intensive margin. These results show that the BigTech lender is more responsive than traditional banks in acquiring new customers when monetary policy eases, yet there is no significant difference in the amount of credit issued to existing borrowers compared to traditional banks. This aligns with the first empirical implication of our theoretical model. As our model suggests, adjustments at the extensive margin are largely influenced by changes in funding costs, as these costs directly influence the optimal threshold for lending. However, since BigTech firms and traditional banks possess similar informational advantages over their chosen firm sizes, the differences in loan amounts or the intensive margin are negligible. These empirical findings resonate with the literature such as Zhou (2022), which shows that FinTech primarily influences the mortgage market's composition rather than its scale, and Liu et al. (2022), which document that loan sizes to small businesses tend to be relatively

inflexible regardless of the firms' risk characteristics.

More specifically, when the monetary policy rate decreases by one standard deviation, the probability of a BigTech lender initiating a new lending relationship with a firm is 0.25 percentage points higher than that of a traditional bank. Given that the average probability of lending is 3.4% (as shown in Table 1), this impact is economically significant. Additionally, the analysis alternates control variables between odd and even columns to assess their impact. The results show that firms with higher sales and network centrality, located in more developed regions, are more likely to establish new lending relationships with either BigTech lenders or traditional banks. Furthermore, the scale of sales and the level of regional economic development are associated with larger loan amounts.

We then conduct several robustness checks. First, we address potential concerns about the comparability between BigTech and traditional bank credits, especially given the differences in credit size and usage highlighted in Table1 and Figure 2. For example, firms might borrow larger amounts from traditional banks for long-term investments, while seeking smaller, short-term loans from BigTech lenders for liquidity needs like bridging debt or financing trade credit. Such differences could affect the comparability of lender responses to monetary policy changes. To address these concerns, we restrict the sample of bank credits to those smaller than the 75th percentile of BigTech credit distributions.[25] We then re-run the previous estimations with this adjusted sample. The results, presented in Table 3, are very similar to or even more pronounced than the baseline results for the extensive margin, while the estimates for the intensive margin remain insignificant. This method ensures that the samples of bank and BigTech credits are comparable in size, enhancing the validity of our comparisons.[26] In addition, we use an extended dataset of the outstanding BigTech credit

[25]According to Table 1, the 75th percentile for BigTech credit is approximately 25,000 Chinese yuan, which falls between the 10th and 25th percentiles of bank credit.

[26]The data consists of aggregated observations of loans for each firm each month, with the 75th percentile cutoff applied at the original loan level. Therefore, the number of firm-month observations remains consistent with the baseline specification.

balance and regress it on the amount of BigTech credit borrowed in the previous month. This analysis provides suggestive evidence against the hypothesis that BigTech credit is predominantly used for liquidity purposes, such as debt rollover. The results are detailed in the appendix, presented in Table A5.

Second, another concern relates to the unsecured nature of BigTech credit and how it compares with secured bank credit. To address this, we differentiate between bank credits that are secured by collateral and those that are not, and we compare BigTech credit with both secured and unsecured bank credits separately. The results, shown in Table 4, confirm that our previous findings are consistent across both subsamples. Again, the special role of BigTech credit is evident only in the extensive margin, not the intensive margin. Furthermore, the minor differences between the coefficients for secured and unsecured credits in the extensive margin suggest that the key distinction in response to monetary policy between BigTech and traditional banks does not stem from differences between earnings- and collateral-based lending models. This finding supports the relative information advantage channel proposed in our theoretical model.

Table 3: Bank Credit and BigTech Credit with Similar Sizes

DepVar	D(New Lending Relationship)		Ln(Loan)	
	(1)	(2)	(3)	(4)
Δ DR007 $\times$ D(BigTech)	-0.028***	-0.028***	-0.281	-0.098
	(0.0004)	(0.0003)	(8.069)	(0.254)
Obs	15,139,162	15,139,162	173,484	173,484
Adj R-Square	0.405	0.166	0.676	0.490
Bank FE	YES	YES	YES	YES
Firm FE	YES	-	YES	-
Month FE	YES	-	YES	-
Firm $\times$ Month FE	NO	YES	NO	YES

Note: The unit of observation is firm-lender type-month, as we include two observations for each firm in each month: one indicating bank loans and the other indicating BigTech loans. Here we restrict the sample of bank credits to those smaller than the 75th percentile of BigTech credit distributions. *D(New Lending Relationship)* is a dummy variable indicating the first time the firm borrows from traditional banks or the BigTech lender. $Ln(Loan)$ is the logarithm of loan amounts issued to the firm. $\Delta DR007$ is the monthly change in the 7-day repo rates in the inter-bank market. $D(BigTech)$ is a dummy variable indicating the BigTech lender. A set of control variables, including $Ln(Sales)$, *Network Centrality*, and $Ln(Regional\ GDP)$, is used in columns (1) and (3). $Ln(Sales)$ is the logarithm of the monthly sales of the firm. *Network Centrality* is a measurement of centrality based on the firms' payments connections. $Ln(Regional\ GDP)$ is the logarithm of the city-level GDP where the firm is located. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the lender level and are shown in parentheses.

Table 4: Comparing BigTech Loans with Secured and Unsecured Bank Loans

DepVar:	D(New Lending Relationship)		Ln(Loan Amount)	
Bank Loan Type:	Secured	Unsecured	Secured	Unsecured
	(1)	(2)	(3)	(4)
$\Delta DR007 \times$ D(BigTech)	-0.028***	-0.026***	-2.226	0.121
	(0.0004)	(0.0005)	(20.161)	(2.803)
Obs	15,139,162	15,139,162	161,184	171,233
Adj R-Square	0.058	0.154	0.492	0.488
Lender FE	YES	YES	YES	YES
Firm $\times$ Month FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

Note: The unit of observation is firm-lender type-month, as we include two observations for each firm in each month: one indicating bank loans and the other indicating BigTech loans. *D(New Lending Relationship)* is a dummy variable indicating the first time the firm borrows from traditional banks or the BigTech lender. $Ln(Loan)$ is the logarithm of loan amounts issued to the firm. $\Delta DR007$ is the monthly change in the 7-day repo rates in the inter-bank market. $D(BigTech)$ is a dummy variable indicating the BigTech lender. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the lender level and are shown in parentheses.

Third, the literature provides mixed evidence on whether the relationship between BigTech lenders (or FinTech lenders in general) and traditional banks is complementary or substitutive (Buchak et al. 2024, Tang 2019, Jagtiani and Lemieux 2018, Erel and Liebersohn 2022). To explore whether this relationship influences our results, we use the density of bank branches as a measure of credit market competition, defined as the number of bank branches per thousand population at the city level.[27] We hypothesize that BigTech credit is more likely to compete and substitute in areas with higher bank branch density. Each firm is assigned a bank branch density based on its city location, and the full sample is then divided into subsamples based on the median value of branch density. Table 5 presents the results for these subsamples. The estimates for the extensive margin are very similar across both subsamples and consistent with the baseline estimation. This suggests that the stronger response of BigTech lenders to monetary policy changes, compared to banks, does not depend heavily on market competition between these two types of financial intermediaries. This is consistent with our theoretical framework, which posits that small businesses are likely unserved or underserved by banks due to information asymmetries, and that advanced risk

[27]Data on bank branches are sourced from the CBIRC, which includes precise locations for all bank branches and we aggregate by city-year, while population data are obtained from each city's bureau of statistics.

management techniques are crucial, thus diminishing the impact of bank branch density.

Table 5: Role of Bank Branch Density

DepVar:	D(New Lending Relationship)		Ln(Loan Amount)	
Bank Branch Density:	High	Low	High	Low
	(1)	(2)	(3)	(4)
$\Delta DR007 \times$ D(BigTech)	-0.026***	-0.026***	-0.227	0.028
	(0.001)	(0.001)	(4.154)	(3.196)
Obs	7,257,970	7,595,938	78,858	91,988
Adj R-Square	0.155	0.175	0.480	0.500
Lender FE	YES	YES	YES	YES
Firm $\times$ Month FE	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES

Note: The unit of observation is firm-lender type-month, as we include two observations for each firm in each month: one indicating bank loans and the other indicating BigTech loans. *D(New Lending Relationship)* is a dummy variable indicating the first time the firm borrows from traditional banks or the BigTech lender. $Ln(Loan)$ is the logarithm of loan amounts issued to the firm. $\Delta DR007$ is the monthly change in the 7-day repo rates in the inter-bank market. $D(BigTech)$ is a dummy variable indicating the BigTech lender. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the lender level and are shown in parentheses.

Finally, we address concerns about other confounding factors from the macroeconomic or firm-specific side that could interact with BigTech's lending decisions, aside from monetary policy. To this end, we include interaction terms between the dummy variable representing BigTech lenders and each of the firm-level control variables, as well as selected macroeconomic variables, thereby conducting a comparative analysis with the monetary policy variable. The macroeconomic variables considered include the real GDP growth rate, inflation rate, and the value-added growth rates of state-owned and private enterprises.[28]

Table 6 shows the results. It indicates that under conditions of lower GDP growth, higher inflation, higher growth in the private sector, and lower growth in the state-owned sector, BigTech lending is more likely to extend credit to new borrowers compared to traditional banks. In addition, factors such as higher network centrality, higher sales, location in less developed regions, and younger, male business owners also influence BigTech's relative lending expansion. Most importantly, the impact of monetary policy remains statistically significant

[28]These time-series data on the Chinese macroeconomy are compiled by Higgins and Zha (2015) and Chang et al. (2016), obtained from the Center for Quantitative Economic Research at the Federal Reserve Bank of Atlanta.

Table 6: Accounting for Confounding Factors

DepVar	D(New Lending Relationship)			Ln(Loan)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta DR007\times$ D(BigTech)	-0.017^{***}	-0.026^{***}	-0.022^{***}	0.142	-0.079	0.057
	(0.0004)	(0.0003)	(0.0005)	(0.376)	(0.328)	(0.376)
Real GDP Growth × D(BigTech)	-0.002^{***}		-0.003^{***}	-0.104^{*}		-0.108^{*}
	(0.0001)		(0.0001)	(0.061)		(0.061)
Inflation × D(BigTech)	0.019^{***}		0.019^{***}	0.186^{***}		0.191^{***}
	(0.0002)		(0.0002)	(0.053)		(0.052)
SOE VA Growth × D(BigTech)	-0.004^{***}		-0.005^{***}	-0.053^{*}		-0.059^{*}
	(0.0001)		(0.0001)	(0.031)		(0.031)
NSOE VA Growth × D(BigTech)	0.001^{***}		0.001^{***}	-0.022		-0.023
	(0.00002)		(0.00002)	(0.017)		(0.017)
L.Network Centrality × D(BigTech)		0.001^{***}	0.001^{***}		0.003	0.004^{*}
		(0.00002)	(0.00002)		(0.002)	(0.002)
L.Ln(Sales) × D(BigTech)		0.002^{***}	0.001^{***}		-0.019	-0.025
		(0.0001)	(0.0001)		(0.026)	(0.026)
L.Ln(Regional GDP) × D(BigTech)		-0.002^{***}	-0.002^{***}		0.028	0.030
		(0.0004)	(0.0004)		(0.050)	(0.049)
D(Male) × D(BigTech)		0.014^{***}	0.014^{***}		0.139	0.163^{*}
		(0.001)	(0.001)		(0.098)	(0.096)
Owner Age × D(BigTech)		-0.002^{***}	-0.002^{***}		-0.021^{***}	-0.021^{***}
		(0.00004)	(0.00004)		(0.007)	(0.007)
Obs	15,139,162	15,139,162	15,139,162	173,484	173,484	173,484
Adj R-Square	0.171	0.189	0.195	0.497	0.494	0.503
Bank FE	YES	YES	YES	YES	YES	YES
Firm × Month FE	YES	YES	YES	YES	YES	YES

Note: The unit of observation is firm-lender type-month, as we include two observations for each firm in each month: one indicating bank loans and the other indicating BigTech loans. *D(New Lending Relationship)* is a dummy variable indicating the first time the firm borrows from traditional banks or the BigTech lender. $Ln(Loan)$ is the logarithm of loan amounts issued to the firm. $\Delta DR007$ is the monthly change in the 7-day repo rates in the inter-bank market. $D(BigTech)$ is a dummy variable indicating the BigTech lender. *Real GDP Growth*, $Inflation$, *SOE VA Growth*, and *NSOE VA Growth* are the national real GDP growth rates, inflation rates, value-added growth rates of state-owned enterprises and non-state-owned enterprises, respectively. *Network Centrality*, $Ln(Sales)$, $Ln(Regional\ GDP)$, $D(Male)$, and *Owner Age* are the measurement of the firm's centrality based on payment connections, the logarithm of sales, the GDP of the city where the firm is located, a dummy variable indicating the firm owner being male, and the age of the firm owner, respectively. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the lender level and are shown in parentheses.

in this analysis, demonstrating that BigTech lenders are more responsive to monetary policy than traditional banks at the extensive margin, but not at the intensive margin.

4.3.2 Asymmetric Effects

Now we proceed to test the second empirical prediction regarding the asymmetric effects between monetary policy easing and tightening. We introduce a dummy variable, $D(Tightening)_t$, set to one when there is a positive change in the monetary policy rate, indicating tightening. This variable is then interacted with the absolute values of the changes in the monetary

policy rate and the BigTech lender dummy. Specifically, we estimate the following equation:

$$\begin{aligned} Credit_{ibt} = \alpha' + \beta_1' |MP_t| \times D(BigTech)_b + \beta_2' D(BigTech)_b \times D(Tightening)_t \\ + \beta_3' D(BigTech)_b \times |MP_t| \times D(Tightening)_t + \delta_b + \theta_{it} + \epsilon_{ibt} \end{aligned} \tag{7}$$

Thus, the relative responsiveness of BigTech lenders compared to traditional banks during monetary policy easing is represented as $-\beta_1'$, and during tightening as $\beta_1' + \beta_3'$. The relative impact of these phases depends on the sign of β_1' and the magnitude of β_3'. For instance, a positive β_1' suggests that BigTech lenders are more responsive to monetary policy easing, specifically in terms of expanding new lending relationships, compared to traditional banks. If both β_1' and $\beta_1' + \beta_3'$ are positive, this indicates that BigTech lenders are less responsive during monetary policy tightening than traditional banks, with a positive β_3' demonstrating a more pronounced absolute difference between the two types of lenders during tightening. Conversely, a negative β_3' would indicate a more pronounced difference during easing. However, if β_1' is positive and $\beta_1' + \beta_3'$ is negative, suggesting that BigTech lenders are more responsive during tightening, the exact nature of this asymmetry depends on the relative size of $|\beta_3'|$ compared to $2\beta_1'$.

Table 7 presents the estimates. It confirms an asymmetric impact on the extensive margin between monetary easing and tightening. Notably, the transmission-enhancing role of the BigTech lender is predominantly evident during periods of monetary *loosening*, with a significant magnitude. Specifically, the coefficients for the relative impact between BigTech and traditional banks during loosening and tightening are -0.102 ($-\beta_1'$) and 0.093 ($\beta_1' + \beta_3'$), respectively. The economic interpretations are as follows: when the monetary policy rate decreases by one standard deviation, the probability of a BigTech lender initiating credit to a new firm is 0.97 percentage points higher than that of a traditional bank (compared to 0.25 percentage points in the baseline results). Conversely, when monetary policy tightens by one

Table 7: Asymmetric Effect between Easing and Tightening

DepVar	D(New Lending Relationship)		Ln(Loan Amount)	
	(1)	(2)	(3)	(4)
| Δ DR007 | × D(BigTech)	0.102***	0.102***	0.323	0.310
	(0.001)	(0.002)	(0.296)	(5.761)
D(BigTech) × D(Tightening)	-0.001***	-0.001***	-0.094**	-0.136
	(0.0001)	(0.0001)	(0.041)	(0.870)
| Δ DR007 | × D(BigTech) × D(Tightening)	-0.009***	-0.009***	-0.651	1.199
	(0.001)	(0.002)	(0.451)	(9.037)
Obs	15,139,162	15,139,162	173,484	173,484
Adj R-Square	0.167	0.405	0.490	0.676
Lender FE	YES	YES	YES	YES
Firm FE	YES	-	YES	-
Month FE	YES	-	YES	-
Firm × Month FE	NO	YES	NO	YES
Controls	YES	YES	YES	YES

Note: The unit of observation is firm-lender type-month, as we include two observations for each firm in each month: one indicating bank loans and the other indicating BigTech loans. *D(New Lending Relationship)* is a dummy variable indicating the first time the firm borrows from traditional banks or the BigTech lender. $Ln(Loan)$ is the logarithm of loan amounts issued to the firm. $\Delta DR007$ is the monthly change in the 7-day repo rates in the inter-bank market. $D(Tightening)$ is a dummy variable indicating that $\Delta DR007$ is positive. $D(BigTech)$ is a dummy variable indicating the BigTech lender. A set of control variables, including $Ln(Sales)$, *Network Centrality*, and $Ln(Regional\ GDP)$, is used in columns (1) and (3). $Ln(Sales)$ is the logarithm of the monthly sales of the firm. *Network Centrality* is a measurement of centrality based on the firms' payments connections. $Ln(Regional\ GDP)$ is the logarithm of the city-level GDP where the firm is located. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the lender level and are shown in parentheses.

standard deviation, the extent of credit contraction on the extensive margin for the BigTech lender is 0.88 percentage points less than that for banks. The last two columns show that the impact on the intensive margin remains insignificant and statistically indifferent between tightening and easing. These findings are consistent with our theoretical implications that BigTech credit is less responsive to monetary policy tightening. This is because, with increased funding costs, BigTech opts to lend to smaller firms where it has a stronger relative advantage over banks. Consequently, BigTech's lending decisions are less sensitive to changes in monetary policy, given its superior understanding of these firms' actual profitability.

In relation to the mechanism behind the asymmetric effects, here we provide further evidence of heterogeneous impacts across firm sizes. Recall that the main distinction between BigTech lenders and traditional banks in our model lies in the level of ambiguity they confront – a higher level of ambiguity towards a firm leads investors to lower their expectations of a firm's returns – and BigTech lenders hold an information advantage over traditional

banks, which diminishes with firm sizes. BigTech lenders would react more strongly to monetary policy changes when their relative information advantage is smaller – as is the case when monetary policy eases, the required expected rate of return for lending is lowered, promoting BigTech lenders to expand their reach to larger firms where their relative information advantage is less pronounced and resulting in larger responses compared to the case when monetary policy tightens.

Specifically, we test the implication that the larger responses to monetary policy by BigTech lenders than traditional banks at the extensive margin will be more pronounced for larger firms. We divide the full sample into four subsamples according to firm size, defined by average sales and organized from the first to the fourth quartiles, We then repeat the baseline estimation for each subsample. Results in Table 8 show that the BigTech lender is consistently more responsive to monetary policy changes across all size groups, with the magnitude of responsiveness increasing with firm size. Specifically, when the monetary policy rate decreases by one standard deviation, the probability that a BigTech lender will establish a new lending relationship with a firm in the fourth quartile of size distribution is 0.37 percentage points higher than that of a traditional bank; for firms in the first quartile, this figure is only 0.12 percentage point. While we also examined the intensive margin, the coefficient shifted from positive in the first quartile to negative in the fourth quartile, yet remained statistically insignificant across all sizes.

5 Further Discussion

In this section, we use an extended dataset to study the impact of monetary policy on other terms of BigTech loans besides the likelihood of credit approval and the loan amount. We also address concerns related to the confounding effects of regulatory policies on BigTech credit. Specifically, we access a dataset that extends the time coverage up to the end of

Table 8: Mechanism Investigation: Heterogeneity across Size

DepVar	D(New Lending Relationship)				Ln(Loan Amount)			
Quartile	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Δ DR007 × D(BigTech)	-0.013 ***	-0.024***	-0.031***	-0.039***	0.819	0.438	0.060	-0.195
	(0.001)	(0.001)	(0.001)	(0.001)	(13.562)	(12.949)	(5.848)	(2.576)
Obs	3,355,370	3,698,164	3,908,142	41,778,128	14,029	32,695	49,905	76,844
Adj R-Square	0.092	0.117	0.117	0.202	0.623	0.199	0.199	0.489
Lender FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm × Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES	YES	YES	YES

Note: The unit of observation is firm-lender type-month, as we include two observations for each firm in each month: one indicating bank loans and the other indicating BigTech loans. The 1st to 4th quartiles are based on firms' monthly sales, serving as a proxy for firm sizes. *D(New Lending Relationship)* is a dummy variable indicating the first time the firm borrows from traditional banks or the BigTech lender. $Ln(Loan)$ is the logarithm of loan amounts issued to the firm. $\Delta DR007$ is the monthly change in the 7-day repo rates in the inter-bank market. $D(Tightening)$ is a dummy variable indicating that $\Delta DR007$ is positive. $D(BigTech)$ is a dummy variable indicating the BigTech lender. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the lender level and are shown in parentheses.

2021 and includes information on the outstanding amount, interest rate, and maturity of BigTech loans.[29] This expansion allows us to investigate the role of regulation, which became prominent in 2021, and to examine how other loan terms are affected by monetary policy.

However, due to data and business privacy reasons, the extended dataset comes with two main limitations. First, the information on interest rates is not provided in its original format but is instead normalized and rescaled to a range between zero and one. Therefore, any interpretations of the findings related to interest rates must be approached with caution. Second, the additional data does not cover traditional bank loans, which prevents us from comparing the impact of monetary policy on other contractual terms between BigTech and traditional bank loans—a central aspect of our prior analysis. This is the primary reason the extended dataset is not used in our baseline analysis. To sum up, the extended dataset covers BigTech credit at the firm-month level only, with cross-sectional variation occurring at the level of the borrowing firm, but not at the lender level. Despite these constraints, the dataset is valuable for exploring other crucial terms of BigTech credit and offers insights into the effects of regulatory policies and the transmission of monetary policy.

[29]We report the summary statistics of these extended variables in the appendix in Table A6.

5.1 Other Contract Terms

Given the different structure of the extended dataset, we are unable to specify borrower-month fixed effects to isolate the demand effects and control for other macroeconomic variables. Therefore, we employ the local projections method (Jordà 2005) to account for changes in credit demand over time and mitigate concerns related to confounding macroeconomic factors. The specification is as follows:

$$Term_i^{t+h} - Term_i^t = \alpha_0^h + \Sigma_{k=0}^{k=2}(\beta_k^h MP_{t-k} + \zeta_k^h Macro_{t-k}) + \gamma^h \Gamma_{i,t-1} + \delta_i^h + \epsilon_{i,t}^h \quad (8)$$

where *Term* indicates various dimensions of BigTech loans, including the logarithm of outstanding loans, the logarithm of newly issued loans, the normalized interest rate index, and the maturity. The dependent variable is the cumulative change in these terms between t and $t+h$, with h set at horizons of 1,2, ..., up to 12 months. As in our baseline analysis, MP_t, the monetary policy variable, is proxied by the change in interest rate $\Delta DR007_t$. *Macro* represents an array of macroeconomic conditions, including GDP growth rate, inflation, and value-added growth rates of state-owned and private enterprises, controlled to mitigate concerns about potential confounding effects. We include both current and two-period lagged terms of monetary policy and macroeconomic variables to account for their dynamics. $\Gamma_{i,t-1}$ indicates a set of firm-level control variables, including the logarithm of outstanding loans, logarithm of sales, network centrality, and the ratio of outstanding loans to sales, which help capture firms' credit demand and determinants of loan terms. These are specified in lagged form to mitigate concerns regarding reverse causality from loan terms to firm performances. δ_i represents firm fixed effects, absorbing all time-invariant firm characteristics, and $\epsilon_{i,t}$ is the error term. We are particularly interested in the estimates of β_0^h for $h = 1, 2, ...12$, as these capture the impact of a one-unit increase (100 basis points) in monetary policy rates at time t on loan terms over a twelve months horizon. To avoid disruption from the pandemic

and maintain consistency with the sample periods in earlier analysis, we restrict the sample here to end in 2019; later we will discuss findings from extended periods when bringing in BigTech regulation policies.

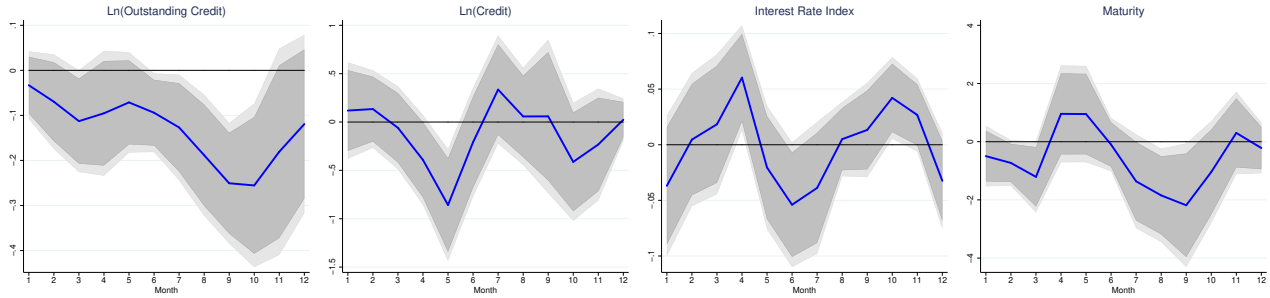


Figure 4: Local Projection: Impact of Monetary Policy on Other BigTech Loan Terms

Notes: It shows the cumulative impulse responses to a one-unit increase in the monetary policy rate, based on the estimation of Equation (8). The light- and dark-shaded areas represent the 68% and 90% confidence bands, respectively.

Figure 4 presents the results. First, we observe that an increase in the monetary policy rate is associated with a significant decline in both outstanding and newly issued loans by BigTech. Specifically, the decrease in outstanding credit becomes statistically significant three months after monetary policy changes and remains so for ten months. Meanwhile, the reduction in new credit issuance is significant four months after the shock, with the impact peaking in the fifth month; however, this effect is temporary, as it becomes insignificant over a longer horizon. In terms of magnitude, a one standard deviation increase in the monetary policy rate is associated with a decrease in outstanding credit by 2% and a decrease in new credit issuance by 8% at the most affected horizon. Second, monetary policy tightening is also significantly associated with an increase in the interest rate and a decrease in loan maturity in the short term. Specifically, a one standard deviation increase in monetary policy rate is associated with a 0.01 unit increase in the interest rate index and a 0.11 month reduction in loan maturity within a quarter. These findings are consistent with the conventional mechanisms of monetary policy transmission (Bernanke and Gertler 1995, Black and Rosen 2018). Furthermore, the opposite findings on the quantity (outstanding and newly issued

loan amounts) and price (interest rate) help distinguish between credit demand and supply effects, suggesting that these outcomes are primarily driven by the credit supply from the BigTech lender.

5.2 Regulation Policy

Next, we explore the regulatory policies on BigTech credit and their impact on credit terms. An alternative interpretation of our findings is that BigTech may engage in regulatory arbitrage when issuing credit, particularly if it is considered part of the shadow banking sector, thereby altering the transmission of monetary policy (Xiao 2020, Hasan et al. 2024). It is crucial to clarify that in our analysis, MYBank, the banking arm of the BigTech company Alibaba Group, operates as a commercial bank and is regulated in the same manner as traditional banks. Thus, the BigTech credit discussed in our paper is not subject to differing regulatory policies. However, we also acknowledge that regulatory policies targeting BigTech credit could indirectly influence the lending decisions of MYBank through the other non-banking financial businesses of the BigTech company. Therefore, it is important to formally address the issue of BigTech regulation in this context.

For this purpose, we construct a measurement for BigTech regulation policy in the following way. First, we review and summarize government policies targeting internet lending in China from 2017 to 2021.[30] We record the announcement dates of each regulation policy and adjust the dates to the nearest trading day following the announcement if they are not on trading days. These 27 specific regulation policies are detailed in Table A7 in the appendix. Second, we calculate the abnormal returns of Alibaba and Tencent within three days following each policy announcement.[31] Alibaba and Tencent are parent companies of

[30] Internet lending encompasses all lending activities on online platforms, including BigTech credit.

[31] Abnormal return is calculated as the deviation between the actual return of the company and the CAPM-predicted return, determined by regressing the actual return against the return of the Hang Seng Index, a major Hong Kong stock market index.

the largest BigTech lenders in China, MYBank and WeBank, respectively. In addition to Alibaba, We include Tencent in our analysis to gauge the impact of regulatory stringency, as its stock market reactions provide valuable insights into the effects of BigTech regulations and offer broader time coverage, while we lack microlevel BigTech credit data for it. Third, we access the search frequency indicators for the keywords "Ant Financial" and "FinTech" on Baidu, the largest search engine in China and the Chinese version of Google. Finally, using the abnormal stock returns of Alibaba and Tencent, along with the search indices for "Ant Financial" and "FinTech", we conducted a principal component analysis (PCA) and extracted the first component as our measure of BigTech regulation policy. In this process, to facilitate interpretation, we reverse the sign of the abnormal stock returns so that an increase in the index indicates tighter regulation.[32]

Figure 5 presents our BigTech credit regulation policy index. A notable observation is that there were not many variations in regulation stringency before mid-2020, aligning with the market consensus that the regulation was relatively lax during the early stages of BigTech development. Moreover, the regulation measurement saw a significant spike in November 2020, which coincided with Jack Ma's controversial speech at the Bund Summit, after which the regulations on BigTech's financial services were significantly tightened.[33] While our baseline sample ends in 2019 a period when regulation did not play a significant role, the extended dataset spanning 2017-2021 enables us to explore the effects of regulatory changes on BigTech credit.

We alter the local projection specification to simultaneously account for regulation stringency and the impact of monetary policy. Additionally, We address the disruptions caused by the COVID pandemic, which began in 2020. The revised specification is as follows:

[32]Table A8 in the appendix shows a good performance of the PCA. All variables have positive loadings on the first factor, which accounts for about 62% of the common variation among the observed variables. This factor is used as a summary index of the regulation policy. Moreover, the abnormal return of Aliababa and the search index for Ant Financial have the largest loadings, offering significant insights given our use of MYBank data in this study.

[33]Jack Ma is the co-founder of Alibaba Group.

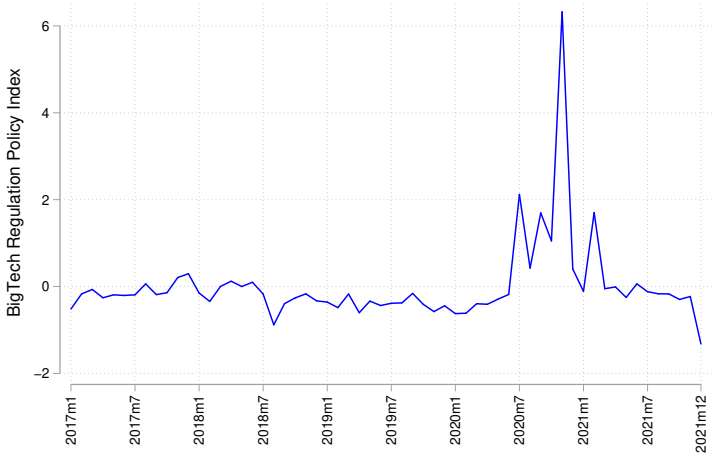
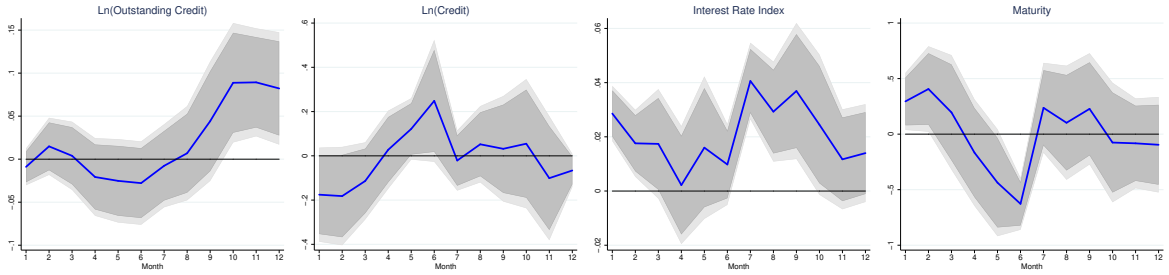


Figure 5: BigTech Regulation Policy Index

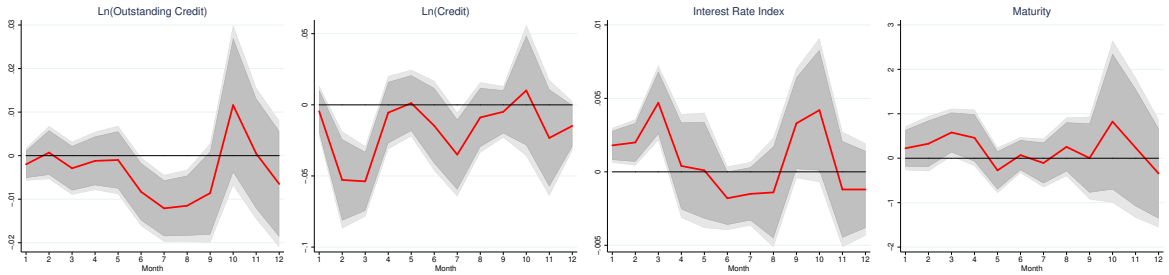
Notes: It shows the time series of the BigTech regulation policy index, which is constructed as the first component from a principal component analysis using the abnormal stock returns of Alibaba and Tencent, and the search indicators of "Ant Financial" and "FinTech".

$$Term_i^{t+h} - Term_i^t = \alpha_0'^h + D(Before)_t \Sigma_{k=0}^{k=2} (\beta'_{mp,k}{}^{h,before} MP_{t-k} + \beta'_{reg,k}{}^{h,before} Reg_{t-k})$$
$$+D(After)_t \Sigma_{k=0}^{k=2} (\beta_k'^{h,after} MP_{t-k} + \beta_k'^{h,after} Reg_{t-k}) + \Sigma_{k=0}^{k=2} \zeta_k'^h Macro_{t-k} + \gamma'^h \Gamma_{i,t-1} + \delta_i'^h + \epsilon_{i,t}'^h \quad (9)$$

where $D(Before)$ and $D(After)$ are dummy variables indicating the period before and after the onset of COVID-19, respectively. Reg_t is our constructed BigTech regulation stringency index, with all other variables remaining as previously defined. In this specification, we treat monetary and regulation policies comparably. We report the impacts of monetary policy ($\beta'_{mg,0}{}^{h,before}$ and $\beta'_{mg,0}{}^{h,after}$) in Figure A8 in the appendix, which affirms our previous findings that monetary policy tightening contracts BigTech credit, even after accounting for regulation policy in the pre-COVID period, while showing that the role of monetary policy becomes less significant in the post-COVID period. Here, we focus on the estimates of $\beta'_{reg,0}{}^{h,before}$ and $\beta'_{reg,0}{}^{h,after}$, which capture the impact of regulation policy on the BigTech loan terms before and after the pandemic. Results are presented in Figure 6.



(a) Pre-COVID



(b) Post-COVID

Figure 6: Local Projection: Impact of Regulation Policy

Notes: It shows the cumulative impulse responses to a one-unit increase in the BigTech regulation policy index, based on the estimation of Equation (9). The pre-COVID sample starts in January 2017 and ends in December 2019, while the post-COVID sample starts in January 2020 and ends in December 2021. The light- and dark-shaded areas represent the 68% and 90% confidence bands, respectively.

It reveals that regulation policy plays distinct roles in the pre- and post-COVID periods. Before COVID, panel (a) shows that when the regulation was relatively lenient, a more stringent regulation policy was associated with increases in both the outstanding BigTech credit and the interest rate over a ten-month horizon. In addition, loan maturity increases within the first two months following regulatory tightening, and decreases after six months. The same changes in quantity and price suggest that these effects are likely driven by credit demand, as firms opt for more BigTech loans with longer maturities in response to a more restrictive regulation environment. Conversely, the post-COVID scenario presents a different picture, reflecting the more substantial and restrictive regulatory measures implemented during this period. Panel (b) shows that regulatory tightening is associated with a significant decrease in loan amounts and a significant increase in interest rates, while changes in loan

maturity remain insignificant. These findings indicate that credit supply is the driver and the BigTech lender contracts credits in response to more pronounced regulatory constraints. Overall, our findings provide evidence that BigTech lenders react to regulatory policies, underscoring the need for policymakers to coordinate monetary and regulatory policies to effectively manage BigTech credit in the market.

6 Conclusion

In this study, we conduct both theoretical and empirical investigations of how monetary policy is transmitted through two types of financial intermediaries: traditional banks and BigTech lenders. Our theoretical model, which incorporates portfolio selection under Knightian uncertainty, suggests that BigTech lenders have stronger information advantages for smaller firms compared to traditional banks, thereby reducing the ambiguity associated with lending to small businesses. The model yields two predictions regarding the relative responses of BigTech lenders to changes in monetary policy, which we have empirically tested using a microlevel dataset. First, we find that BigTech lenders are significantly more responsive to monetary policy changes at the extensive margin than traditional banks, while the differences at the intensive margin are negligible. Second, this responsiveness is more pronounced during periods of monetary easing than during tightening. Additionally, our study discusses other BigTech loan terms, including interest rates and maturity, and examines the impact of BigTech regulation policies.

Our findings carry important policy implications. Policymakers should consider the amplifying role of BigTech lenders and their asymmetric impact on the financial markets, particularly for small businesses. It is crucial to integrate macroeconomic and regulatory policies to optimize the use of BigTech credit and enhance financial access for small firms.

Acknowledgement: For comments, discussion, and suggestions, we thank Gene Ambrocio, Guido Ascari (discussant), Christoph Basten, Christiane Baumeister, Jonathan Benchimol (discussant), Sally Chen (discussant), Nicolas Crouzet, Marco Di Maggio (discussant), Sebastian Doerr, Thomas Drechsel, Zuzana Fungáčová, Andreas Fuster, Leonardo Gambacorta (discussant), Emilia Garcia-Appendini, Alexandra Gutsch, Jiayin Hu (discussant), Yi Huang, Yigitcan Karabulut, Boreum Kwak, Erica Xuenan Li, Wei Li (discussant), Nicola Limodio, Chang Ma, Aakriti Mathur, Camelia Minoiu, Mrinal Mishra, Steven Ongena, Melina Papoutsi, Malte Rieth, Matthias Rottner, Alessandro Sardone, Samad Sarferaz, Christoph Schult, Rui C. Silva, Laura Solanko, Ilhyock Shim, Ruben Staffa, Gregor von Schweinitz, Yongjie Zhang, and other scholars at the China Financial Research Conference; the AsianFA Conference; the Bank of England workshop on Advanced Analytics: New Methods and Applications for Macroeconomic Policy, the Central Bank Research Association Annual Meeting, the 9th Annual Conference of MIT Golub Center for Finance and Policy, the ECB China Expert Network Workshop, the BFSU-CKGSB Workshop, the 11th Ghent Workshop on Empirical Macroeconomics, the LAPE-FINEST Spring Workshop, CIRF&CFRI Joint Conference, and CCER Summer Institute; and seminars at the University of Zurich, Bank of Finland, BIS, and Halle Institute for Economic Research. Any remaining errors are ours alone. The authors acknowledge and appreciate the support from the Digital Economy Open Research Platform (www.deor.org.cn). All data was anonymized and analyzed remotely in the Ant Group Open Research Laboratory, which is accessible only for remote empirical analysis.

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Online Appendix

A1 Theoretical Proofs

A1.1 Proof of Proposition 1

Proof. According to Girsanov's Theorem, if there exists a model specification different from the reference model, the result of this change of probability is a drift adjustment to the reference process. In this way, let us denote the drift component adjustments for the exogenous processes R and X are Δ_R and Δ_X, respectively.

To begin with, we can easily show that with our model assumptions, for both financial intermediations, the optimal extensive margin choice is a simple cutoff strategy. The perceived expected return for group n firms is calculated as $\mu_{R,n} - r - \Delta_{R,n}$. In addition, the profitability requirement asks that the preceived return should be higher than some threshold $\underline{\mu}$. In other words, each financial intermediation chooses to lend as long as $\mu_{R,n} - r - \Delta_{R,n} \geq \underline{\mu}$. According to our Assumption 1, we know that $\mu_{R,n}$ is a constant term across different groups n, and for both financial intermedations $\Delta_{R,n}$ is a monotone function of n as the information advantage is a monotone function of asset group n. In this way, the optimal investment decision is a simple cutoff strategy. As the BigTech's information advantage is decreasing in firm size, meanwhile the bank's advantage is increasing, the optimal investment portfolio for the traditional bank is $[n^*_{\mathcal{B}}, N]$, where $n^*_{\mathcal{B}}$ satisfies the condition that $\mu_{R,n^*_{\mathcal{B}}} - r + \Delta^{\mathcal{B}}_{R,n^*_{\mathcal{B}}} = \underline{\mu}$. Meanwhile, the optimal investment portfolio for the BigTech is $[1, n^*_{\mathcal{F}}]$, where $n^*_{\mathcal{F}}$ satisfies the condition that $\mu_{R,n^*_{\mathcal{F}}} - r + \Delta^{\mathcal{F}}_{R,n^*_{\mathcal{F}}} = \underline{\mu}$.

After that, for the chosen subset they want to invest in, we can write the Hamilton-Jacobi-Bellman (HJB) equation for the financial intermediation's utility maximization problem as follows:

$$
\begin{aligned}
0 &= \sup_{c,\pi}\inf_{\Delta_X,\Delta_R}\left\{u(c)-\rho\mathcal{J}+\mathcal{J}_t+\omega\mathcal{J}_\omega\left[r+\pi(\mu_R-r)-\frac{c}{\omega}\right]\right. \\
&+ \frac{\omega^2}{2}J_{\omega\omega}\pi^T\sigma_R\sigma_R^T\pi+\mathcal{J}_R\mu_R+\mathcal{J}_X\mu_X \\
&+ \frac{1}{2}tr\left[\left(\begin{bmatrix}\mathcal{J}_{RR} & \mathcal{J}_{RX}\\ \mathcal{J}_{XR} & \mathcal{J}_{XX}\end{bmatrix}\right)\left(\begin{bmatrix}\sigma_R\\ \sigma_X\end{bmatrix}\right)\left(\begin{bmatrix}\sigma_R\\ \sigma_X\end{bmatrix}\right)^T\right]+\omega\pi\sigma_R\sigma_X^T\mathcal{J}_{\omega X}+\omega\pi\sigma_R\sigma_R^T\mathcal{J}_{\omega R} \\
&+ \left. J_\omega\omega\pi\Delta_R-\mathcal{J}_X\Delta_X-\mathcal{J}_R\Delta_R+\frac{\psi(\mathcal{J})}{2}\Delta^T\Gamma\Delta\right\} \qquad (10)
\end{aligned}
$$

where ψ is the usual normalization term used in this literature. The first several terms are the same as those in the standard Bellman equation without ambiguity. In addition, $J_\omega\omega\pi\Delta_R-\mathcal{J}_X\Delta_X-\mathcal{J}_R\Delta_R$ reflect the drift adjustment due to the change of probability measure. The last term $\mathcal{J}_R\Delta_R+\frac{\psi(\mathcal{J})}{2}\Delta^T\Gamma\Delta$ is the penalty function for choosing alternative model specifications compared to the reference model.

The first-order conditions to the HJB equation above can be computed as follows:

$$
\begin{aligned}
u'(c)-\mathcal{J}_\omega &= 0 \qquad (11)\\
\mathcal{J}_\omega[(\mu_R-r)-\Delta_R]+\sigma_R\sigma_X^{\mathrm{T}}\mathcal{J}_{\omega X}+\sigma_R\sigma_R^{\mathrm{T}}\mathcal{J}_{\omega R}+\omega\mathcal{J}_{\omega\omega}\sigma_R\sigma_R^{\mathrm{T}}\pi &= 0 \qquad (12)\\
\begin{bmatrix}\mathcal{J}_{\omega\omega}\omega_\pi+\mathcal{J}_R\\ \mathcal{J}_X\end{bmatrix}^{\mathrm{T}}-\psi(\mathcal{J})\begin{bmatrix}\Delta_R\\ \Delta_X\end{bmatrix}^{\mathrm{T}}\Gamma &= 0 \qquad (13)
\end{aligned}
$$

Rewriting the equations above give us the optimal intensive margin choice shown as below:

$$\pi = -\frac{1}{\omega \mathcal{J}_{\omega\omega}}[\sigma_R \sigma_R^T]^{-1} \left(\mathcal{J}_\omega(\mu_R - r) + \sigma_R \sigma_X^T \mathcal{J}_{\omega X} + \sigma_R \sigma_R^{\mathrm{T}} \mathcal{J}_{\omega R} - \mathcal{J}_\omega \begin{bmatrix} I_R & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta_R \\ \Delta_X \end{bmatrix} \right) \tag{14}$$

and

$$\begin{bmatrix} \Delta_R \\ \Delta_X \end{bmatrix} = \frac{\mathcal{J}_{\omega\omega}}{\psi(\mathcal{J})} \Gamma^{-1} \begin{bmatrix} I_R \\ 0 \end{bmatrix} \pi - \frac{1}{\psi(\mathcal{J})} \Gamma^{-1} \begin{bmatrix} \mathcal{J}_R \\ \mathcal{J}_X \end{bmatrix} \tag{15}$$

■

A1.2 Proof of Proposition 2

Proof. First, we can show that the extensive margin difference in monetary policy shocks for these two financial intermediations. The equilibrium cutoff strategy requires that $\mu_{R,n_i^*} - r + \Delta^i_{R,n_i^*} = \underline{\mu}$, where $i \in \{\mathcal{B}, \mathcal{F}\}$. By taking the derivative of r, we have the following:

$$\frac{\partial n_i^*}{\partial r} \frac{\partial \Delta^i_{R,n_i^*}}{\partial n_i^*} = -1 \tag{16}$$

■ which gives $\frac{\partial n_i^*}{\partial r} = -\frac{1}{\frac{\partial \Delta^i_{R,n_i^*}}{\partial n_i^*}}$. According to Proposition 1, we can easily compute $\frac{\partial \Delta^i_{R,n_i^*}}{\partial n_i^*}$ for each financial intermediation i at n_i^*:

$$\frac{\partial \Delta^i_{R,n_i^*}}{\partial n_i^*} = \frac{\mathcal{J}_\omega \omega_\pi + \mathcal{J}_R}{\psi(\mathcal{J})} \left(\frac{\partial \gamma^i_{n_i^*}}{\partial n_i^*} \right)^{-1} \tag{17}$$

In this way, we can easily see that, the elasticity of monetary policy shocks $\frac{\partial n_i^*}{\partial r}$ is decreasing in the elasticity of information advantage across different firms $\frac{\partial \gamma^i_{n_i^*}}{\partial n_i^*}$. With Assumption 1, we know that compared to the bank, the relative elasticity of information advantage of BigTech is decreasing in firm size group. With Proposition 1, we know that the equilibrium

investment threshold for BigTech $n^*_{\mathcal{F}}$ is decreasing in r. As a result, when monetary policy is easing, the BigTech starts to lend to larger firms, where it has relative flat elasticity of information advantage. In this way, it becomes more sensitive to monetary policy shocks. However, when monetary policy is tightening, the BigTech retreats back to lend to smaller firms, where it has relative steep elasticity of information advantage. In this way, it becomes less sensitive to monetary policy shocks.

Second, we can look at the the intensive margin difference in monetary policy shocks for these two financial intermediations. With proposition 1, we can compute the response of portfolio weight to monetary policy changes as below:

$$\frac{\partial \pi}{\partial r} = \frac{\mathcal{J}_\omega}{\omega \mathcal{J}_{\omega\omega}} [\sigma_R \sigma_R^T]^{-1} \tag{18}$$

According to the equation above, the level of such a response does not link to the information advantage matrix Γ directly. With Assumption 1, we can easily see that $\frac{\partial \pi_{\mathcal{B}, n_{\mathcal{B}}}}{\partial r} \approx \frac{\partial \pi_{\mathcal{F}, n_{\mathcal{F}}}}{\partial r}$ for $n_{\mathcal{B}} \in [n^*_{\mathcal{B}}, N]$ and $n_{\mathcal{F}} \in [1, n^*_{\mathcal{F}}]$.

A2 Additional Figures and Tables

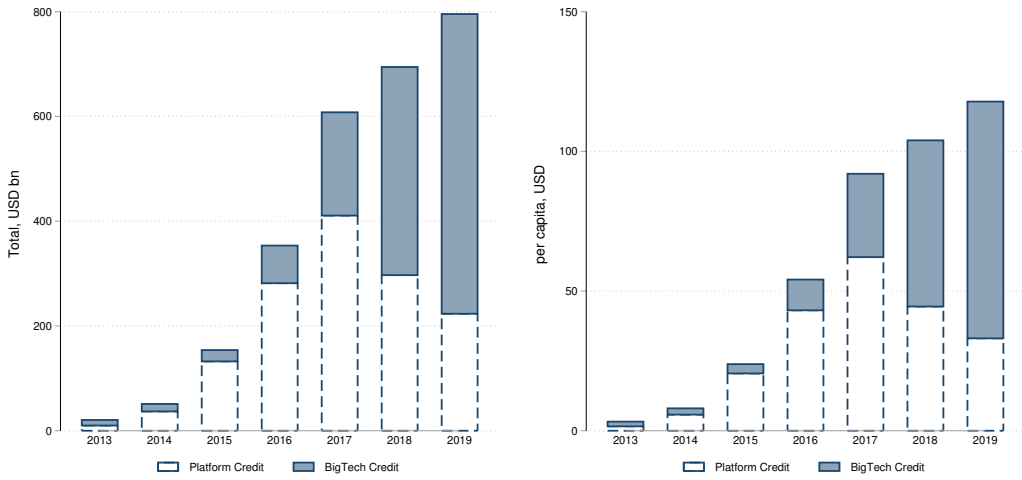


Figure A1: Global FinTech Credit

Source: Cornelli et al. (2020).

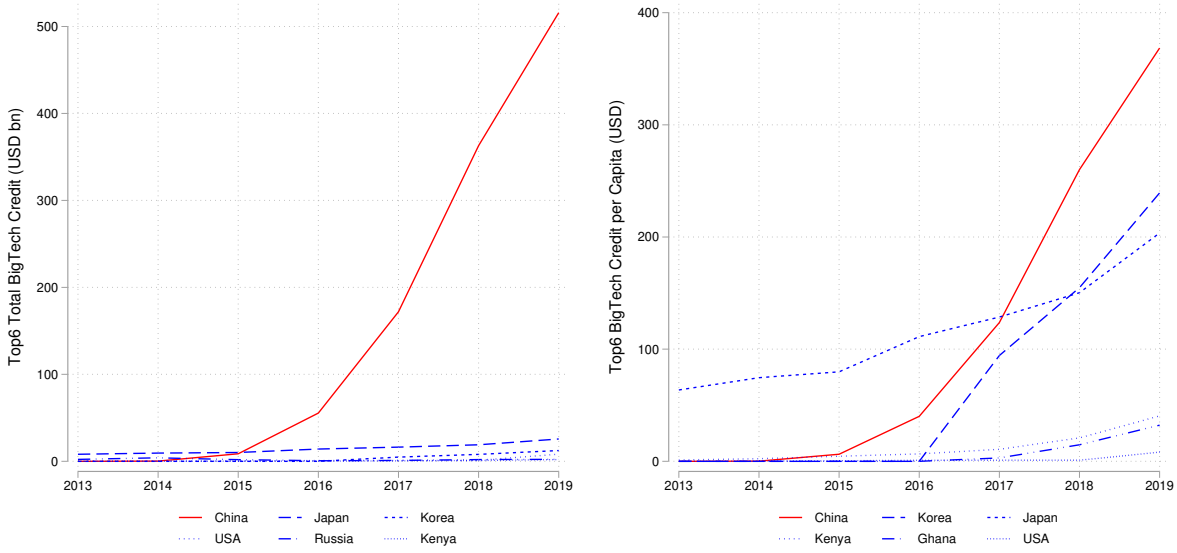


Figure A2: Top Six Countries in BigTech Credit

Source: Cornelli et al. (2020).

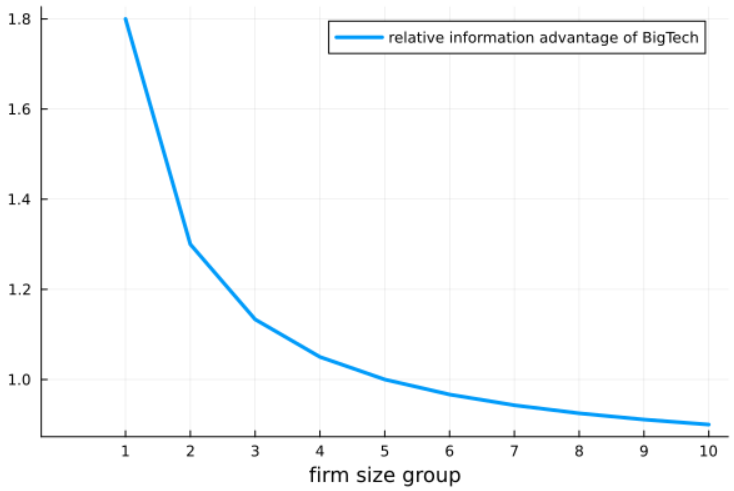


Figure A3: Illustration: Firm Sizes and Relative Information Advantage of BigTech to Banks



Figure A4: Business Subsidiaries of Ant Financial

Source: CB Insights, "Big Tech In Financial Services Primer: How Ant Financial Is Evolving Beyond Payments", Aug 15, 2019. `https://www.cbinsights.com/research/ant-financial-services/`

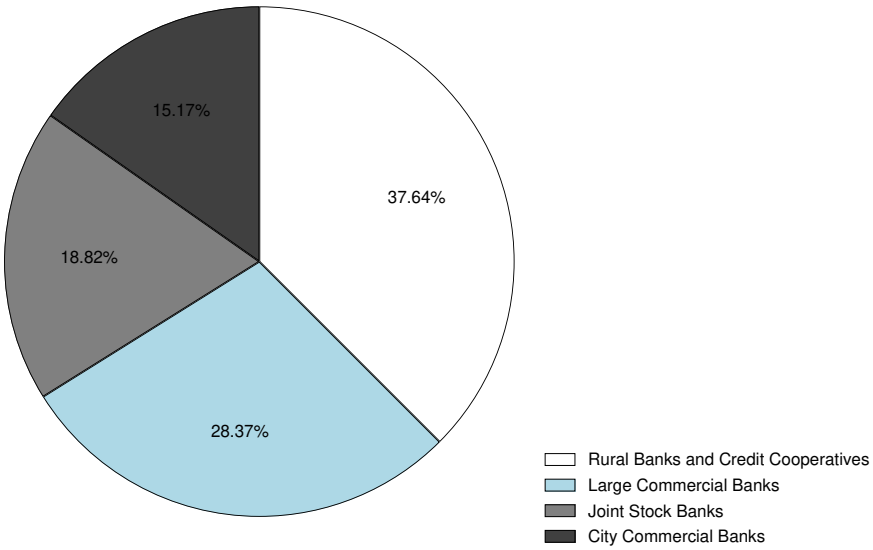
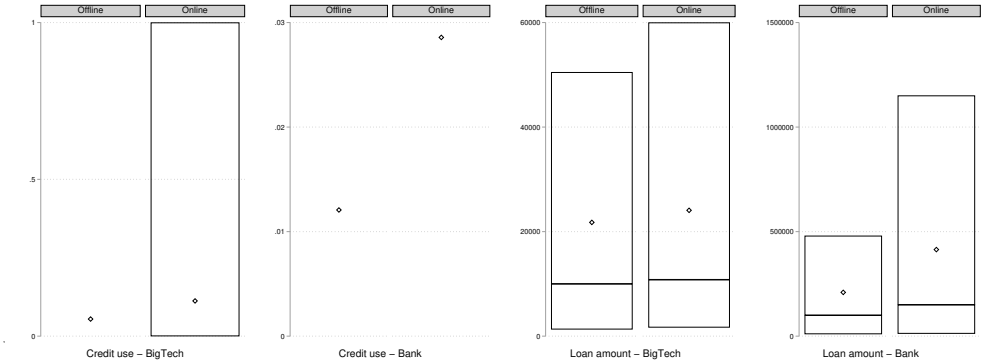
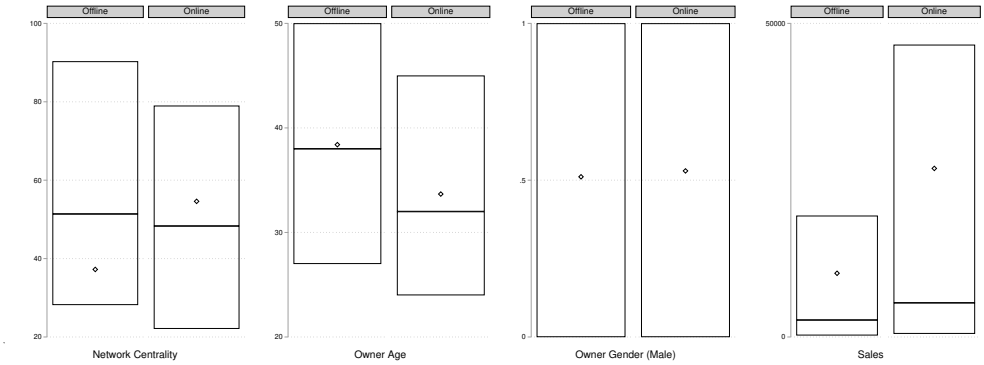


Figure A5: SMEs Loans by Traditional Banks as of 2019

Note: We obtain the outstanding loans to SMEs by types of traditional banks from the People's Bank of China, and then calculate the share of each type of banks.



(a) Loan Characteristics



(b) Firm Characteristics

Figure A6: Loan and Firm Characteristics by Online and Offline Firms

Note: The diamond mark indicates the mean, the lower and upper bound indicates the 10th and 90th percentile, and the middle line shows the median value. "Online" is the group of firms that operate in the e-commerce platform, "Offline" is the group of firms that only have physical presence but not digital presence. Both types of firms collect payments via Alipay, the former directly in the online payment system and the latter via QR code.

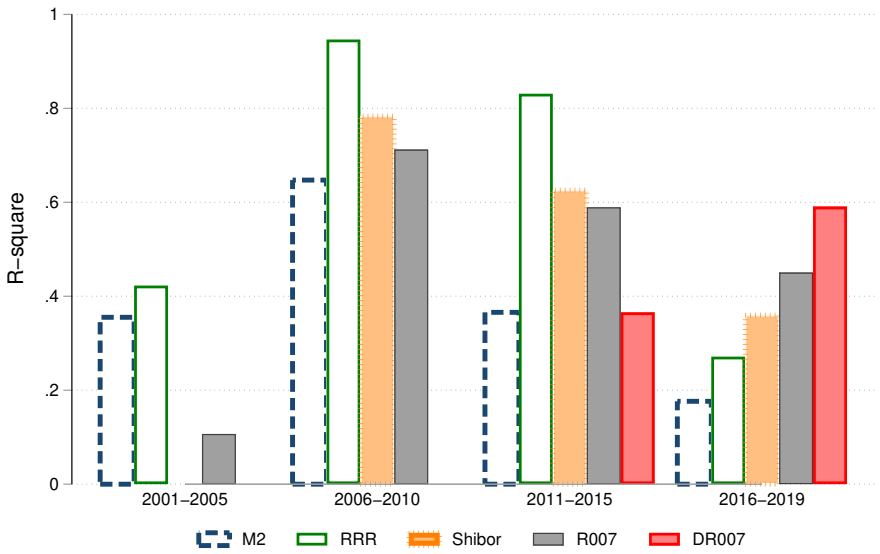
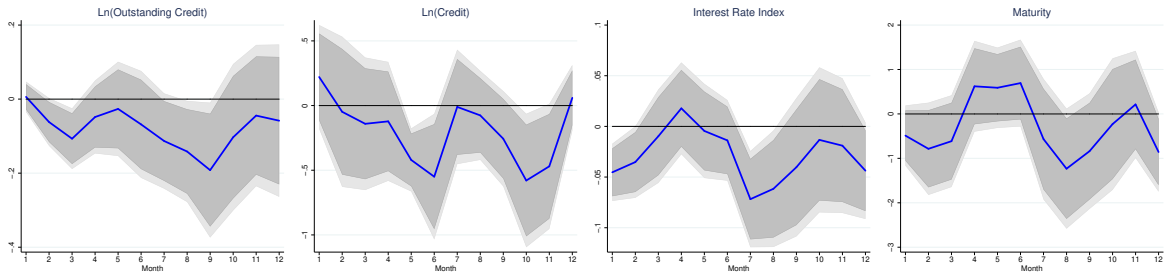
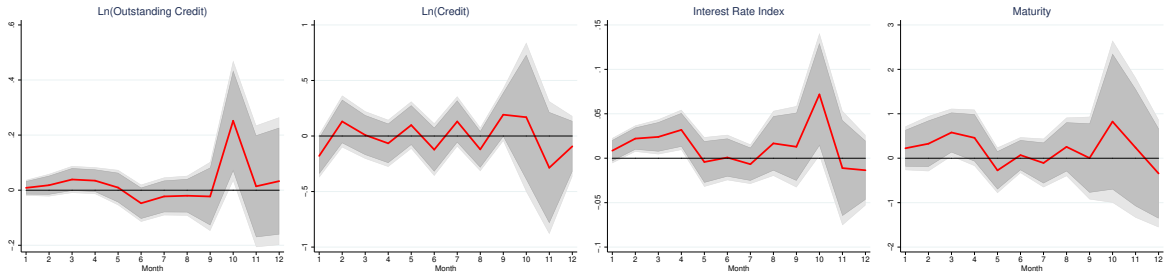


Figure A7: R-square using different variables to capture monetary policy

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



(a) Pre-COVID



(b) Post-COVID

Figure A8: Local Projection: Impact of Monetary Policy After Controlling for Regulation Policy

Notes: It shows the cumulative impulse responses to a one-unit increase in the monetary policy rate, based on the estimation of Equation (9). The pre-COVID sample starts in January 2017 and ends in December 2019, while the post-COVID sample starts in January 2020 and ends in December 2021. The light- and dark-shaded areas represent the 68% and 90% confidence bands, respectively.

Table A1: Variable Definition

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

Table A2: Three BigTech Lenders in China

	MYBank	WeBank	XWBank
Parent BigTech Company	Alibaba	Tencent	Mi
Outstanding Loan Amount (in bn RMB)	70,029.81	158,642.88	32,388.13
(in bn USD)	10,004.26	22,633.27	4,626.88
Cumulative Served Customers (mn)	20.87	200	31
Cumulative Per Capita Balance (in RMB)	3,355.53	793.21	1,044.78
(in USD)	479.36	113.17	149.25

Source: Annual Reports of MYBank, WeBank, and XWBank. Note: (1) the data here are based on the annual reports of 2019; (2) the loan amounts include all types of loans including individual consumption loans and business loans, since there is no decomposition by different types of loans as of 2019.

Table A3: Sector Distribution

Sectors	Proportion
Catering services	35%
Grain, oil, food, drink, alcohol and tobacco	11.40%
Clothing, shoes and hats, needles and textiles	10.90%
Local life services	7.90%
Furniture	4.50%
Cultural and entertainment services	3.80%
Healthcare services	3.70%
Motor vehicles	3.60%
Drug	3.10%

Table A4: Impact of MSMEs and Retail Sector on Chinese Economy, 2018

% in Total Economy	MSME	Retail Sector
Establishments	99.8	29.8
Employment	79.4	10.5
Sales	68.2	29.9

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

Table A5: Newly-issued and Outstanding BigTech Credit

DepVar: Ln(Outstand BigTech Credit)	(1)	(2)
L.Ln(BigTech Credit)	0.258***	0.257***
	(0.009)	(0.009)
Obs	158,795	158,795
Adj R-squared	0.802	0.802
Controls	YES	YES
Firm FE	YES	YES
Month FE	YES	YES

Note: The unit of observation is firm-month. The dependent variable $Ln(OutstandingBigTechCredit)$ is the logarithm of outstanding BigTech credit; details about the extended data of outstanding BigTech credit can be found in Section 5.1. $Ln(BigTechCredit)$ is the logarithm of the newly-issed BigTech credit. This analysis is specific to BigTech credit, as equivalent data for traditional bank loans are unavailable. Control variables include the lags of the logarithm of sales, network centrality, and regional GDP. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses.

Table A6: Summary Statistics of Extended Variables of BigTech Loans

Variables	Mean	St. Dev	P25	Median	P75
Panel A: Pre-COVID					
Interest Rate Index (0-1)	0.51	0.21	0.45	0.55	0.64
Maturity (months)	7.61	4.61	2.64	7.52	12.00
Outstanding Credit (Chinese Yuan)	53,597.46	84,913.26	9,600	24,708	56,200
Panel B: Post- COVID					
Interest Rate Index (0-1)	0.51	0.20	0.45	0.53	0.64
Maturity (months)	9.07	4.37	6.00	11.40	12.00
Outstanding Credit (Chinese Yuan)	77,319.02	99,615.35	15,000	43,011	93,032.25

Note: This table presents summary statistics for the extended variables of BigTech loans. The interest rate index is normalized and rescaled to a range between zero and one, and the maturity is expressed in months. The pre-COVID sample starts in January 2017 and ends in December 2019, while the post-COVID sample starts in January 2020 and ends in December 2021.

Table A7: Regulation Policy on Internet Lending

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

Table A8: Regulation Policy Index: Principal Component Analysis

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

Note: *Abnormal Returns* are calculated as the deviation between the actual return of the company (Alibaba or Tencent) and the CAPM-predicted return within three days following each policy announcement, determined by regressing the actual return against the return of the Hang Seng Index, a major Hong Kong stock market index. *Search Index* are the search frequency indicators for the keywords "Ant Financial" and "FinTech" on Baidu, the largest search engine in China and the Chinese version of Google.