When Funding Constraints Dominates Data: BigTech Credit as an Amplifier of U.S. Monetary Policy Spillovers*

Jialin Liu† Rongyu Cui‡

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Abstract

While BigTech credit is widely praised for utilizing data and informational advantages to mitigate local financial frictions, its resilience to global macroeconomic shocks remains largely unexplored. This paper examines the role of BigTech credit in transmitting the international spillovers of U.S. monetary policy. Contrary to the prevailing view that BigTech acts as a buffer, we document a striking amplification effect. Using a unique individual-level monthly panel of 100,000 Chinese consumers, we find that a one-standard-deviation contraction in U.S. monetary policy leads to a 4.79% disproportionate decline in BigTech credit relative to traditional bank loans. We show that this vulnerability stems from the regulatory framework of joint-lending, which heavily tethers BigTech platforms to traditional bank funding. Consequently, an international risk-taking channel dominates: as the US tightens contracts domestic banks' risk appetite, these banks trigger a "flight to quality" by disproportionately withdrawing funding from BigTech partnerships, effectively overriding the platforms' data and information advantages. Finally, we demonstrate that this financial amplification extends to the real economy, with consumers heavily reliant on BigTech credit experiencing a 0.86% greater reduction in consumption following U.S. rate hikes.

Keywords: BigTech credit; U.S. monetary policy; Spillovers; Consumption

JEL classification: F42; E52; O33; G21

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†School of Economics and Management, Beijing University of Chemical Technology; Institute of Digital Finance, Peking University; liujialin@buct.edu.cn

‡National School of Development, Peking University; Institute of Digital Finance, Peking University; rycui2018@nsd.pku.edu.cn

1 Introduction

The rapid ascent of BigTech lending has fundamentally reshaped credit markets in emerging market economies (EMEs). In China alone, BigTech credit now accounts for 2-3% of GDP (Huang et al. 2023a), providing hundreds of millions of consumers with a crucial alternative source of borrowing beyond traditional banks. Existing literature extensively documents that BigTech credit promotes consumption, reduces inequality, and helps cushion against external shocks by alleviating constraints and reducing asymmetry in the credit market (Bharadwaj et al. 2019; Suri et al. 2021; Yang and Zhang 2022; Huang et al. 2023b). However, we have no clear understanding of how BigTech lending responds to global macro-financial shocks in an open economic environment. For instance, a large and growing literature documents that U.S. monetary policy shocks spill over to EMEs primarily through the traditional banking system via cross-border capital flows, bank risk-taking, and collateral constraints (Mishkin 1996; Bruno and Shin 2015; Miranda-Agrippino and Rey 2020; Kalemli-Özcan 2019; Georgiadis and Jarociński 2025). Against this backdrop, a fundamental question arises: *Does the rapid growth of BigTech credit amplify or dampen the international transmission of U.S. monetary policy to emerging economies?*

The answer is theoretically ambiguous. On the one hand, BigTech lenders possess a pronounced information advantage derived from big data and machine learning. This data-driven credit assessment reduces the reliance on physical collateral (Gambacorta et al. 2023), thereby dampening the classic financial accelerator effect—a primary driver of credit procyclicality.[1] Thus, when U.S. monetary policy tightens and capital inflows from multinational banks to emerging market economies decrease, reducing the bank loan supply, BigTech lenders may offer alternative credit and behave as a "shock absorber" that mitigates the overall transmission of U.S. monetary policy. On the other hand, this buffering capacity may be fundamentally compromised if BigTech's credit decisions are deeply intertwined with traditional financial institutions. In the China context, regulatory funding requirements often mandate BigTech platforms to co-lend with banks, making them heavily reliant on bank funding rather than stable retail deposits. When the U.S. raises interest rates, China's banks decrease their risk-taking, and this reduced risk tolerance is likely to spill over to BigTech lenders because they are not entirely independent in their credit provision. Furthermore, since BigTech credit is typically provided to high-risk, unbanked populations who are inherently more vulnerable to economic downturns, this funding dependence can exacerbate credit contractions. Thus, BigTech lending might instead act as a "shock amplifier," magnifying the procyclicality of U.S. monetary policy through the international risk-taking channel.

In this paper, we explore this question empirically based on a unique dataset from one of the largest BigTech platforms in China and provide the first individual-level evidence that BigTech credit acts as an **amplifier**—not a buffer—of U.S. monetary policy spillovers: since BigTech lenders rely on banks for funding, the amplification effect through the international risk-taking channel *dominates* the mitigating effect of their information advantage in credit assessment when facing external shocks. China provides an ideal institutional and empirical setting to explore this question for four compelling reasons: (1) As the largest emerging market economy, China offers a typical case for the international spillovers of U.S. monetary policy. It offers an environment to evaluate how domestic household behaviors, such as credit demand and consumption, respond to U.S. dollar liquidity fluctuations. (2) China boasts one of the most advanced and widely adopted BigTech credit markets globally. While BigTech credit accounts for roughly 2%-3% of the gross domestic product (Huang et al. 2023a), the sheer scale of this market ensures that the macroeconomic implications of digital credit are economically highly significant, rather than merely marginal. (3) China's unique and evolving regulatory environment provides an unprecedented laboratory to identify the boundaries of cooperation between digital and traditional finance. Specifically, regulatory requirements regarding BigTech funding structures (e.g., the transition of joint-lending rules) have structurally reshaped the relationship between BigTech platforms and traditional commercial banks. This dynamic institutional setting allows us to cleanly identify how this cooperative dependence dictates BigTech credit's capacity to absorb or amplify external shocks. (4) Ant Group, one of the largest Chinese digital platforms offers a unique, individual-level dataset including consumption, BigTech credit borrowing (e.g., Huabei and Jiebei), and traditional credit card borrowing. Because we simultaneously observe a single consumer's BigTech borrowing (e.g., Huabei) and

[1] When borrowers are facing an external shock, the fair value of collateral will fluctuate with the economic environment, and the information asymmetry in the credit market will amplify the impact of this shock on the economy, which is called the financial accelerator effect (e.g. Gertler and Gilchrist 1994).

traditional bank credit card usage, we can construct strict within-individual variations. Thus, it helps reduce aggregation bias common in macro-level analyses.

Our study makes three primary contributions to the literature on US monetary policy spillover and BigTech. First, we provide the first micro-level evidence on how BigTech credit alters the international transmission of U.S. monetary policy. While previous studies predominantly explore these spillovers at the macro or firm level, our identification exploits *within-individual* variation. By observing the same consumer's BigTech credit (Huabei) and traditional bank credit card borrowing simultaneously, we can differentiate out individual-level demand shocks and isolate the differential supply-side response of BigTech versus bank credit to U.S. monetary policy shocks. Second, we advance the literature on the interplay between digital and traditional finance by shifting the focus from the conventional "substitution versus complementarity" debate to the boundaries and models of their cooperation. Existing studies rarely explore how specific collaborative structures between BigTech firms and commercial banks affect the efficacy of BigTech credit. By uncovering two specific mechanisms: *Dependence on Joint Lending channel* and *Flight to Quality channel*, through which the international risk-taking channel operates differently for BigTech credit, we reveal that this cooperative relationship fundamentally constrains BigTech's ability to act as an independent shock absorber. We exploit a regulatory shock (the CBIRC's 2021 regulation on joint internet loans) to causally identify that BigTech's funding dependence on banks is the key transmission link. Third, we trace the real-economy consequences of this amplified transmission. We document that consumers more reliant on BigTech credit experience sharper consumption declines following U.S. tightening. By linking global macro-financial shocks to micro-level consumer behavior, we establish a novel "BigTech credit channel" of international monetary policy transmission to household welfare.

We start the empirical analysis by randomly sampling 100,000 Chinese consumers' individual-month level data obtained from the Alipay platform during the period from January 2020 to April 2023.[2] For each consumer, we observe monthly BigTech credit usage (Huabei), traditional credit card borrowing, and consumption expenditure on the platform. We measure U.S. monetary policy shocks using the high-frequency policy surprises of Bauer and Swanson (2023), which capture exogenous changes in interest rates under the overnight window of the monetary policy announcements of the Federal Open Market Committee (FOMC). Our baseline specification compares, within the same individual and month, the response of BigTech credit relative to bank credit to U.S. monetary policy shocks. We find that a tightening of US monetary policy reduces Chinese consumers' BigTech credit more than credit from banks. Specifically, on average, a one-standard-deviation contraction in U.S. monetary policy reduces BigTech credit by 4.79% more than traditional bank credit.

A key methodological challenge lies in isolating the effects of domestic policies, particularly Chinese monetary policy. To address this, we first incorporate Chinese monetary policy indicators into our baseline model as control variables. Furthermore, we exploit the high-frequency nature of our monthly dataset to examine a narrow time window following a U.S. monetary policy shock, thereby minimizing potential confounding effects from contemporaneous changes in Chinese policy. Specifically, we focus on the U.S. monetary tightening shock in March 2022 and limit the sample period from January 2020 to April 2022—a window that precedes the shift in China's monetary policy stance.[3] In addition, we perform several other robustness checks, including using alternative measures of U.S. monetary policy shocks and BigTech credit, as well as controlling for loan demand factors. All of these tests yield results consistent with our main findings.

Delving deeper, we find that the international risk taking channel plays a dominant role in the U.S. monetary policy international transmission through BigTech credit. The impact of U.S. monetary policy on traditional financial institutions' risk-taking behavior transmits to BigTech companies, which subsequently affects their credit decisions. Specifically, we decompose the international risk-taking channel into two distinct mechanisms: *Dependence on Joint Lending channel* and *Flight to Quality Channel*. For *Dependence on Joint Lending channel*, we use both a bank-level dataset and the regulatory change introduced by the CBIRC's 2021 regulation, which imposed mandatory requirements on BigTech companies and reduced their reliance on bank funding for credit supply, to test this channel. We find that when a tightening U.S. monetary policy shock decreases bank loans by increasing external debt pressure, reducing the dependence of Big Tech platforms on bank funding will prevent a decline in BigTech credit, meaning that U.S. monetary policy shocks

[2]Alipay is a digital platform belonging to one of the largest BigTech companies, Ant Group.

[3]China adopted a looser monetary policy in late April 2022.

will be transmitted to BigTech credit through the financial linkages between banks and Big Tech companies. For the *Flight to Quality Channel* , we find that in regions with higher exposure to bank external debt risks, BigTech credit declines more sharply than traditional bank credit. This indicates that the tightening of U.S. monetary policy and contraction of bank credit have led BigTech credit providers to raise credit thresholds and reduce more credit supply.

Besides, we find that the BigTech credit to high-risk consumers declined much more than credit to low-risk consumers when there is a tightening U.S. monetary policy shock, which is also consistent with *Flight to Quality Channel*. Moreover, BigTech companies have advantages in risk assessment over traditional financial institutions, which enables them to identify high-risk borrowers more quickly. Thus, we find that the response of BigTech credit to the U.S. monetary policy shock is stronger in areas with more dependence on BigTech credit supply (lower level of traditional financial availability). We also conduct other heterogeneous analysis and find that the relative response of BigTech credit to U.S. monetary policy shocks is more pronounced in areas with higher levels of financial openness.

Furthermore, we extend the study on international transmission of the US monetary policy shock through BigTech credit to the real economy. From the perspective of China's household consumption, we find that consumers who rely more on BigTech credit will experience a sharper decline in consumption. Specifically, a one-standard-deviation increase in the U.S. monetary policy shock causes a relative 0.86% reduction in total consumption and a 1.31% reduction in online consumption. Thus, a tightening US monetary policy shock led to a more significant decline in China's household consumption through a larger contraction in BigTech credit.

Related Literature. First, our paper relates to the literature that explores the international transmission of U.S. monetary policy. Early studies explored the impact of US monetary policy shocks on emerging market economies from two perspectives. From the financial stability perspective, Miranda-Agrippino and Rey (2020) and Dées and Galesi (2021) document that U.S. monetary policy shocks trigger a high comovement of international variables—the Global Financial Cycle—which causes resonance among the economic and financial variables of various countries through cross-border capital flows and fluctuation of exchange rate (Georgiadis 2016; Georgiadis and Mehl 2016). A central insight from this strand of literature is that cross-border bank lending is the primary transmission channel (Bruno and Shin 2015; Kalemli-Özcan 2019). Specifically, expansionary US policies often trigger excessive capital inflows and fuel domestic credit booms in EMEs (Ostry et al. 2012), while contractionary signals, such as tapering news, lead to sharp reversals characterized by currency depreciation, equity market sell-offs, and surging sovereign risk (Aizenman et al. 2014). Consequently, this US-driven cycle of rapid credit expansion and currency mismatch breeds severe financial vulnerabilities (Gourinchas and Obstfeld 2012; Schularick and Taylor 2012; Boissay et al. 2016). Finally, when these exogenous credit booms artificially compress the risk premium of financial assets, they significantly increase the probability of banking crises in EMEs (Coimbra and Rey 2024). From the perspective of real economy, Feldkircher and Huber (2016) document that a US monetary policy tightening produces particularly negative output effects across countries. Chen et al. (2016) also find that unconventional US monetary policy shock, like Quantitative Easing, prevented the US and other advanced economies from prolonged recession. We extend this literature by showing that non-bank BigTech credit constitutes a quantitatively important-and previously undocumented-amplification channel for both domestic credit and real economy.

Second, our paper adds to the emerging literature at the intersection of BigTech credit, its interplay with traditional banking, and their differential responses to monetary policy shocks. A vast body of existing literature explores whether BigTech acts as a substitute or a complement to traditional financial institutions, predominantly attributing these dynamics to technological progress and information advantages (Hau et al. 2019; Jagtiani and Lemieux 2018; Claessens et al. 2018; Agarwal et al. 2025; Frost et al. 2019;Parlour et al. 2022; Bian et al. 2023). However, an emerging strand of research, notably highlighted by Buchak et al. (2018), argues that technology and regulation jointly shape this relationship, with regulatory frameworks often exerting a more dominant influence than technological innovation alone.

Building on this debate, literature offers two competing views regarding how BigTech and bank credit respond to external macro-financial shocks, e.g. monetary policy shock. On the one hand, several studies document that BigTech credit mitigates the transmission of monetary policy. By alleviating information asymmetry (Suri et al. 2021) and reducing reliance on physical collateral, BigTech credit can dampen the classic "financial accelerator effect" (Gambacorta et al. 2023). Recently, Cornelli et al. (2024) claim that because

BigTech lenders operate under distinct regulatory frameworks, they can absorb unmet credit demand when traditional banks become constrained, thereby exhibiting lower reactivity to monetary tightening. On the other hand, other studies claim that BigTech strengthens the transmission of monetary policy. For instance, Huang et al. (2023a) find that Big Tech credit amplifies monetary policy transmission mainly through the extensive margin by comparing BigTech credit and traditional credit of micro, small, and medium-sized enterprises (MSMEs). They attributed this effect to the information and risk assessment advantage of BigTech lenders. Similarly, De Fiore et al. (2023) offers an alternative channel, noting that BigTech facilitates firms' trade matching and extends working capital, thus adding another layer of transmission parallel to bank loans.

However, these prior studies mainly discuss the change brought by BigTech credit in a closed economy. Our paper departs from this literature by exploring whether BigTech credit behaves differently from traditional credit and affects the international spillover of external shocks (U.S. monetary policy) in an open economy. Specifically, we make two main distinctions from the two closely related papers of Huang et al. (2023a) and De Fiore et al. (2023). First, our paper shows that BigTech credit makes a stronger response to U.S. monetary policy shock than bank credit because the international risk-taking channel dominates the information advantage of BigTech lenders during the international transmission of U.S. monetary policy. We document that despite BigTech's superiority in data screening and trade matching, its strict funding reliance on traditional banks will restrict the utilization of data of BigTech lenders. By revealing how regulatory boundaries can offset, or even reverse, the technological advantages of BigTech, our findings provide profound insights into determining the optimal collaborative frameworks between BigTech and traditional banks. Second, while the impact of monetary policy shocks on firm-level outcomes is well-documented, micro-level evidence regarding how individual consumers adjust their welfare and consumption via BigTech credit when facing U.S. monetary policy shocks remains exceptionally scarce. Our paper strengthens the BigTech credit channel through which U.S. monetary policy impact Chinese real economy.

Third, our paper also complements the literature on the impact of BigTech on individual consumption. By overcoming traditional information asymmetries based on massive digital footprints and machine learning algorithms, BigTech credit significantly relaxes liquidity constraints for people who are underserved by banks. A consensus in empirical studies suggests that access to such digital credit not only boosts overall household expenditure but also promotes consumption upgrading, enabling low-income households to afford durable goods and higher-quality services (Bharadwaj et al. 2019; Yang and Zhang 2022). Beyond stimulating consumption, BigTech credit serves as a crucial buffer against external shocks (Huang et al. 2023b). For instance, Hu et al. (2024) document that when uncertainty affects economic growth and borrowing, BigTech credit can still maintain resilience and maintain consumption stability by providing additional financial supply. Different from literature which strengthens the role of BigTech credit from the liability side, Liu et al. (2025) explores the role of BigTech from the asset side by claiming that digital wealth management offered by Big Tech companies will also smooth consumption during uncertainty shocks by complementary to BigTech credit. While the existing literature extensively documents the domestic implications of BigTech credit, acting as an engine for consumption smoothing against shocks, its role in the international transmission of macroeconomic shocks remains conspicuously underexplored. Our paper uncovers a novel "BigTech credit channel" of cross-border monetary spillovers. Diverging from the conventional wisdom that BigTech credit strictly serves as a buffer, our core finding demonstrates that BigTech credit significantly amplifies the impact of US monetary policy shocks on Chinese household consumption.

The remainder of the paper is structured as follows. The Section 2 provides institution background of BigTech credit and testable hypotheses. Sections 3 present the data, sample, and specification. Section 4 shows the baseline results, robustness checks, the results of mechanisms and heterogeneity analysis. Section 5 further discusses the impact on the real economy, and Section 6 concludes.

2 Institution background and testable hypotheses

This section introduces the development landscape and funding sources of BigTech credit in China, and proposes the hypothesis that U.S. monetary policy shocks are transmitted through BigTech credit.

2.1 Institution background of BigTech credit

We first discuss its global rise and unique local characteristics, then detail the regulatory-driven shift in funding models towards bank-partnered joint lending, and finally introduce a specific case of Ant Consumer Finance.

2.1.1 The Rise of BigTech Credit: Global Trends and the Chinese Context

BigTech credit represents a paradigm shift in financial intermediation, where big technology companies leverage digital platforms and proprietary data to provide financing to individuals and micro- and small-enterprises (MSEs) that are often underserved by traditional banking.

The rapid diffusion of this model is propelled by the confluence of technological progress, data advantages, and unmet market demand. Through advances in cloud computing and artificial intelligence (AI), BigTech lenders can process massive volumes of non-traditional data—including consumption patterns, social footprints, and real-time cash flows—to mitigate the information asymmetries inherent in traditional lending. This ecosystem-based approach allows for precise profiling of "long-tail" customers, i.e., the large number of small-value clients that conventional banks find unprofitable to serve, significantly reducing customer acquisition and risk assessment costs compared to traditional banks.

Globally, BigTech credit has exhibited strong growth momentum. According to reports by the Bank for International Settlements (BIS) [4], large technology firms have entered financial services and become important participants in payment markets across several advanced and emerging market economies, with particularly notable penetration and growth rates. In emerging markets such as Southeast Asia and Africa, BigTech firms often "leapfrog" underdeveloped banking infrastructure to deliver inclusive finance directly via mobile payments (e.g., M-Pesa in Kenya). Conversely, in advanced economies like the United States, BigTech firms typically operate through partnerships with licensed financial institutions to complement existing credit markets (BIS, 2019).

In China, the proliferation of digital payments and e-commerce has provided a fertile environment for BigTech credit. Supported by the exceptionally high penetration of mobile payments and the ecosystem dividends of e-commerce platforms, and driven by rising demand from consumers and micro and small enterprises for fast, convenient, and low-threshold financial services, BigTech credit platforms have expanded rapidly and attracted a large user base. Representative products such as Ant Group's Huabei and Jiebei, as well as WeBank's Weilidai under Tencent, have enabled near-instant approval and highly accessible credit through scenario-based modeling.

2.1.2 The Evolution of Funding Models: From Asset Securitization to Joint Lending

In the development of BigTech credit, its capital sources have changed alongside the evolution of financial regulation. Early development of BigTech credit in China relied heavily on the "originate-to-distribute" model, where platforms funded loans through their own balance sheets and rapidly recycled capital via Asset-Backed Securities (ABS). However, regulatory tightening in recent years has forced a fundamental shift toward "Joint Lending" (Lianhe Daikuan) and "Loan Facilitation" (Zhudai). For example, the former China Banking and Insurance Regulatory Commission (CBIRC) issued the "Interim Measures for the Management of Internet Loans by Commercial Banks" (CBIRC Order No.9 [2020]) in July 2020 and the "Notice on Further Regulating the Internet Loan Business of Commercial Banks" (CBIRC Office Document [2021] No.24) in February 2021, respectively. These regulations specify the scope and risk control measures for commercial banks and internet loans, as well as capital contribution ratios, concentration management of cooperative institutions, and total loan amounts for internet loans jointly issued by commercial banks and cooperative institutions. As illustrated in Figure 1, the current model operates through a partnership between digital platforms and commercial banks. In the "Joint Lending" arrangement, the BigTech platform and a partner bank jointly issue a loan. The BigTech firm uses its data and information advantage for risk screening and customer matching, while the partner bank provides the majority of the funding. Crucially, regulations effective from January 1, 2022, mandate that the platform's capital contribution must not be less than 30%. This "skin-in-the-game" requirement directly ties the BigTech platform's credit supply capacity directly to

[4] Big Techs vs Banks: https://www.bis.org/publ/work1037.pdf
Big techs in finance: https://www.bis.org/publ/work1129.pdf

the liquidity conditions of its banking partners. In the "Loan Facilitation" model, the platform acts purely as an intermediary, providing credit assessment and technology services in exchange for service fees, while the bank assumes the credit risk and provides 100% of the funding.

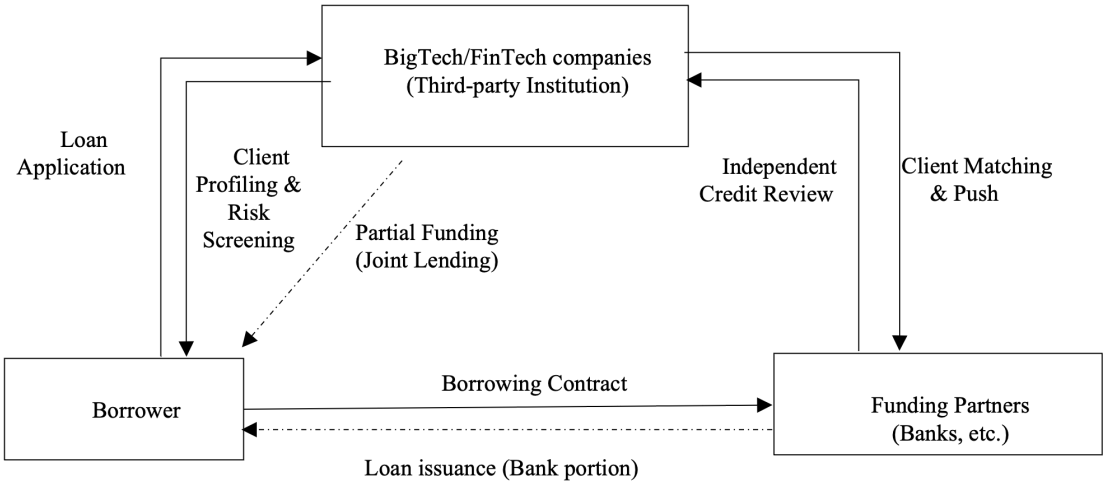


Figure 1: The Structure of BigTech Joint Lending and Loan Facilitation

Note: Solid lines represent information flows (e.g., credit assessment data), while dashed lines represent capital flows (loan disbursals). Under the joint lending model, both the BigTech platform and the partner bank contribute funding, whereas, in the loan facilitation model, the bank provides the majority of the funds.
Source: Author

This regulatory evolution has cemented a structural framework where commercial banks serve as the primary liquidity providers for BigTech credit. Consequently, the availability and pricing of BigTech loans are no longer isolated within the platform's ecosystem but are deeply integrated into the formal banking system. This integration implies that BigTech credit is now highly sensitive to the balance sheet constraints of partner banks, which are, in turn, influenced by domestic and international interest rates, liquidity fluctuations, and credit spreads.

2.1.3 Case Study: Ant Consumer Finance and Exposure to Global Shocks

To better understand the transmission mechanism of global monetary shocks through BigTech credit, we focus on Chongqing Ant Consumer Finance Co., Ltd. (Ant ConsFin), the licensed consumer finance subsidiary of Ant Group. Ant ConsFin operates the Huabei and Jiebei products and serves as a representative case of the industry's funding structure.

Ant ConsFin's funding mix demonstrates a high degree of integration with global financial markets. Notably, Ant ConsFin recently raised a RMB 4 billion syndicated loan led by Mizuho Bank, with participation from 14 domestic and international banks, including institutions from the United States, Japan, South Korea, and Thailand (e.g., Fubon Bank, Hana Bank, and Woori Bank). This specific financing case highlights two critical channels of exposure to U.S. monetary policy. On the one hand, Ant ConsFin actively utilizes cross-border syndicated loans. When U.S. monetary policy tightens, leading to a contraction in global dollar liquidity or rising financing costs, the cost of these foreign-sourced funds increases directly. On the other hand, more broadly, under the joint lending model, Ant relies on a vast network of domestic partner banks. Many of these partners are large joint-stock or city commercial banks with significant foreign liabilities or exposure to global financial cycles. When the Federal Reserve hikes rates, these banks face balance sheet pressures, compelling them to contract lending to non-core assets—specifically, their joint lending portfolios with BigTech platforms.

Therefore, despite being a domestic consumer credit product, the credit supply of Ant Group is intrinsically linked to the liquidity conditions of the traditional banking system, providing a plausible channel for U.S. monetary policy shocks to transmit to Chinese consumers' borrowing and spending.

2.2 Testable hypotheses

US monetary policy spillovers affect EMEs' domestic credit through both trade and financial channels (Georgiadis and Jarociński 2025). First, the trade channel suggests that U.S. monetary policy triggers exchange rate fluctuations via cross-border capital flows, affecting EMEs' export competitiveness and corporate credit demand. Second, and often more dominantly, the financial channel operates by altering the debt and asset structures of banking and non-banking sectors in EMEs, increasing currency mismatch risks and financial instability (Bruno and Shin 2015). Bruno and Shin (2023) recently document that when EME firms are highly exposed to dollar funding, the contractionary financial channel effect outweighs any positive trade channel improvements.

Based on the financial channel, a tightening U.S. monetary policy generally reduces Chinese domestic credit. However, the specific response of BigTech credit—compared to traditional bank credit—remains theoretically ambiguous, with two opposing forces at play.

On the one hand, BigTech credit may serve as a "shock absorber." When US monetary policy tightens and the capital inflows of multinational banks to emerging market economies decrease, the loanable funds of domestic banks in emerging market economies decrease (Bruno and Shin 2015). Thus, domestic banks in emerging market economies are reducing the supply of credit, including that for consumer credit. At the same time, a tightening US monetary policy decreases asset prices and lowers local borrowers' collateral value which further amplify the negative effect of US monetary policy on Chinese domestic credit. However, BigTech lenders offer credit by utilizing big data and AI, which are helpful to reduce the correlation between credit and traditional collateral value, effectively easing collateral constraints (Gambacorta et al. 2023). By easing collateral constraints, BigTech credit may be less sensitive to the asset price shocks induced by U.S. monetary policy shock (Cornelli et al. 2024). In addition, regulatory arbitrage and competition between BigTech and banks may also make BigTech mitigate the overall transmission of U.S. monetary policy (Buchak et al. 2018; Elliott et al. 2019; Beirne et al. 2023; Hasan et al. 2024).

On the other hand, BigTech may serve as an "amplifier" according to the international risk-taking channel. U.S. monetary tightening triggers balance sheet adjustments in Chinese banks, reducing their overall risk-taking capacity (Bruno and Shin 2015). Since BigTech lenders often rely on banks for funding rather than holding stable retail deposits, they may be more exposed to these banking sector liquidity shocks. If BigTech credit is viewed as a "marginal" asset by banks or if BigTech platforms themselves react pro-cyclically to macro shocks, the contraction could be amplified. In addition, banks are more constrained by prudential regulation than BigTech lenders, which means that external monetary policy tightening could lead to lower leveraging of BigTech companies relative to traditional banks. Thus, we have

Hypothesis 1a: BigTech credit will mitigate the negative impact of US monetary policy tightening on the domestic credit of emerging market economies.

Hypothesis 1b: BigTech credit will amplify the negative impact of US monetary policy tightening on the domestic credit of emerging market economies.

From the perspective of the cooperation mode between big technology companies and banks, the internet platform which belongs to the big technology company has technical advantages on conducting credit investigation and controlling risk based on big data, and provide support for bank credit supply. For example, in 2007, Alibaba, China Construction Bank, and Industrial and Commercial Bank of China launched a lending business, forming the "first type" of internet lending business. Alibaba provides borrower information, and the China Construction Bank and the Industrial and Commercial Bank of China issue loans. In 2015, the "microparticle loan" product, jointly issued by WeBank and banking institutions through the "joint loan platform," was launched. WeBank is responsible for customer screening, risk control and clearing based on big data and AI technology, and only issues a small amount of loans, while banking institutions are responsible for issuing most of the loans. WeBank contributes a low proportion of funding and relies on leverage to expand its model. During this period, Ant Group, JD Technology and other internet platforms have launched similar businesses. In the cooperative lending business model described above, U.S. monetary policy not only leads to bank credit contraction but also induces BigTech companies to raise their interest

rate risk awareness. This transmission, which relies on BigTech's funding dependence on partner banks, is referred to as the *Dependence on Joint Lending channel*.

However, although U.S. monetary policy shock will impact both bank credit and BigTech credit, the international risk-taking channel of U.S. monetary policy could lead to credit convergence between banks and BigTech lenders. First, BigTech credit is often considered a 'non-core business" or 'marginal asset" for banks. When banks face liquidity constraints (due to external debt pressures), they prioritize cutting funding to external partners (BigTech companies) to protect their core clients. Second, this channel is amplified by the unique technological features of BigTech lending. Unlike traditional banks that rely on soft information and relationship lending, BigTech platforms utilize real-time data and advanced algorithms for risk assessment. These algorithms are highly sensitive to macroeconomic fluctuations. When U.S. monetary policy tightens and deteriorates the borrowers' outlook, BigTech platforms can identify potential default risks faster and more accurately than banks. As a result, the contractionary impact of U.S. monetary policy is more pronounced for BigTech credit compared to traditional bank credit. This underlying mechanism operates as a *Flight to Quality Channel*. Thus, we have

Hypothesis 2: If BigTech credit amplifies the external shock, it may work through two mechanisms: (i) the "Dependence on Joint Lending Channel", and (ii) the "Flight to Quality Channel".

Since BigTech credit has the advantage on reducing information asymmetry and being available to more people, it has a positive effect on increasing and smoothing consumption. Thus, the role of BigTech credit has an important impact on the U.S. monetary policy transmission to Chinese consumption. On the one hand, if BigTech credit can mitigate the negative impact of U.S. monetary policy tightening on the Chinese domestic credit, it will help mitigate the decline in consumption by offering alternative credit to consumers. On the other hand, if BigTech credit amplifies the transmission effect of U.S. monetary policy on credit, consumers who rely on BigTech credit will reduce consumption much more than those who don't. Specifically, when U.S. monetary tightening transmit to the Chinese economy, tightening domestic liquidity conditions constrain BigTech credit supply. Because BigTech borrowers are predominantly liquidity-constrained individuals with a high marginal propensity to consume (MPC), this abrupt credit contraction forces them to decrease consumption much more aggressively than their traditionally banked counterparts, thereby exacerbating the transmission of external macro-shocks into the real domestic economy.

Hypothesis 3: The role of BigTech credit in U.S. monetary policy transmission will also impact the effect of U.S. monetary policy on Chinese consumption.

3 Data, sample, and specification

In this section, we introduce the unique dataset, the construction of main variables and empirical specification.

3.1 Data

3.1.1 Individual-level monthly data and loan-level data

Our individual-level monthly dataset originates from Alipay, one of the largest BigTech platform in China. The analysis was remotely conducted on the Ant Open Research Laboratory in an Ant Group Environment.[5] All data was sampled and desensitized, and was analyzed on the Ant Open Research Laboratory. The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis and individual observations are invisible. The main regression variables include basic variables, investment variables, and consumption variables.

For this study, we randomly selected 100,000 Alipay users who had at least one consumption payment record per month since January 2018. The dataset is structured at the individual-month level, spanning from May 2019 to April 2023. It encompasses a wide range of financial and behavioral variables, including: (1) basic individual characteristics, such as gender, age, and risk preference; (2) consumption behavior, categorized into service goods consumption, durable goods consumption, and nondurable goods consumption; (3) borrowing and payment instruments, covering credit card, debit card, Buy-Now-Pay-Later, and monetary

[5] https://www.deor.org.cn/labstore/laboratory

fund (analogous to bank deposit); and (4) financial investment activities, including total financial assets, assets allocation, and return on risky assets. The dataset provides a comprehensive foundation for analyzing consumer financial behaviors within a FinTech ecosystem, leveraging its extensive information and high-frequency data to offer distinct advantages over traditional household datasets.

We use the borrowing and payment information to construct proxy variables for individuals' monthly loan or credit volumes borrowed from BigTech lenders and those borrowed from traditional banks. Specifically, we use the (log) amount of Buy-Now-Pay-Later to represent an individual's BigTech loan or credit, and the (log) amount of credit card usage to represent non-BigTech loan or credit (traditional bank loan or credit). In the robustness analysis, we also employ these credit scaled by consumption as other proxy variables.

Moreover, we aggregate individuals' BigTech and non-BigTech credit data to transform individual-monthly data into loan-level data. Thus, we construct a dummy variable indicating whether a loan or credit qualifies as BigTech loan or credit.

3.1.2 Bank level data

We obtain Chinese bank-year level data over the period 2008–2024 from Bankfocus dataset which covers state-owned commercial banks, joint-stock commercial banks, city commercial banks, and foreign banks. Financial data are also obtained primarily from the CSMAR and Wind databases. Subject to data availability and completeness, the final sample consists of 42 listed banks.

We use the logarithm of the total annual loan volume of each bank as the bank-level loan proxy variable. To identify the impact of U.S. monetary policy shock on total bank loans, we first manually collected information on the currency composition of banks' assets and liabilities from their annual reports. Then, according to Du et al. (2025), we construct a variable measuring banks' foreign debt exposure to identify the impact of U.S. monetary policy shock on bank loans as follow:

$$Foreign_debt_exposure_{bt} = \frac{FX_Liability_{bt}}{Total_liability_{bt}}$$

where $FX_Liability_{bt}$ represent the total foreign currency liabilities of bank b and $Total_liability_{bt}$ is the total liability of the bank. In the following analysis, we divide banks or individual credit based on the sample median of banks' foreign debt exposure.

3.1.3 U.S. monetary policy shock

Monetary policy surprises serve as a key tool for analyzing unexpected shocks in monetary policy from the perspective of financial market participants. The measures are particularly helpful in empirical research on the monetary transmission mechanism, capturing the impact of policy shifts on financial market variables. While the choice of empirical methodology depends on the specific research context, inference about the causal effects of monetary policy typically requires an appropriate measure of exogenous policy changes, for which monetary policy surprises provide a valuable proxy. Existing studies employ high frequency identification measures of policy surprises as external instruments in a set of VARs to identify the effects of monetary shocks (Gertler and Karadi 2015;Miranda-Agrippino and Rey 2020). Other studies like Kuttner (2001), Gurkaynak et al. (2005), Nakamura and Steinsson (2018), etc. use unexpected changes in federal funds rate and Eurodollar futures on Federal Open Market Committee (FOMC) dates to measure policy surprises. The major strength of this approach is that it addresses the concern that monetary policy actions are endogenous to macroeconomics news.

We use the quantitative index of U.S. monetary policy surprises recently constructed by Bauer and Swanson (2023), which also captures exogenous changes in interest rates over tight windows the monetary policy announcements of the Federal Open Market Committee (FOMC). It consists of two measures: raw surprises, based on changes in money market futures rates, and orthogonalized surprises, which are adjusted for publicly available information prior to the announcements. To be more specific, the raw surprises are a weighted average (the first principal component) of 30-minute changes in money market futures rates around the FOMC announcements. These futures rates correspond to contracts covering the next four quarters, meaning that the surprises primarily reflect changes in expectations for the future path of the short-term interest rate over the next year. The orthogonalized surprises are the residuals from a regression

of the raw surprises on six economic and financial variables that Bauer and Swanson (2023) have found to be relevant predictors of the interest rate changes around FOMC announcements.

In the following text, we use the analysis based on orthogonalized surprises as the baseline results, while the results based on other method serve as a robustness check.

3.2 Sample and summary statistics

We focus on the borrowing and consumption behaviors of Alipay users between January 2020 and April 2023. We exclude users who do not report their gender or risk preferences. We applied a 1% winsorization to the consumption and asset variables. The descriptive statistics for the variables used in the study are presented in Table 1.

Table 1: Summary statistics

	Mean	Std	Min	P50	Max	N
Panel A: Dependent variables						
Loan amount (log)	3.3705	3.5762	0	1.0986	9.8934	6554934
Loan amount (ratio)	27.2122	37.1943	0	0.0695	100	6554934
Consumption amount (log)	7.7574	1.3995	3.0350	7.7890	11.0714	2435957
Panel B: Independent variables						
MPS	-0.0003	0.0739	-0.3780	0	0.1084	6554934
BigTech	0.4969	0.5000	0	0	1	6554934
GSS	0.0385	0.1021	-0.2102	0.0122	0.3039	3907656
NS	0.0085	0.0224	-0.0401	0.0028	0.0056	3907656
Panel C: Control variables						
Financial asset position (log)	4.7805	3.8844	0	4.7304	12.1560	6554934
M2 growth	10.2344	1.4355	8.1000	10.4000	12.9000	6554934
ΔDR007	-0.0067	0.2187	-0.4672	0.0307	0.4709	6554934

Notes: The consumption and asset variables were winsorized at the 1% level.

3.3 Empirical design

We outline the empirical strategy used to examine the impact of U.S. monetary policy shocks on consumer credit, with a focus on the role of BigTech loans. The empirical model utilizes loan-level data for the period from January 2020 to April 2023.

To identify the impact of U.S. monetary policy changes on consumer credit, we use the US monetary policy surprise constructed by Bauer and Swanson (2023) as a proxy for monetary policy. We estimate the following regression model:

$$ln(Y_{ijt}) = \alpha + \beta_1 \cdot (U.S.MPS_{t-1} \times BigTech_{jt}) + Controls_{it} + \gamma_i + \eta_t + \theta_j + \epsilon_{ijt}$$

where Y_{ijt} is the log-transformed loan size (amount) for loan j of individual i at time t. $U.S.MPS_{t-1}$ represents the U.S. monetary policy surprise at time $t-1$, capturing the monetary policy shock in the U.S. during the period. $BigTech_{jt}$ is a dummy variable indicating whether the loan j is categorized as a BigTech loan at time t. $Controls_{it}$ include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. γ_i, η_t, and θ_j represent individual fixed effects, year-month fixed effects and lender-type fixed effects to account for unobserved heterogeneity at the individual's demand, time and lender type, respectively. ϵ_{ijt} is the error term. We expect that as monetary policy tightening, reflected by an increase in the U.S. monetary policy shock, will lead to a reduction in the loan size, particularly for loans not associated with BigTech.

4 Empirical results

In this section, we provide an empirical examination of the role of BigTech credit in international spillover effect of US monetary policy, including the baseline results, robustness checks, mechanism analysis, and

heterogeneity analysis.

4.1 Baseline results

The result reports in Table 2. The coefficients of interaction term between U.S. monetary policy shock and BigTech are significantly negative in both columns, indicating that when there is tightening U.S. monetary policy shock, BigTech credit decrease more than non-BigTech credit in Chinese credit market. In Column (1), the U.S. monetary policy contraction by one standard deviation has caused a 4.79% (=0.0739*0.6488*100%) decline in BigTech credit. Therefore, BigTech credit amplifies the negative impact of US monetary policy tightening on the Chinese domestic credit.

Notably, we also compare the response of BigTech credit to Chinese monetary policy shock and find it is different from that to U.S. monetary policy shock. We use the ΔDR007 to represent Chinese monetary policy shock according to Huang et al. (2023a) and find their coefficients are positive. That means BigTech credit increases than non-BigTech credit when Chinese monetary policy tightened. That may be because when China tightens its monetary policy, the supply of bank loan decreases and the individual have to switch to BigTech credit. Therefore, BigTech credit and non-BigTech credit behave consistently (BigTech credit even has a larger relative response) in an open economy.

Table 2: The impact of U.S. monetary policy shock on individuals' loan

	Loan (log)	
	(1)	(2)
U.S.MPS × BigTech	-1.0468***	-0.6488***
	(0.0191)	(0.0171)
CN.M2gh × BigTech	-0.2649***	-0.2221***
	(0.0024)	(0.0021)
CN.ΔDR007 × BigTech	0.0971***	0.2174***
	(0.0063)	(0.0057)
Other Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	No
Lender-type FE	Yes	Yes
City*Time FE	No	Yes
Obs.	6554934	6554934
adj-R squared	0.4474	0.4462

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the logarithm of individual's loan. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *CN.M2gh* is the lagged term of Chinese monetary policy indicator such as monthly M2 growth rate. *CN.ΔDR007* is the lagged term of the first-difference of the DR007. *Other Controls* include lagged asset holdings of individuals. Standard errors are reported in parentheses and are clustered by individual.

4.2 Robustness check

To ensure the robustness of the results, we conduct several tests to check the consistency of the findings.

4.2.1 Excluding the confounding impact of Chinese Monetary Policy

Although we have control the impact of Chinese monetary policy on BigTech credit in baseline specification, it is necessary to further exclude the impact of confounding factors brought by the change of Chinese monetary policy. Therefore, we leverage the high-frequency nature of our monthly data to select a specific U.S. monetary policy shock and choose a period following the shock that excludes changes in China's monetary policy, in order to explore the response of BigTech credit to the U.S. monetary policy shock. Specifically, we follow the identification strategy in Erel et al. (2023) by exploiting the sharp U.S. monetary policy shock—the Federal Reserve's benchmark interest rate hike from near zero in March 2022 to approximately 5% by April 2023. To isolate the U.S. monetary shock from domestic policy changes, we construct a time dummy variable

indicating the period in or after March 2022. Notably, China implemented an interest rate cut in late April 2022. Thus, we estimate the result by using the sample from January 2020 to April 2022.

In Table 3, the results show a significant decline in credit extended by big technology firms following the March 2022 US monetary policy shock. This indicates that following a tightening U.S. monetary policy shock, the average response of BigTech credit during short windows that exclude changes in Chinese monetary policy is also negative. This finding remains consistent with our baseline estimates and confirms that the identified effect is driven by the U.S. monetary tightening episode rather than contemporaneous Chinese monetary policy actions.

Table 3: Robustness test: Impact of U.S. Monetary Policy Shock Before and After March 2022

	Loan (log)	
	(1)	(2)
Post-March 2022 × BigTech	-1.0088***	-0.9683***
	(0.0116)	(0.0108)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	No
Lender-type FE	Yes	Yes
City*Time FE	No	Yes
Obs.	4355417	4355417
adj-R squared	0.4905	0.4900

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the logarithm of individual's loan. The independent variable *Post-March 2022* equals 1 if time is after March 2022 and 0 otherwise. *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. The sample period is from January 2020 to April 2022. Standard errors are reported in parentheses and are clustered by individual.

4.2.2 Using alternative measurement of key variables

We first consider several alternative measurement of U.S. monetary policy surprises to ensure the robustness of our findings. Specifically, we use the U.S. monetary policy surprises constructed by Gurkaynak et al. (2005), Nakamura and Steinsson (2018) as relevant predictors of interest rate changes around FOMC announcements. In Table 4, we also find significantly negative coefficients for interaction terms, indicating that the results remain consistent with those from the baseline regressions, further supporting the validity of our conclusions.

Table 4: Robustness test: Using alternative measurement of U.S. monetary policy shock

	Loan (log)			
	(1)	(2)	(3)	(4)
GSS × BigTech	-2.5574***	-2.2105***		
	(0.0479)	(0.0344)		
NS × BigTech			-12.3834***	-12.9773***
			(0.2031)	(0.1793)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	No	Yes	No
Lender-type FE	Yes	Yes	Yes	Yes
City*Time FE	No	Yes	No	Yes
Obs.	3907656	3907656	3907656	3907656
adj-R squared	0.4517	0.4513	0.4517	0.4515

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the logarithm of individual's loan. The independent variable *GSS* is the lagged term of the U.S. monetary policy surprises constructed by Gurkaynak et al. (2005), *NS* is the lagged term of the U.S. monetary policy surprises constructed by Nakamura and Steinsson (2018). *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

Second, we also explore other measurement of individual's domestic credit. In our baseline, we use the logarithm of consumer credit to represent individual's loan. Although this method helps remove the linear trend in credit, it cannot exclude the influence of changing consumption levels on credit. Here, we use the ratio of credit to consumption as an alternative proxy variable to exclude the impact of consumption level on results. In Table 5, the coefficients are all significantly negative, indicating negative impact of a tightening U.S. monetary policy shock. Therefore, it further supports the validity of our conclusions.

Table 5: Robustness test: Using alternative measurement of loan level

	Loan (ratio)	
	(1)	(2)
U.S.MPS × BigTech	-12.1743***	-9.0779**
	(0.2559)	(0.2346)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	No
Lender-type FE	Yes	Yes
City*Time FE	No	Yes
Obs.	6554934	6554934
adj-R squared	0.3321	0.3313

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the ratio of credit on consumption. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

4.2.3 Isolating the loan demand channel

In our baseline results, we have included individual fixed effect to control the effect of credit demand change on results. In addition, to further isolate the loan demand effect, we follow the approach of Jiménez et al. (2014) and Li et al. (2021) and focus on the subsample of consumers who borrow from both bank and BigTech lenders which allows us to control for time-varing demand factors. Again, in Table 6, we find negative and significant effects of U.S. monetary policy tightening on individual loans as in the baseline regression.

Table 6: Robustness test: Regression using a subsample that simultaneously borrows from bank and BigTech lenders

	Loan (log)	
	(1)	(2)
U.S.MPS × BigTech	-1.4183***	-0.8790***
	(0.0386)	(0.0323)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	No
Lender-type FE	Yes	Yes
City*Time FE	No	Yes
Obs.	2364372	2364372
adj-R squared	0.2896	0.2871

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. We select subsample which includes consumers who both borrow from bank and BigTech lenders according to consumers' borrowing history before 2020. The dependent variable is the logarithm of individual's loan. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

4.3 Mechanism analysis

The baseline results demonstrate that international risk-taking channels have played a pivotal role in BigTech credit amplifying the transmission of U.S. monetary policy shock. In this section, we further examine two channels: *Dependence on Joint Lending Channel* and *Flight to Quality Channel* through which international risk-taking mechanisms operate.

4.3.1 Dependence on joint lending channel

We first examine the response of bank loan to U.S. monetary policy based on bank-level dataset. Specifically, we categorized banks into two groups based on the sample median of their foreign debt risk exposure (foreign currency liability as a percentage of total liabilities), and constructed dummy variables. If a bank's foreign debt risk exposure exceeded the median, the dummy variable was assigned a value of 1; otherwise, it was assigned a value of 0. We then estimated the bank loan amount (logarithm) using this dummy variable and the interaction term with U.S. monetary policy shocks. The results are presented in the table below. The coefficients of the dummy variable and the interaction term with U.S. monetary policy shocks were significantly negative, indicating that tighter U.S. monetary policy led to a more pronounced decline in loan amount for banks with higher foreign debt risk exposure.

Table 7: Mechanism analysis: the impact of U.S. monetary policy shock on bank loan (bank-level)

	Bank Loan (log)	
	(1)	(2)
U.S.MPS × Foreign_debt_high	-2.6234**	-0.6244*
	(1.0930)	(0.3421)
Size		0.9214***
		(0.0619)
Ldr		0.7255***
		(0.1018)
Lev		0.4258
		(0.7578)
Constant	27.7037***	0.9439
	(0.0025)	(1.7702)
Bank FE	YES	YES
Year FE	YES	YES
Obs.	370	370
adj-R squared	0.9926	0.9989

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the logarithm of bank loan. The independent variable *U.S.MPS* is the orthogonalized U.S. monetary policy surprises. *Foreign_debt_high* is a dummy variable which takes for 1 if the bank which foreign debt exposure risk is higher than sample median. *Size* is the logarithm of bank asset. *Ldr* is the ratio of loan to deposit. *Lev* is the leverage of banks. The sample includes data of 42 listed banks during period from 2008 to 2024. Standard errors are reported in parentheses and are clustered by bank.

To further validate the mechanism that BigTech credit contracts due to its reliance on bank funding, we exploit a quasi-natural experiment provided by the CBIRC's 2021 regulation, "Notice on Further Regulating Internet Loan Business of Commercial Banks." This regulation imposed a mandatory requirement that the platform partner (BigTech) must fund at least 30% of any joint loan, effectively reducing the leverage of BigTech credit on bank capital and decreasing its dependence on bank liquidity. We hypothesize that if the transmission of U.S. monetary policy shocks operates primarily through the contraction of bank loan supply, then reducing the reliance on bank funding should attenuate the negative impact of the shock.

Therefore, we construct a dummy variable *Post_regulation* based on the timing of regulatory enforcement which equals 1 in or after January 2022, otherwise equals 0. We interact this dummy variable with U.S. monetary policy shock and BigTech credit dummy. In Table 8, we find that the sensitivity of BigTech credit to U.S. monetary policy tightening is significantly dampened in the post-regulation period. Specifically, the interaction term between U.S. monetary policy, BigTech credit dummy, the post-regulation dummy is positive and significant, offsetting the baseline negative effect. This result provides compelling evidence that the joint-lending funding structure serves as the primary conduit for transmitting global financial shocks to the domestic BigTech credit market. By forcing BigTech firms to increase their "skin in the game," the regulation partially insulated the credit supply from the volatility of bank balance sheets. Our estimates confirm this hypothesis.

Table 8: Mechanism analysis: dependence on joint lending channel

	Loan (log)	
	(1)	(2)
U.S.MPS × BigTech × Post_regulation	1.7328***	2.2647***
	(0.0763)	(0.0640)
U.S.MPS × BigTech	-0.0643***	0.0287
	(0.0190)	(0.0175)
U.S.MPS × Post_regulation	-0.3493**	-0.6035***
	(0.0447)	(0.0368)
BigTech × Post_regulation	-1.5076***	-1.4676***
	(0.0112)	(0.0105)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	No
Lender-type FE	Yes	Yes
City*Time FE	No	Yes
Obs.	6554934	6554934
adj-R squared	0.4531	0.4524

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the logarithm of individual's loan. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *Post_regulation* is a dummy variable which takes for 1 in or after January 2022. *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

4.3.2 Flight to Quality Channel

We continue to examine the mechanism by which BigTech credit decline more than bank loan due to flight to quality phenomenon. First, we show that if *Flight to Quality Channel* holds, banks should be more likely to reduce risk-taking conditional on U.S monetary policy tightening. Due to data limitations on specific bank-BigTech matching, we exploit geographical heterogeneity in banking structure to identify the supply-side shock. Specifically, we construct a city-level measure of banking system vulnerability, denoted as $Foreign_debt_exposure_{c,t}$ with two methods. First, this index is calculated as the weighted average of the foreign debt exposure (the share of foreign liability in total liability) of listed commercial banks operating in the city c, weighted by their local branch market shares. Second, this index is represented by the city-level share of foreign deposits in the total deposit of all financial institutions.

We assign the foreign debt exposure variable to each individual based on the city where he or she is located and construct a dummy variable $Foreign_debt_exposure_high$ that represents a higher foreign debt exposure based on the median value in the sample data. By interacting the U.S. monetary policy shock and BigTech credit dummy with this regional exposure, we can test whether BigTech credit contracts disproportionately in regions with more vulnerable banking systems. As Table 9 shown, the significant negative coefficient on the interaction term between U.S. monetary policy, BigTech credit dummy, the foreign debt exposure high dummy indicates that BigTech credit declines more in areas with higher bank foreigen debt exposure. Thus, it provides robust evidence that the contraction in BigTech credit is indeed driven by the banks' flight to quality under international risk-taking channel.

Table 9: Mechanism analysis: flight to quality channel (city-level foreign debt exposure)

	Loan (log)			
	Weighted average of listed banks		All financial institutions	
	(1)	(2)	(3)	(4)
U.S.MPS × BigTech × Foreign_ debt_exposure_high	-0.6020***	-0.4076***	-1.0471***	-1.2480***
	(0.0434)	(0.0580)	(0.0373)	(0.0498)
U.S.MPS × BigTech	-1.2066***	-0.7545***	-1.1932***	-0.5926***
	(0.0247)	(0.0248)	(0.0249)	(0.0238)
U.S.MPS × Foreign_ debt_exposure_high	0.8353***	0.6656***	1.0555**	0.9628***
	(0.0239)	(0.0273)	(0.0220)	(0.0247)
BigTech × Foreign_ debt_exposure_high	0.2801***	0.3843***	-0.4769***	-0.4874***
	(0.0113)	(0.0144)	(0.0239)	(0.0244)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	No	Yes	No
Lender-type FE	Yes	Yes	Yes	Yes
City*Time FE	No	Yes	No	Yes
Obs.	6554934	6554934	6554934	6554934
adj-R squared	0.4481	0.4470	0.4487	0.4474

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the logarithm of individual's loan. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *Foreign_ debt_exposure_high* is a dummy variable which takes for 1 if the share of foreign debt in total deposit is higher than the sample median. This variable is constructed by calculated as the weighted (local branch market shares) average of the foreign debt exposure (the share of foreign liability in total liability) of listed commercial banks operating in the city c in column (1)-(2) and constructed by the city-level share of foreign deposits in the total deposit of all financial institutions in column (3)-(4). *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

4.4 Heterogeneity analysis

Here, we test the heterogeneous effects of U.S. monetary policy shock on BigTech credit both from personal and regional characteristics.

4.4.1 Heterogeneous effects across individuals: financial risk

According to Li et al. (2021) and "Flight to Quality" channel, BigTech lenders tend to reduce credit supply to borrowers with higher financial risk. For example, younger people and females usually have greater difficulty accessing financial services than older or male individuals, due to higher financial risks associated with lower savings and tighter financing constraints.

Thus, we construct dummy variables representing their risk indicators based on individual-level characteristics (gender, age). In this analysis, we categorize the sample by age and construct a dummy variable $Young$, which takes the value of 1 for individuals younger than 35 years (the median age of the sample), and 0 otherwise. Additionally, we create a dummy variable $Female$, which takes the value of 1 for female consumers and 0 for male consumers. The results are shown in Table 10.

Table 10: Mechanism analysis: flight to quality channel (individual-level characteristics)

	Loan (log)	
Panel A		
	(1)	(2)
U.S.MPS × BigTech × Young	-1.3237***	-0.8438***
	(0.0385)	(0.0370)
U.S.MPS × BigTech	-1.2569***	-0.7039***
	(0.0298)	(0.0279)
U.S.MPS × Young	1.2810***	0.8093***
	(0.0206)	(0.0178)
BigTech × Young	0.6834***	0.6830***
	(0.0297)	(0.0297)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	No
Lender-type FE	Yes	Yes
City*Time FE	No	Yes
Obs.	6554934	6554934
adj-R squared	0.4494	0.4481
Panel B		
	(1)	(2)
U.S.MPS × BigTech × Female	-0.8541***	-0.4788***
	(0.0368)	(0.0358)
U.S.MPS × BigTech	-1.3042***	-0.8267***
	(0.0252)	(0.0233)
U.S.MPS × Female	1.0755***	0.7245***
	(0.0214)	(0.0194)
BigTech × Female	0.0108	0.0104
	(0.0248)	(0.0248)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	No
Lender-type FE	Yes	Yes
City*Time FE	No	Yes
Obs.	6554934	6554934
adj-R squared	0.4475	0.4462

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. Panel A and Panel B represent the heterogeneous analysis results based on age and gender, respectively. The dependent variable is the (log) of credit. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *Young* is a dummy variable where individuals under the median (aged 35 or younger) are assigned a value of 1. *Female* is a dummy variable where individuals who are female are assigned a value of 1. *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

4.4.2 The impact of traditional financial service accessibility

We find that international risk-taking channels will play a primary mechanism role in transmission of U.S. monetary policy shock. The tightening of U.S. monetary policy exacerbates banks' external debt pressure, leading to credit contraction and reduced risk appetite in banks, as well as decreased risk appetite for BigTech lenders. The relationship between banks and BigTech companies varies across regions in terms of financial accessibility, which may result in differential impacts of U.S. monetary policy shocks on BigTech credit. Specifically, in regions with high bank financial accessibility, banks play a greater role in credit supply, making BigTech credit relatively less affected by U.S. monetary policy shocks. Conversely, in regions with low bank financial accessibility, BigTech companies play a more significant role in credit supply, thus making its credit more susceptible to U.S. monetary policy shocks.

To explore this issue, we constructed a bank financial accessibility indicator based on the number of bank branches per thousand people within county-level regions. We matched this indicator with the county-level regions where the population resides and divided the population into two groups according to the median

value of the indicator in the sample.

Table 11 reports the results. In Columns (1) and (2), the coefficients of interaction between *U.S.MPS*, *BigTech* and *bank_branch_low* is negative at 1% significant level, indicating that the stronger reaction of BigTech credit to U.S. monetary policy shock is more pronounced in areas with lower level of traditional financial service accessibility. In areas where individuals rely on BigTech credit, BigTech lenders' credit supply decision and risk assessment plays a decisive role.

Table 11: Heterogeneous effect: traditional financial service accessibility

	Loan (log)	
	(1)	(2)
U.S.MPS × BigTech × Bank_branch_low	-0.8278***	-0.5203***
	(0.0429)	(0.0471)
U.S.MPS × BigTech	-1.1012***	-0.6863***
	(0.0213)	(0.0196)
U.S.MPS × Bank_branch_low	0.8262**	0.5893***
	(0.0259)	(0.0265)
BigTech × Bank_branch_low	0.4678***	0.4677***
	(0.0266)	(0.0266)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	No
Lender-type FE	Yes	Yes
City*Time FE	No	Yes
Obs.	6554934	6554934
adj-R squared	0.4483	0.4470

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the logarithm of individual's loan. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *Bank_branch_low* is a dummy variable which takes for 1 if the number of bank branches per thousand people is lower than its median according to their distribution in 2019 (before the sample period). *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

4.4.3 The impact of financial openness

The level of financial openness will also influence the response of BigTech credit to U.S. monetary policy shock (Lakdawala et al. 2021). In areas with higher level of financial openness, the impact of external polich shock will be greater due to more frequent capital flows. Here, we construct a dummy variable to represent the level of financial openness according to province-level FDI (foreign direct investment) amount. We matched this variable with the province-level regions where the individual resides and divided the individuals into two groups based on the median value of the variable in the sample.

Table 12 reports the results. We find coefficients of interaction between *U.S.MPS*, *BigTech* and *Financial_openness_high* are both negative at 1% significant level, indicating that the stronger reaction of BigTech credit to U.S. monetary policy shock is more pronounced in areas with higher level of financial openness.

Table 12: Heterogeneous effect: financial openness

	Loan (log)	
	(1)	(2)
U.S.MPS × BigTech × Financial_openness_high	-0.9432**	-0.9871***
	(0.0373)	(0.0516)
U.S.MPS × BigTech	-1.1776***	-0.6577***
	(0.0241)	(0.0228)
U.S.MPS × Financial_openness_high	0.9789***	0.8702***
	(0.0222)	(0.0257)
BigTech × Financial_openness_high	0.0049	0.0048
	(0.0250)	(0.0250)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	No
Lender-type FE	Yes	Yes
City*Time FE	No	Yes
Obs.	6554934	6554934
adj-R squared	0.4475	0.4462

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the logarithm of individual's loan. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech* is a dummy variable which takes for 1 if the credit are offered by BigTech company. *Financial_openness* is a dummy variable which takes for 1 if the FDI (foreign direct investment) amount is no less than its median according to their distribution in 2019 (before the sample period). *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

5 Further analysis: The real effects of BigTech credit and U.S. monetary policy shock

Above analysis shows that the U.S. monetary policy shock would have an amplification spillover effect on BigTech credit. As BigTech credit has become an important alternative financing source for the real economy—for example, supporting consumption and the investment of small, medium, and micro enterprises—it is worth exploring whether the amplification effect transmits to the real economy.

Therefore, we further discuss the impact of U.S. monetary policy shock on Chinese real economy from the perspective of consumption. Specifically, we divide consumers into two groups based on whether their consumption was more reliant on BigTech credit before the sample period began and explore if the impact of U.S. monetary policy shock is more obvious among these consumers.

Table 13 reports the consumption results. We find that the coefficients of interaction term between $U.S.MPS$ and $BigTech_use$ are negative significantly. Specifically, the U.S. monetary policy contraction by one-standard-deviation has caused a 0.86% (=0.0739*0.1170*100%) decline in consumption amount for consumers who are more reliance on BigTech credit than those who are not. Thus, the amplification spillover effect of U.S. monetary policy shock through BigTech credit will transmit to the real economy.

Table 13: Further analysis: the real impact of BigTech credit and U.S. monetary policy shock on consumption

	Consumption (log)	
	Amount	Numbers
	(1)	(2)
U.S.MPS × BigTech_use	-0.1170***	-0.1497***
	(0.0140)	(0.0081)
Controls	Yes	Yes
Individual FE	Yes	Yes
Year-month FE	Yes	Yes
City*Time FE	Yes	Yes
Obs.	2435957	2435957
adj-R squared	0.5055	0.5676

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable is the (log) consumption amount and numbers of purchases. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech_use* is a dummy variable which takes for 1 if the consumer is more reliance on BigTech (if consumers' credit from BigTech lenders accounts for a higher proportion of total spending than credit from bank lenders). *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

We also explore the effect on both online consumption and offline consumption. As shown in Table 14, the coefficients of the interaction term between $U.S.MPS$ and $BigTech_use$ are significantly negative for online consumption, while they show no robust significance for offline consumption, suggesting that the spillover effect of U.S. monetary policy shock through BigTech credit is more pronounced for online consumption. Specifically, the U.S. monetary policy contraction by one-standard-deviation has caused a 1.31% (=0.0739*0.1774*100%) decline in online consumption amount for consumers who are more reliance on BigTech credit than those who are not. This result is reasonable because BigTech credit is mostly used online.

Table 14: Further analysis: the real impact of BigTech credit and U.S. monetary policy shock on online and offline consumption

	Online consumption (log)		Offline Consumption (log)	
	Amount	Numbers	Amount	Numbers
	(1)	(2)	(3)	(4)
U.S.MPS × BigTech_use	-0.1774***	-0.1252***	0.0081	-0.0729***
	(0.0142)	(0.0080)	(0.0200)	(0.0111)
Controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
City*Time FE	Yes	Yes	Yes	Yes
Obs.	2393787	2393787	2214620	2214620
adj-R squared	0.5251	0.5859	0.4275	0.5521

Notes: ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively. The dependent variable in Column (1) and (2) is the (log) online consumption amount and numbers of purchases. The dependent variable in Column (3) and (4) is the (log) offline consumption amount and numbers of purchases. The independent variable *U.S.MPS* is the lagged term of the orthogonalized U.S. monetary policy surprises. *BigTech_use* is a dummy variable which takes for 1 if the consumer is more reliance on BigTech (if consumers' credit from BigTech lenders accounts for a higher proportion of total spending than credit from bank lenders). *Controls* include lagged logarithm of individual's total asset which invested in the BigTech platform, the interaction term between Chinese monetary policy indicator such as monthly M2 growth rate, the first-difference of the DR007 and *BigTech*. Standard errors are reported in parentheses and are clustered by individual.

6 Conclusion

In this paper, we explore the international transmission of U.S. monetary policy and its mechanisms through two types of financial intermediaries: traditional banks and BigTech companies. Based on an individual-month level dataset randomly selected from one of the largest Big Tech firms in China which include nearly 100,000 individuals' borrowing and consumption activities from January 2020 to April 2023, our paper shows that BigTech credit responds more strongly to U.S. monetary policy shocks than traditional credit does. Specifically, following a one-standard-deviation increase in the U.S. monetary policy shock, BigTech credit decreases by 4.79%. Thus, BigTech credit will amplify the international transmission of U.S monetary policy shock on emerging market economies. We further find that international risk-taking between banks and BigTech companies acts as the primary transmission channel. Moreover, the amplification effect is more pronounced among high-risk consumers, in areas with lower level of traditional financial service accessibility and higher level of financial openness. Furthermore, we discuss whether the amplification effect of U.S. monetary policy through BigTech credit transmits to the real economy. We observe that consumers who are more reliant on BigTech credit decrease their total consumption amount by an additional 0.86% following a one-standard-deviation tightening of U.S. monetary policy. Notably, if we decompose total consumption into online and offline consumption, we find that consumers who are more reliant on BigTech credit decrease their consumption more (1.31%) following a tightening of U.S. monetary policy.

The policy implication is that policymakers in emerging market economies must guard against the mechanisms through which BigTech credit providers amplify external shocks to domestic financial markets. Meanwhile, macroprudential and BigTech credit regulatory policies are essential for these economies to establish "digital financial buffers" and smooth consumption during periods of heightened external policy stress.

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