# FinTech, Banking and Monetary Policy Transmission

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# FinTech, Banking and Monetary Policy Transmission

**Abstract:**

This study investigates whether and how FinTech influences retail banking and the effectiveness of monetary policy transmission, with a focus on the competition between FinTech companies and banks in the deposit market. Using proprietary data from a leading Chinese FinTech company, we study a money market fund with deposit-like features, available through a widely adopted payment platform in China. With a Bartik-style instrumental variable approach, we document several novel findings: (i) in the short run, FinTech competition induces negative deposit demand shocks and crowds out bank deposits. In response, banks more exposed to Fintech competition do not cut their lending, but reduce liquid assets and financial investments and issue more bonds; (ii) after the removal of the deposit rate ceiling in 2015, more exposed banks experience higher deposit and loan growth because they are more likely to offer innovative deposit products and raise deposit interest rates higher in the long term; (iii) banks' endogenous responses to attract more depositors due to intense FinTech competition lead to smaller declines in loan and deposit growth during monetary tightening, mitigating the effects of monetary contraction. Further mechanism tests rule out alternative channels that can explain the muted monetary policy transmission, including the risk-shifting channel, the funding substitution channel, and the lending competition channel.

**Keywords:** FinTech, Deposit channel, Bank intermediation, Monetary policy, China

**JEL classification:** E52, G21, G23, G28

## 1. Introduction

Over the past decade, the world has witnessed a rapid rise of big-tech companies (BigTech) and financial technology (FinTech), substantially contributing to increasing affordability, accessibility, and convenience of modern financial services.[1] However, FinTech innovations can also disrupt existing financial industry structures, blur industry boundaries, revolutionize how financial firms create and deliver products and services, facilitate strategic disintermediation, and democratize access to financial services (Philippon, 2016). Although FinTech is generating so much excitement and research interest because it bypasses traditional intermediaries while offering financial services (Thakor, 2020), little systematic empirical evidence is available on how the development of FinTech affects banking and the effectiveness of monetary policy transmission (henceforth, MPT). Identifying the impact of FinTech on banking and MPT is challenging due to the presence of different channels through which FinTech can affect banks and MPT. Empirical findings can be inconclusive and depend largely on the classification of FinTech products, the country group, the period covered, and the concrete channel of MPT studied.

A small but growing literature has explored how FinTech, including BigTech, competes with traditional banks in the lending market and how their responses to monetary policy changes differ in lending behaviros.[2] However, little attention has been paid to the deposit market. In fact, FinTech has gradually changed the way people deposit money. Individuals can now transfer funds via mobile devices, compare investments online and even shop directly with money market fund shares, leading to significant reductions in search costs, widened geographic scope, and enhanced competitiveness in financial markets.[3] Meanwhile, online banks are taking an increasing share of total deposits by offering much higher rates on deposits than traditional banks do through their branches (Erel et al., 2023).[4] There are more and more deposit-taking FinTech companies in the

[1] In terms of the interpretation of the term "FinTech", the Financial Stability Board provides a definition which was adopted by the Basel Committee on Banking Supervision: "technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions, and the provision of financial services". (Thakor 2020)

[2] FinTech competes with banks in mortgage lending (Buchak et al., 2018; Fuster et al., 2019; Bartlett et al., 2022), peer-to-peer lending (Tang, 2019) and small business lending (Gopal and Schnabl, 2022; Erel and Liebersohn, 2022). Gambacorta et al. (2022) and huang et al. (2022) look at BigTech's response to monetary policy changes.

[3] Consumers in China can use Yu'ebao money market fund to shop directly via the Alipay platform. See section 3.2 for a more detailed introduction about Yu'ebao money market fund.

[4] By 2022, online bank deposits constituted about 5 percent of the total deposits held by the U.S commercial banks (Erel et al., 2023).

U.S., such as Square, Acorns, Qapital, Chime and Current that attract depositors by delivering a more powerful and emotional set of technology-based saving services to their end-users. BigTech companies (e.g., Apple Inc.) have also stepped into the deposit market by partnering with large banks (e.g., Goldman Sachs Bank), which may pose a threat to the deposit base of small banks, e.g., community banks. How will FinTech competition in the deposit market change individuals' deposit demand and the sensitivity of deposit demand to monetary policy shocks? How do traditional banks respond to such competition by adjusting deposit and credit supply? How does this competition influence the effectiveness of monetary policy through the deposits and lending channel? These are all questions that remain underexplored in the existing literature.

In this paper, we address the above questions by studying a money market fund (MMF) with deposit-like features, available through an already widely adopted household payment platform in China. In June 2013, Alipay, already a trusted and dominant FinTech player in payments, introduced Yu'ebao (YEB) MMF. Unlike a traditional MMF, YEB MMF, coupled with Alipay's payment system, offers T+0 liquidity, enabling investors to shop directly with their YEB shares, as they do with demand deposits. In contrast to bank deposits, YEB's yield is not subject to the deposit rate ceiling and is thus closer to the market interest rates. Combining the high-yield feature of MMF and the liquidity service value of payment technology, YEB has become a close substitute for bank deposits (Buchak et al., 2021).

We then investigate how the FinTech competition (i.e., the introduction of YEB MMF) in the deposit market affects banks' deposit-taking, loan issuance, and pricing strategies, as well as MPT through banks' lending and deposits channels (Drecheler et al., 2017). To measure the FinTech exposure at the bank level, we use proprietary data from a leading Chinese FinTech company, Ant Group, and quantify the exposure to FinTech competition in the deposit market for each bank in China following Buchak et al. (2021). Then, we investigate whether and how FinTech impacts retail banking and MPT. A potential concern with the ordinary least squares (OLS) approach is that there could be other confounding factors simultaneously affecting the monetary policy stance, banks' exposure to FinTech, and growth of banks' loans or deposits. Moreover, unobserved local economic conditions could also influence the YEB penetration and bank performance at the same time, resulting in biased OLS estimates. To mitigate the endogeneity concern, we first adopt the exogenous M2 growth rate to measure monetary policy shocks, following Chen et al. (2018) and then consider the lags of the FinTech exposure to alleviate the simultaneity problem.[5] Next, we control for local business cycles in banks' local markets by aggregating city-level macroeconomic variables to the bank-level and implementing a robustness check that limits the sample to "local" banks operating predominantly within a single city, with city-level controls reflecting local demand (Chowe and Choi, 2021). Finally, we estimate the causal effect of FinTech on banking, and the interaction of FinTech and monetary policy changes on bank activities using a two-stage least squares (2SLS) estimation. Following Hasan et al. (2023), Hong et al. (2020), and Buchak et al. (2021), we use the penetration ratio of the Alipay platform and the distance to Hangzhou city (Alipay's headquarters) as instruments for banks' exposure to YEB.[6]

We begin the empirical analysis by first examining the direct impact of FinTech on banks in the short run (from 2012 to 2014) when the ceiling regulation remained effective. We find that banks whose depositor base was more exposed to FinTech competition experienced a stronger deposit outflow due to negative deposit demand shocks, mainly from the household deposit market. However, more exposed banks did not reduce their loan provisions. Instead, they reduced the liquid assets and financial investments and issued more bonds to mitigate the impact of deposit losses. We, then, continue to explore the impact of FinTech on banks after 2015 when the official deposit rate ceiling was removed. Empirical findings show that, in contrast to the results before 2015, banks more exposed to FinTech experienced higher deposit and loan growth rates from 2015 to 2018 relative to banks less exposed to FinTech competition. The rise in deposit growth was mainly driven by the growth of firm deposits which are not affected by YEB in the beginning and household time deposits.

Why does more exposure to FinTech cause higher deposit and loan growth after 2015? To solve the puzzle, we explore the reversed effects of FinTech on banks in the long term compared to that before 2015. Specifically, we show that more exposed banks are more likely to roll out innovative deposit products and raise deposit interest rates after the removal of the official deposit rate ceiling. These responses not only offset the original impact of YEB but also attract more depositors who are not directly affected by YEB in the first place, giving rise to the net inflow of deposits for more exposed banks.

[5] M2 is a measure of the money supply that includes cash, checking deposits, and easily convertible near-money, such as savings deposits, money market securities and other time deposits. It is closely watched as a target of central bank monetary policy in China (Chen et al., 2018).
[6] We also adopt the driving distance to Hangzhou as an alternative instrumental variable for a robust test.

A natural extension, then, is to analyze the influence of FinTech on MPT through the banking system. We propose two hypotheses. First, the competition from FinTech could strengthen the deposit outflows in periods of monetary tightening because liquid deposits become relatively more expensive, especially when households could conveniently substitute YEB MMF that provides both liquidity value and a higher yield for deposits. If banks cannot make up for the loss of deposits with wholesale funding due to information problems in the market for equity and corporate debt (Bernanke and Blinder, 1992), banks more exposed to FinTech competition would be expected to contract their lending more in response to monetary tightening than banks less exposed to FinTech competition (i.e., FinTech strengthens the transmission of monetary policy through bank lending). Second, based on the findings of the direct impact of FinTech from 2015 to 2018, if more exposed banks are more likely to roll out their own innovative deposit products and raise deposit rates to attract more depositors in response to intense FinTech competition during monetary tightening, one would expect deposits and lending to decline less in periods of monetary contraction for more exposed banks. In other words, FinTech could mitigate the effectiveness of MPT.

To test these two hypotheses, we first analyze how the price and quantity of YEB MMF and commercial bank deposits change with the 7-day repo rate.[7] We find that the spread between the YEB 7-day annualized yield and bank deposit interest rates widens when the 7-day repo rate rises. In other words, YEB MMF becomes more attractive in terms of yield in periods of monetary tightening. Consistent with conventional wisdom (Drechsler et al., 2017), we show that high 7-day repo rates are associated with low growth rates of commercial bank deposits, especially demand deposits. However, the growth rate of the YEB fund rises with the 7-day repo rate. Overall, these results reveal that the FinTech competition becomes more intense during monetary tightening.

Next, we proceed to examine MPT by estimating the impact of FinTech on the sensitivity of bank lending to monetary policy shocks. Consistent with the second hypothesis, empirical results suggest a mitigated impact of FinTech on the transmission of monetary policy through bank lending. Specifically, for the whole sample period, more exposed banks experienced a smaller decline in loan growth rate during monetary tightening. For a 1% decline in M2 growth, a bank at the 75$^{th}$ percentile of the YEB penetration rate experienced a 2.15% higher increase (i.e., a smaller

[7] The PBOC has been attempting to develop a short-term target rate, such as the U.S. Fed Fund rate, as its policy instrument. The 7-day repo rate (R007) market is the most liquid market. 7-day repo rate is the collateralized interbank repo rate between all financial institutions and can be approximately regarded as the short-term policy instrument.

decline) in loan growth relative to a bank at the 25th percentile. This mitigating effect on MPT was significant only after 2015 and for non-state-owned banks, such as city commercial banks and rural banks, as well as small and medium banks (SMBs). City-level results also confirm that, in the aggregate, cities more exposed to FinTech competition are less responsive to monetary policy shocks in terms of real GDP growth and bank loan growth.

To better understand the muted MPT via bank lending due to FinTech exposure, we propose a "catfish" effect channel, wherein a strong competitor in the external environment motivates the weaker players to better themselves. The key idea behind this channel is that YEB stimulates banks to endogenously offer more innovative deposit products and raise deposit rates to attract more depositors, many of whom are not affected by YEB in the first place. We provide two pieces of evidence in support of this presumption. First, we show that more exposed banks witness a higher deposit growth rate, mainly driven by household time deposits and firm demand deposits in periods of monetary tightening. Second, we find that deposit interest rates of banks that are more exposed to FinTech competition rise higher than those of less exposed banks during monetary tightening. These two pieces of evidence suggest that banks more exposed to FinTech increase the deposit supply by raising deposit interest rates. It is the increased deposit funding that allow banks to expand their credit supply during monetary contraction, mitigating the effectiveness of MPT.

Guided by the literature, we also rule out several other alternative channels that could causally explain the muted MPT when banks are under competitive pressure from FinTech companies, such as the risk-shifting channel (Keeley, 1990； Hellmann et al., 2000), the funding substitution channel (Choi and Choi, 2021), and the lending competition channel (Hansan et al., 2020). Keeley (1990) and Hellmann et al. (2000) show that increased competition may erode banks' franchise values, and increase the moral hazard behavior of banks, such as excessive risk-taking due to risk-shifting. As the crowding-out effect of the YEB fund is stronger during monetary tightening, more exposed banks may have incentives to lend more and lend to riskier borrowers, leading to muted MPT via bank lending. We provide three pieces of evidence suggesting that this mechanism cannot explain the main findings. First, we find no significant impact of the FinTech competition on the franchise value of publicly listed banks. Second, the FinTech competition does not induce banks to take more risks, which are measured from three aspects: loan portfolio risk (Shim, 2013), default risk (Berger et al., 2014), and leverage risk (Gropp and Vesala, 2004). Third, we find that more exposed banks invest more in safe assets, such as cash and reserve, contradicting the increased risk-taking incentives.

The second possible alternative explanation is the potential presence of funding substitution, especially during monetary tightening. As shown in Choi and Choi (2021), banks could mitigate the policy effectiveness through the lending channel by replacing deposit outflows with wholesale funds, and a bank with higher funding composition sensitivity tends to lend more during monetary tightening than a bank with lower funding sensitivity. If more FinTech exposure causes banks to turn to other sources of funds (e.g., wholesale funding) with low costs in terms of the reserve and thus engage more actively in funding substitution, it could mitigate MPT via bank lending, especially during monetary tightening. Yet, we find no evidence in support of this channel. The last possible alternative channel is that the constructed measure of FinTech exposure in the deposit market may partially capture, at least to some extent, banks' exposure to FinTech in the loan market. If this were the case, then muted MPT may be due to the competition between FinTech credits and bank loans (Hansan et al., 2020), especially when they substitute for bank lending, as evidenced by Buchak et al. (2020). Yet, we show that the lending competition channel is not consistent with the reversed effect of FinTech on MPT after 2015, relative to pre-2015 periods.

Overall, our empirical results suggest that FinTech competition in the deposit market can induce banks' endogenous responses. In the short run and with the deposit rate ceiling, banks more exposed to FinTech competition lose more deposits but do not reduce lending. With the removal of ceiling regulation, more exposed banks are more likely to engage in deposit innovation and raise deposit rates to attract more depositors. However, there is no evidence that they will transfer the increased funding costs from the liability side to loan rates on the asset side. Instead, more exposed banks tend to increase lending at a lower loan interest rate. The impact of FinTech competition on banks, thus, generates welfare redistribution: when banks pay a higher interest rate on deposits and charge a lower interest rate on loans, more benefits are passed on from the banking sector to depositors and borrowers. However, there is also an unintended consequence that the banks' endogenous responses to attract more depositors facing intense FinTech competition during monetary contraction could mitigate the tightening effect of contractionary monetary policy shocks.

As digital payment and other non-traditional financial services grow fast worldwide and FinTech has already started challenging the banking industry's monopoly in the financial intermediation space, this study provides, to the best of our knowledge, the first empirical evidence to understand FinTech's role in the banking industry and monetary policy transmission in China, offering important lessons for monetary policymaking and financial regulation in other countries.[8]

The rest of this article is organized as follows. The next section discusses the related literature. Section 3 describes the institutional background of the interest policy in China and the introduction of YEB MMF. Section 4 details the data and presents the empirical methodology. In Section 5, we conduct cross-sectional analyses to examine the direct impact of FinTech on banks in the short- and long-term. Then, we explore the impact of FinTech on the sensitivity of bank lending to monetary policy shocks in Section 6. In Section 7, we propose and examine the main channel, as well as ruling out other alternative channels. Section 8 concludes with policy implications.

## 2. Related Literature

This work contributes to the literature in several ways. First, to the best of our knowledge, this is the first study that examines the impact of FinTech on MPT through the banking system, especially from the perspective of deposit market competition. A small but growing literature investigates the nexus between FinTech and banking but lacks the perspective of its broad interaction with monetary policy.[9] Few papers exploring the effect of FinTech on MPT are either limited to theoretical discussions (Bossu et al., 2021) or aggregate macro-level analyses (IMF, 2016; Hasan et al., 2023). Two papers closest to ours are Hasan et al. (2023) and Erel et al. (2023). Hasan et al. (2023) use an interacted panel vector autoregression model to analyze how the effects of monetary policy shocks vary by regional-level FinTech adoption. Consistent with our findings, they document a muted MPT due to more FinTech adoption. However, their study focuses on the whole FinTech industry from a macroeconomic perspective and lacks convincing micro-founded mechanisms to explain the muted transmission. Instead, we use the data of a specific FinTech product widely used in China and trace its impact on banking and the sensitivity of banks' lending, deposit-taking, and pricing strategies to monetary policy changes. More importantly, we propose and empirically test a possible channel through which FinTech can influence MPT by affecting the deposit channel (Drechsler et at. 2017). Erel et al. (2023) study the role of online banks in

[8] Chen et al. (2018) show that the transmission of monetary policy impulses to the rest of the economy in China is similar to the transmission process in advanced economies.
[9] See Thakor (2020) for a good summary of this literature.

interest rate pass-through and the deposits channel of monetary policy but remain silent on the implication on bank lending and the endogenous responses of traditional banks.

Indeed, there are already some studies investigating the effects on MPT from the perspective of nonbanks and shadow banks (e.g., Elliott et al., 2020; Buchak et al., 2020). However, we highlight the role of FinTech penetration, which arises from BigTech companies outside the financial sector, and is thus different from the competition between nonbanks and shadow banks. Moreover, while all these papers discussing the impact of non-banks and shadow banks focus on the credit supply effect, we provide micro-evidence on the transmission mainly through the deposit supply effect that is underexplored in the existing literature.

Second, this study contributes to the literature on the competition between FinTech and traditional banks. Several studies have examined how banks and FinTech lenders compete and how their competition differs across various product markets, such as mortgage lending (Buchak et al., 2018; Fuster et al., 2019; Bartlett et al., 2022), peer-to-peer lending (Tang, 2019), small business lending (Gopal and Schnabl, 2022; Erel and Liebersohn, 2022), payments (Ghosh et al., 2022; Parlour et al., 2020) and asset management (Hong et al., 2019). Our paper joins Xiao (2020), Ma et al. (2020) and Buchak et al. (2021) in examining the competitive structure of deposit-like products. As opposed to Xiao (2020) and Ma et al. (2020) who study the effect of traditional MMF and mutual funds on banks that respond inactively, we study FinTech MMF and emphasize the role of banks' endogenous responses to FinTech competition. Buchak et al. (2021) also study the YEB MMF but focus on the impact of YEB on banks' deposits in their early stages, e.g., before 2015. We show that the impact of FinTech products in early stages is different from that in the long term, especially after regulatory policy changes. We also complement their work by exploring the effect of FinTech on banks' loan provision and pricing strategies.

Third, this study examines how banks endogenously change their loan supply, deposit supply, and pricing strategies in response to FinTech competition. While many articles have discussed the competitive effects of FinTech, few have examined traditional banks' responses (Boot, 2017; Vallee and Zeng, 2019). We show that, in response to FinTech competition in the deposit market, banks endogenously expand their deposit supply and roll out innovative deposit products. Unlike the competition within the banking system, FinTech competition outside the financial system brings a change to the whole banking sector and has heterogenous effects on banks of different sizes and ownership type.[10] Furthermore, we show that, contrary to the concern of many regulators (e.g., Largarde, 2018) that FinTech may make banks less relevant in providing financial services, the catfish effect found in this paper stimulates banks to engage more in financial intermediation. The stimulative impact of FinTech on banks can also alleviate the financial disintermediation problem due to deposit rate ceilings documented in the literature (Koch, 2015).

Fourth, the results regarding the impact of FinTech on bank intermediation shed light on the discussion about the influence of central bank digital currency (CBDC) on the banking system. A prominent argument against CBDC and neo-bank entrants is that CBDC encourages depositors to shift money from bank deposits to digital cash. As a result, those deposits no longer fund bank loans, and the introduction of CBDC leads to bank disintermediation (Mancini-Griffoli et al., 2018; Bank of International Settlements, 2020). Indeed, YEB MMF, by combining payment technology and MMF features, creates a close substitute for bank deposits and can be regarded as a form of digital currency that pays interest, similar to CBDC. We find that, even though more exposed banks lose deposits to YEB in the short run, they do not cut lending but reduce liquid assets and financial investments. Moreover, we show that FinTech competition can promote bank intermediation in the long term, in consistent with the model prediction of Chiu et al. (2023). They show that, when the CBDC interest rate is not too high, CBDC will stimulate banks to supply more deposits that lead to more lending and a lower loan rate, thus, in general, promoting bank intermediation. Our results provide indirect empirical evidence in support of their conclusions.

Finally, this work adds to the literature regarding the factors affecting MPT, i.e., the state dependence of monetary policy, by focusing on the role of FinTech competition outside the banking system. Previous work shows that the effectiveness of monetary policy can be affected by macroeconomic factors, such as inflation (Jordá et al., 2020), uncertainty (Castelnuovo and Pellegrino, 2018), business cycles (Tenreyro and Thwaites, 2016), the market power of creditors (Scharfstein and Sunderam, 2016), the home equity value (Beraja et al., 2019), and the financial health of the banking sector (Indarte, 2020). Our findings suggest that FinTech competition can also be an important factor influencing MPT. We also complement the literature on the impact of bank competition on MPT (e.g., Fungáčová et al., 2014) by showing how the entry of a competitor

[10] In face of more competition within the banking system, banks can collude in equilibrium. However, they cannot do so when there is a new competitor outside the banking industry, such as YEB MMF.

outside of the original banking system can reshape the competition within the banking system and its interaction with monetary policy.

# 3. Institutional Background about China

## 3.1 China's Interest Rate Policy

China's interest rate policy is exercised through banks that dominate the country's financial system and is characterized by price controls over deposit and loan interest rates, as well as quantity-based controls over loan volumes. Price-based control involves capping the deposit interest rate and putting a floor on the loan interest rate to transfer wealth from savers to borrowers (Lardy, 2008). At the same time, it keeps the interest-rate margin of banks sufficiently wide to maintain the aggregate profitability of the banking system (He and Wang, 2012). In contrast to the heavily regulated interest rates in the banking system, the other side of the dual-track system is market-determined wholesale interest rates in the interbank money and bond markets, which are accessible to almost all domestic institutional investors.

[Figure 1 here]

Figure 1 shows the dual-track interest rates under ceiling regulation in China. There are four key features of the interest rates evolutions. First, the interest rate ceiling on the deposit rate (e.g., the 3-month time deposit) stays below the market-determined interest rate of the same maturity most of the time.[11] Second, similar to the regulated deposit rate ceiling, the actual average deposit rate in the banking system is not very responsive to the business cycle.[12] Third, the discrepancy between the regulated deposit rate and the market rate is wide, especially during periods when the market rate rises. Fourth, the yield of the YEB MMF traces the market rate well and is substantially higher than the regulated deposit rate. The considerable interest rate wedge between the YEB MMF and banks' deposit rates creates incentives for households to transfer money from their bank accounts to YEB accounts (Buchak et al., 2021).

Compared to the scenario in China, the deposit rate ceiling imposed by Regulation Q in the US before 1986 had a similar effect, wherein depositors were induced to shift money from deposits to

[11] Here, we use the 3-month Shanghai Inter-Bank Offered Rates (SHIBOR) as an example.

[12] The average deposit rate here is computed as the average value of the deposit rates of all banks in the sample. The standard deviation of the average deposit rate for all banks is 0.29 vs. 1.23 for the 3-month SHIBOR in the period from 2015Q1 to 2019Q4.

high-yielding assets, such as state savings bonds when market interest rates exceeded the legally binding ceiling (Koch, 2015).[13] However, before 2013Q2, there were no significant deposit outflows under ceiling regulations in China compared to the US under Regulation Q due to a lack of diversity in terms of investment options. Most households in China chose bank deposits as the only form of financial assets and cannot directly invest in the bond market since there was a high investment threshold for other wealth management products, such as MMFs.

The official loan rate floor and deposit rate ceiling were removed in China in 2013 and 2015, respectively. Even so, bank deposit rates were still largely constrained by the regulator's window guidance and the self-regulation mechanism of market interest rate pricing. In Figure 1, another notable observation is that the average deposit rate, which used to be below the ceiling of 3-month time deposits, exceeded the corresponding self-regulatory limit after 2015. This is because the self-regulatory limit is not mandatory by law, generating regulatory arbitrage opportunities for banks to circumvent this limit. In Section 5, we provide some examples to illustrate how banks can create innovative deposit products to bypass the implicit deposit rate ceiling.

## 3.2 The Emergence of FinTech product - Yu'eBao

Digital payment has been a default option for households in China. People use their e-wallets, e.g., Alipay and WeChat Pay, to shop both online and offline, pay utility bills, buy insurance products, and make financial investments. Alipay, incorporated in 2004, has long been the leading third-party digital payment platform in China.[14] In June 2013, Alipay launched Yu'e Bao, which means "leftover treasure." In the beginning, the media called it a "new bottle for old wine" because it was still a MMF, and there were already over two hundred of them in 2013. However, several distinctive and useful features distinguish YEB from a traditional MMF.

Firstly, YEB offers a "T+0" real-time unlimited redemption option at almost no cost. Investors can withdraw their money from the YEB MMF within seconds. Second, it allows for the share payment function, which means that consumers can use a YEB share, including principals and the proceeds calculated every day, to shop directly both online and offline. Third, unlike most of the

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[13] Regulation Q. Section 11(b) of the Banking Act of 1933 prohibited all member banks from paying interest on demand deposits. The same section empowered the Federal Reserve Board with the authority to set the interest rate on time and savings deposits. Regulation Q was phased out until March 31, 1986 at which point all interest rate ceilings were completely eliminated in the US.

[14] According to Statista (https://www.statista.com/statistics/426679/china-leading-third-party-online-payment-providers/), Alipay led the online payment industry with a market share of 56% as of 2020 Q2.

MMFs before 2013, YEB requires no minimum investment amount. Investors can invest as little as 1 CNY ($0.15), suggesting that YEB is accessible to essentially all households. In contrast, investing in a traditional MMF before June 2013 required a minimum investment threshold of 50,000 CNY ($7,500), and such an MMF only allowed T+2 redemption. These three features of YEB make it far more attractive than other traditional MMFs in terms of its liquidity service value. More importantly, YEB also provides yields that are comparable to other MMFs and much higher than banks' deposit rates (see Figure 1). A combination of MMF market-determined yield and liquidity service value makes YEB a close substitute to bank deposits, especially retail demand deposits.

Since its first launch in 2013, YEB has become highly successful in China. In March 2018, YEB became the world's largest money market fund, managing as much as $268 billion of assets and serving over 600 million active users. Its great success also stimulated other internet companies to provide similar financial services. In January 2014, another Chinese high-tech firm, Tencent, which had a huge user base on its QQ and WeChat platforms, also rolled out its MMF called Licaitong. Over time, in response to the introduction of YEB, existing incumbents in the MMF industry, e.g., banks and broker-dealers, have also improved their products by adding T+0 fast redemption features or lowering the investment threshold. According to Buchak et al. (2021), there was a structural change in the MMF industry around the time of YEB's introduction: the ratio of MMF to household deposit was no more than 2% before 2013, but it increased dramatically to nearly 13% as of 2018Q3. This evidence suggests that the impact of FinTech on banking and the effectiveness of MPT could be even stronger than we document in this study, if we think of the whole MMF industry as a competitor for deposits in the banking system.[15]

## 4. Data and Empirical Methodology

In this section, we outline the data sources and empirical strategies. Our dataset comes from three sources: (1) the data of Yu'ebao and Alipay serving as the key variables of interest from the largest Fintech company in China-Ant Group; (2) financial data and branch network data on Chinese

[15] Xiao (2020) finds that MMFs in the US compete in the deposit market by creating liquid claims which, in many ways are similar to commercial bank deposits, yet provide higher yields. One concern for our study could be that other competing FinTech MMFs may impact the YEB fund. However, as Buchak et al. (2021) showed, YEB accounts for more than 50% of the market share for all non-bank distributed T+0 MMFs, rendering it a representative deposit-like FinTech product of the whole FinTech MMF market.

commercial banks; (3) prefecture-level (i.e., city-level) and macroeconomic data as important control variables in the empirical analyses. We also combine macro time-series data with the data from the Annual Report on the Work of Government, e.g., the real GDP growth target, to compute monetary policy shocks in China following Chen et al. (2018). Our empirical strategies, then, examine how bank-level outcomes, including loan growth rates, deposit growth rates, changes in the deposit rates, and banks' sensitivity of outcome variables to monetary policy shocks, vary across banks with varying levels of exposure to YEB.

## 4.1 Data

**Alipay data.** Our data on YEB and Alipay come from their parent company, Ant Group. Alipay was launched in 2004 and has been the leading third-party provider of online payments in China, with a market share of almost 56 percent as of 2020Q2.[16] Yu'ebao was launched in June 2013, with useful features that distinguish it from traditional MMFs, as discussed in Section 2. The proprietary dataset from Ant Group includes the city-quarter-level number of active YEB and Alipay users, as well as the total balances in the YEB and Alipay accounts. Given these data, we can compute the account penetration ratio of YEB (Alipay) as the number of active users on YEB (Alipay) divided by the local population. We also consider the penetration ratio in terms of the balance, as the amount of total balance of YEB (Alipay) divided by the local nominal GDP.

**Bank network data.** The data on commercial banks and their registered branches come from the China Banking and Insurance Regulatory Commission (CBIRC), the official regulatory authority of the banking industry in China. Before opening a new branch, banks are required to obtain CBIRC's approval. The registration form provides the name, exact address, head office name, approval date, and exit date for each bank. However, the registration dataset in CBIRC only records banks that exit the market within the most recent year. To fix the issue, we complement the registration data from CBIRC with the business information data from the National Enterprise Credit Information Publicity System managed by State Administration for Market Regulation in China to obtain the complete bank branch network data. Then, we merge this branch network dataset with the list of commercial banks and 336 prefecture- and above-level cities to calculate each bank's share in the national branch network, i.e., *branchshare*, and thus each city's relative

[16] The closest competitor of Alipay is Tencent's Tenpay which includes the company's payment software WeChat Pay and QQ Wallet, with a market share of 38.8 as of 2020Q2. Data source: Statista (https://www.statista.com/statistics/426679/china-leading-third-party-online-payment-providers/)

importance based on branch number to each bank, i.e., bank_city_weights, at the quarterly level. We remove banks without any branches from the sample.

**Bank balance sheet data.** We collect the banks' balance sheet data from WIND database (Chinese Bloomberg) and banks' official websites. The bank-level data include total assets, liability, equity, loan, deposits, liquidity assets, financial investments, wholesale funding, bond issuance, non-performing loan ratio, return on asset (ROA), net interest margin (NIM), net interest spread (NIS), the average loan rate and the average deposit rate.[17] The detailed variable definitions for bank-level data are summarized in the Appendix−List of Variables. We remove from our sample (i) banks with less than two years of data, (ii) bank-quarter observations whose deposit to liability ratio or loan to asset ratio is less than 10%, (iii) foreign banks, and (iv) privately-owned banks. The refinement leaves more than 800 banks (bank-holding companies), representing more than 95% of bank assets in China as of 2019Q4.

**City- and state-level macroeconomic data.** We obtain city-year-level macroeconomic panel data, such as nominal GDP, population, and loan balance, from China City Statistical Yearbook from 2002 to 2019. To accurately measure each city's distance to Hangzhou (the headquarter of Alipay) as an instrumental variable, we first attain the exact longitude and latitude of each city's geographical center from the database of the Distance Matrix API in Google Map Platform.[18] Given the geographical coordinates, each city's Euclidean distance to Hangzhou city is calculated using ArcGIS. The macroeconomic data, including the 7-day repo rate, come from the People's Bank of China's (PBOC) website and time-series data of China's Macroeconomy from the Fed Reserve Bank of Atlanta. The real GDP growth rate target and inflation target are from the State Council's Annual Report on the Work of Government.

Table 1 presents the summary statistics for all key variables in main regression models, including the cross-sectional regressions over 2012-2014 and 2015-2018, as well as the panel estimations from 2014Q1 to 2018Q4. The median and mean values of monetary policy shocks (MP) are both negative, suggesting that most of our sample periods are during monetary tightening.

[Table 1 here]

[17] Deposits data include eight subcategories, i.e., demand vs. time deposits, household vs. firm deposits, household demand and household time deposits, firm demand and firm time deposits. Liquidity assets include cash and reserve due from other banks, placements with banks and other financial institutions, and reverse repurchase financial assets.
[18] https://cloud.google.com/maps-platform/routes/?apis=routes

## 4.2 Key Variable Definitions

The main independent variables of interest are the commercial banks' exposure to the FinTech competition in the deposit market measured with the YEB data. Coupled with the bank branch network data, we construct a bank b's exposure to YEB at time t as follows:

$$Exp_{b,t}^{YEB} = \sum_c w_{bct} Exp_{c,t}^{YEB}, \tag{1}$$

where $w_{bct}$ is bank b's branch share in the city c at time t, and $Exp_{c,t}^{YEB}$ is city c's exposure to YEB at time t, defined as follows:

$$w_{bct} = \frac{\#Branches_{bct}}{\sum_k \#Branches_{bkt}} \tag{2}$$

$$Exp_{c,t}^{YEB} = \frac{Users_{ct}^{YEB}}{Population_{ct}} or \frac{Balance_{ct}^{YEB}}{NGDP_{ct}} \tag{3}$$

Where $NGDP_{ct}$ is the nominal GDP in city c at time t. We measure a city's or a bank's exposure to YEB from two aspects. One is from the perspective of user or account penetration ratio, and the other is defined as YEB balance penetration ratio. I, then, define a bank's exposure to Alipay as $Exp_{b,t}^{Alipay} = \sum_c w_{bct} Exp_{c,t}^{Alipay}$, where $Exp_{c,t}^{Alipay}$ is defined similarly as in equation (3). The effective distance to Hangzhou city as $dis\_HZ_{b,t} = \sum_c w_{bct} dis\_HZ_{c,t}$, where $dis\_HZ_{c,t}$ is the logarithm of city c's geographic distance to the Ant Group's headquarters in Hangzhou. Other city-level data are aggregated to the bank level similarly with bank branch weights. For the purpose of confidentiality, the data provider normalizes the raw data, e.g., the number of active user accounts and the amount of balance, to an index, using the corresponding mean value of the sample from 2013Q2 (2012Q2 for Alipay) to 2017Q4 as a benchmark. Therefore, we also normalize $Population_{ct}$ and $NGDP_{ct}$ for a city with mean values of population and normal GDP across all cities for the whole sample, respectively.

[Figure 2 here]

Figure 2 shows the YEB account penetration rate (panel A) and Alipay account penetration rate (panel B) across all prefecture-level cities in China. It is found that, there are significant variations in FinTech exposure across cities. Generally, capital cities of provinces and cities located on the southeast coast are more exposed to YEB and Alipay. If we aggregate the city-level

FinTech exposure to the bank level, Figure 3 shows that there are also huge variations in banks' exposure to YEB, both across banks within a single quarter and for all banks across different periods.

[Figure 3 here]

**Monetary policy shocks**. The specifications of the monetary policy rule and identification of its shock are crucial for investigating the transmission of monetary policy in the economy. The shifts in the PBOC's monetary policy stance in response to incoming news about inflation and GDP growth can also affect economic agents' expectations on the future evolution of the economy. If households in cities more exposed to FinTech competition are more sensitive to the monetary policy changes because of the information effect (Nakamura and Steinsson, 2018), their financial decision-making, e.g., deposit saving and loan application, might be affected, thus biasing the OLS estimates. It is, therefore, important to isolate this systematic component of monetary policy (Bernanke and Blinder, 1992). However, as the monetary policy in China is mainly quantity-based and the Chinese monetary authority takes M2 growth rate as the policy target (Chen et al., 2018), it is difficult to study MPT using high-frequency identification, as is used for the Federal fund rate in the US (Gertler and Karadi, 2015; Nakamura and Steinsson, 2018).

In the baseline analysis, we measure monetary policy shocks in China following Chen et al. (2018). They describe that the primary goal of monetary policy in China is to achieve an annual GDP growth target rather than an inflation target and that the M2 growth rate is the most important intermediate target. Although interest rate liberalization has started in recent years, it is still incomplete, and there is no official policy rate recognized by PBOC. The M2 growth target, an important monetary indicator in the annual government report, is often used to guide the government's work in the next year.[19] Chen et al. (2018) capture the monetary policy decision-making process in China as PBOC adjusts M2 growth rates every quarter in response to the inflation and GDP growth in the previous quarter. Specifically, they consider the following monetary policy rule:

$$m_t = \gamma_0 + \gamma_m m_{t-1} + \gamma_\pi(\pi_{t-1} - \pi^*) + \gamma_{y,t-1}(y_{t-1} - y^*_{t-1}) + \epsilon_t, \tag{4}$$

[19] Beginning in 1994, the State Council's Annual Report on the Work of Government specified M2 growth targets until 2018.

where m is the M2 growth rate, $\pi$ is the CPI inflation rate, $y$ is the GDP growth rate, and $\pi^*$ and $y^*$ are the growth targets for inflation and GDP set by the State Council, respectively.[20] $y^*$ denotes a lower bound for monetary policy. We estimate the equation (4) with a regime-switching approach. The monetary policy shock, i.e., MP in this paper, is calculated as the difference between the actual M2 growth rate and the endogenous M2 growth that captures the systematic expectation of M2 changes. Figure 4 presents the monetary policy shocks generated with the method in Chen et al. (2018) and the 7-day repo rate (R007). Note that there are several easing and tightening cycles in China. In our sample over 2013- 2018, periods 2013-2014 and 2016-2018 are generally the ones with monetary contraction. In general, the M2 growth rate is negatively correlated with the 7-day repo rate ($\rho = -0.464$ ), and our measure of monetary shocks (MP shock) is also negatively correlated with the change in the 7-day repo rate ($\rho = -0.191$). A fall in the exogeneous M2 growth rate represents contractionary monetary shocks.

[Figure 4 here]

We complement our analysis with the 7-day repo rate as the second monetary policy measure for robustness checks, although it may not be purely exogenous. The PBOC has emphasized that it is trying to target the 7-day repurchase (repo) rate for depositary institutions (or DR007 for short). This is the rate at which banks lend to each other over periods of seven days, similar to the Federal funds rate in the US. The PBOC uses open-market operations, including regular injections and withdrawals of liquidity, to influence DR007. For the broader financial system, including non-banks, funding costs are reflected by the 7-day repo rate (R007). This market-determined rate closely follows DR007, which indicates that banks can arbitrage between the two. We use R007 for robustness checks and in regressions when independent variables are spreads between the YEB 7-day annualized yield and the average bank deposit rates.

### 4.3 Empirical Design

Next, we examine the effects of FinTech/YEB competition on banks and MPT. To do this, we consider a variety of bank-level outcome variables, including the growth rate of loans, the growth rate of various types of deposits, the change in loan rates and different deposit rates, banks'

[20] In Chen et al. (2018), the quarterly inflation target is set at 0.875% (annual rate of 3.5%), as the monetary policy executive reports released by PBOC each quarter indicate the inflation target is around 3-4%. The real GDP growth rate is set by the central government of China.

wholesale funding cost, profitability, and risk-taking activities. The empirical design for each outcome variable is similar. When estimating the impact of FinTech that is unconditional on monetary policy shocks, we conduct cross-sectional studies with cross-section data over 2012-2014 and 2015-2018. Then, we investigate the impact of FinTech on MPT with a panel-data estimation. For the cross-sectional analysis, we estimate the following equation:

$$\Delta Y_{b,t1-t2} = \alpha + \beta log E_{b,t1}^{YEB} + X'_{b,t1}\gamma + \delta_b, \tag{5}$$

where $\Delta Y_{b,t1-t2}$ is the average annual change in the log of an outcome variable, e.g., total loans, for bank b over the period from $t_1$ to $t_2$. The key explanatory variable, $log E_{b,t1}^{YEB}$, is the log of bank b's exposure to YEB at $t_1$. The set of bank-level control variables, $X_{b,t1}$, are selected following Kashyap and Stein (2000), Jiménez et al. (2014), and Buchak et al. (2021). These bank-specific attributes are the log value of total assets (size), the ratio of bank equity to total assets (capital ratio), the ratio of total net income to total assets (ROA), the ratio of liquid assets to total assets (liquidity asset ratio), the nonperforming loan ratio (NPL ratio), the log of bank branch share (lnbkshare), and the deposit to liability ratio, as well as the level of the outcome variable at $t_1$ controlling for the mean-reversion effect as in Buchak et al. (2021). We also add into the regression model multiple bank-city-level characteristics, which involves the log of population, the log and the growth rate of GDP per capita to control for the local business cycle, e.g., loan and deposit demand, in banks' local markets following Choi and Choi (2021).

Before estimating the impact of FinTech on MPT, we first conduct a panel-data estimation to study the sensitivity of YEB spread, defined as the difference between the YEB 7-day annualized yield and the average bank deposit rate, on the 7-day repo rate. The model specification is as follows:

$$\left(YEB\ Yield_t - DepRate_{b,t}\right) = \alpha + \beta 7dRepoRate_t + X'_{b,t-1}\gamma + K_b + \tau MacroTS_t + \delta_{bt}, \tag{6}$$

where $YEB\ Yield_t$ is the average YEB 7-day annualized yield over quarter t, and $DepRate_{b,t}$ is the average annualized deposit rate in the previous year for bank b at time t.[21] $7dRepoRate_t$ is the

[21] For publicly listed banks in China, we can directly get the average deposit rate over the previous year in quarter t from quarterly financial reports. However, non-listed banks do not report average deposit rates. We compute the average annualized deposit rate as total domestic deposit expense divided by total domestic deposits, following Drecheler et al. (2017).

7-day repo rate. $X_{b,t-1}$ represent bank-level control variables defined the same as before. For the panel-data estimation, all control variables are measured with values at the end of the previous year, i.e., at time t-1. $K_b$ represents the fixed effects at the bank level, controlling for time-invariant attributes of the bank b that might impact the YEB spread, such as its ownership and the location of its head office. $MacroTS_t$ represents some macro-level variables, such as the GDP deflator inflation rate and the real GDP growth rate, as in Xiao (2020).

We, then, consider the monetary policy changes and estimate the influence of FinTech on MPT. To this end, we estimate the following equation:

$$\Delta Y_{bt} = \beta_0 + \beta_1 MP_t + \beta_2 logE_{b,t-1}^{YEB} + \beta_3 logE_{b,t-1}^{YEB} * MP_t + X'_{b,t-1}\gamma + K_b + \mu_t + \varepsilon_{bt}, \quad (7)$$

where $\Delta Y_{bt}$ is the percentage change of the bank-level outcome variables over the previous year, i.e., over quarter *t* and *t*-4, at quarter *t*. $MP_t$ is the exogeneous M2 growth rate from quarter *t*-4 to *t*, which is estimated with the above-mentioned regime-switching method in Chen et al. (2018). $logE_{b,t-1}^{YEB}$ is the log value of bank *b*'s exposure to YEB at the end of the previous year at time *t*. $X_{b,t-1}$ and $K_b$ are defined similarly as in the equation (6). $\mu_t$ are year-quarter fixed effects, controlling for seasonal and yearly time-varying macroeconomic conditions for all banks, such as fiscal policy changes. $\varepsilon_{bt}$ denotes the idiosyncratic error term clustered by banks. If, for instance, *Y* is bank lending and the coefficient on the interaction term ($\beta_3$) is positive, then lending becomes more sensitive to monetary policy shocks when a bank is more exposed to FinTech competition. A negative $\beta_3$, in contrast, suggests that when M2 growth rate declines during monetary contraction, the tightening effect on loan growth is weakened for more exposed banks, indicating a muted MPT to bank lending.

A potential concern with the OLS approach is that there could be other confounding factors affecting the MP, exposure to YEB, and banks' loan growth or deposit growth simultaneously. For example, an economic boom may increase the YEB penetration rate and bank lending, and trigger monetary policy tightening. Moreover, local business conditions may impact the YEB penetration and bank loan growth at the same time. To mitigate the concern of endogeneity, we first use the exogeneous M2 growth rate to measure MP shocks. Second, we consider lags of the FinTech exposure to alleviate the simultaneity problem. Third, we control for local business cycles in banks' local markets by aggregating city-level macro variables to the bank-level and implement a robustness check that limits our sample to "local" banks that operate predominantly within a single city, with city-level controls reflecting local demand, following Choi and Choi (2021).

In addition, we estimate the causal effect of the interaction between FinTech exposure and monetary policy shocks on banks' lending in the equations (5) and (7) using the two-stage least squares (2SLS) method. Following Hasan et al. (2023), Hong et al. (2020), and Buchak et al. (2021), we adopt as instrumental variables (IVs) for banks' exposure to YEB (i) a penetration ratio of the Alipay platform and (ii) an Euclidian distance to Ant Group's headquarter in Hangzhou city (), as well as the driving distance to Hangzhou for robustness checks. The rationale for the IV's relevance assumption for the distance is that, usually, a geographical distance plays a critical role in the interpersonal communication and information exchange of user experience, thus influencing the spread of new products and services from FinTech companies. Therefore, geographically speaking, the level of FinTech adoption is supposed to be higher for regions close to its originating place.[22] Moreover, the geographic distance is arguably exogenous and shows no direct effect on the regional economy's response to monetary policy.[23] As for the Alipay penetration ratio, the relevance condition holds since it is much easier and less costly for Alipay users to start using YEB if they have already used Alipay for other purposes. The Alipay penetration also satisfies the exclusion restriction because: (i) Alipay was introduced in 2004, before the introduction of YEB in 2013, which mitigates the concern of a simultaneity issue; (ii) Alipay is a digital payment platform and does not compete directly with bank deposits, which means a bank's exposure to Alipay only affects its deposit growth by influencing its exposure to YEB.[24] In our following empirical analysis, we show that, in general, *F*-statistics in the first stage, results of weak and under-identification tests, as well as over-identification tests all support the strong relevance and validity of these IVs (see Tables 2 and 5 for details).

## 5. Impact of FinTech on Banking

In this section, we first show how the competition from FinTech in the deposit market affects banks' deposit-taking with a cross-sectional analysis from 2012 to 2014. We find that banks more exposed to FinTech competition experience a stronger deposit outflow due to negative deposit

[22] Hong et al. (2020) find that the expansion of Alipay's financial services centers around its headquarter city and gradually penetrates nearby cities and then distant provinces.
[23] The headquarter of Alipay was established in 1999, far before the introduction of YEB in 2013.
[24] With an Alipay account, consumers still need to link their bank accounts or debt cards to Alipay for shopping.

demand shocks, mainly from the household deposit market. However, more exposed banks do not reduce loan provisions. Instead, they reduce the liquid assets and financial investments and issue more bonds to mitigate the impact of deposit losses. Then, we investigate how the impact of FinTech on banks evolves in the long-term with a cross-sectional study from 2015 to 2018. Empirical results show that, after the removal of the official deposit rate ceiling in 2015, more exposed banks experienced higher deposit and loan growth rates. Subsequently, we provide detailed explanations for the reversed effects after 2015.

## 5.1 Impact of FinTech on Banking: Evidence from 2012-2014

### 5.1.1 Impact on banks' liabilities (2012-2014)

The competition between Yu'ebao MMF and banks primarily takes place in the deposit market. We first evaluate how banks respond to the FinTech exposure in the deposit market and then extend our analysis to the asset side. YEB MMF is the best substitute particularly for retail demand deposits since it offers instant liquidity through an electronic platform oriented towards retail users. We should expect a lower growth rate of household demand deposits for banks more exposed to FinTech competition because depositors shift money from the banks to the YEB fund. In addition, YEB provides yields comparable to market interest rates, which at times are even higher than the deposit rate for household time deposits with shorter maturities, e.g., less than or equal to one year. Figure 5 presents that the average YEB 7-day annualized yield in 2014 was 4.85%, much higher than the average interest rates of household time deposits, i.e., 3.45%, indicating that YEB could also compete with retail time deposits for depositors that are more yield-sensitive.

[Table 2 here]

Table 2 summarizes the impact of FinTech/YEB penetration on household deposit growth rates from 2012 to 2014. Controlling for bank-level and bank-city-level characteristics, the point estimates of ln(exposureYEB) in all columns are negative and statistically significant, implying that more exposed banks experience lower deposit growth rates for both household demand and time deposits, consistent with our hypothesis. The substitution effects of FinTech are not only statistically significant but also economically huge. According to the estimates in column (3), a positive one standard deviation of the FinTech exposure (0.674), measured by account penetration, reduces the growth rate of household demand deposits by about 4.86% (-7.221%*0.674 = -4.86%), which is sizable compared to the sample mean of 9.88%. The reductions in the deposit growth for household time deposit and total household deposit are 3.53% (mean = 21.36%) and 3.11% (mean=17.69%), respectively, which are also economically significant.

The estimation results from the first stage regressions in Table 2 are displayed in Appendix Table A1. The instrumental variables are significantly associated with the exposure to YEB. The shorter the distance from the headquarters of Alibaba, the stronger a bank's exposure to YEB. In addition, the Alipay penetration ratio confirms to be strongly correlated with the YEB penetration, indicating that the state-of-the-art FinTech payment technology substantially facilitates the popularity of the YEB MMF. The F-statistic values from these regressions are larger than 10 (shown in Table 2), suggesting that instruments are relevant. P-values of overidentification tests in Table 2 indicate that we cannot reject the null hypothesis that all instruments are exogenous. Overall, these tests support the validity of the identifying assumptions for the 2SLS estimates.

Do the negative effects of FinTech on household deposit growth result from a drop in deposit demand or deposit supply from depositors' perspective? Next, we investigate how FinTech affects the growth of firm deposits and total deposits. First, this investigation can help determine whether the shock comes from the supply-side or demand-side. If the lower household deposit growth rate is due to a decline in deposit supply, e.g., a decreased loan demand associated with FinTech exposure that reduces banks' supply for deposits, we should expect a lower growth rate of firm deposits simultaneously assuming that banks cut back part of firm deposits with less need for deposit funding. Second, the analysis of firm deposits can serve as a placebo test. If the causal relationship identified in Table 2 is driven by YEB penetration, no significant impact of YEB on firm deposit growth rate should be found since the low investment threshold and no cash-out fee features of YEB appeal mainly to retail investors.

[Table 3 here]

Columns (3) to (8) in Table 3 show empirical results from the regression (5) for firms' total, time, and demand deposits. All the estimates of ln(exposureYEB) are not significantly different from zero, indicating no influence of FinTech on the growth rate of firm deposits. However, the impact of FinTech on banks' total deposit growth is still significantly negative, as displayed in columns (1) and (2). A positive one standard deviation increase in FinTech exposure (0.674) decreases the total deposit growth rate by 1.38% (-2.051%*0.674). The significant impact of YEB penetration on the total deposits arises from the household deposits constituting nearly half of the total deposits in China.[25]

To further rule out the possibility that there are unobserved characteristics of banks being correlated with FinTech exposure and deposit growth simultaneously, we perform another placebo test by investigating whether the FinTech exposure in 2013 can predict the deposit growth from 2010-2012.[26] If the FinTech exposure is correlated with other characteristics that can also influence the deposit growth, i.e., the shock resulting from FinTech competition is not random, some predictive power of FinTech exposure for deposit growth rates in the pre-2013 period might exist. For example, if households prefer stocks over deposits or there are stock market investors in the local cities where more exposed banks primarily operate, the FinTech exposure in 2013 could predict a lower deposit growth before 2013 if the situation does not change much over time. The empirical results presented in Table A2 in the Appendix verify that the pre-YEB deposit growth rates from 2010 to 2012 cannot be predicted by a bank's subsequent FinTech exposure. This placebo test alleviates the concern for an omitted variable bias in our estimation. Banks more exposed to FinTech exposure are not systematically different from less exposed banks in terms of other attributes apart from exposure to FinTech that can also impact their deposit growth.

#### 5.1.2 Impact on banks' assets (2012-2014)

When FinTech competition in the deposit market crowds out core deposits that serve as an important funding source for banks (Drechsler et al., 2017), will the banks cut credit provisions? If the banks cannot completely make up for deposit loss with wholesale funding due to information problems in the market for equity and corporate debt (Bernanke and Blinder, 1992), those more exposed to FinTech should be expected to contract their lending. To test this hypothesis, we estimate the equation (5) with bank loans as the dependent variable.

The estimation results are presented in column (1) of Table 4. We find that banks more exposed to FinTech competition do not reduce their loan provisions in response to the loss of deposits to YEB MMF. Instead, the empirical results displayed in columns (3) to (8) suggest that they reduce the amount of liquid assets and financial investments and issue more bonds to mitigate the impact

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[25] According to our calculation, the average ratio of household deposits to total deposits was 48% as of 2012Q4 for 258 banks in the sample from 2012 to 2014. This ratio was higher (60.5%) for the sample of rural banks back then.

[26] One such omitted variable not included in our set of control variables is the education level of depositors of banks. The more educated people prefer to invest their money in other financial assets (e.g., stocks) than to depositing it with banks. At the same time, they may be more likely to use YEB because they are more open to new technologies.

of deposit losses. This is consistent with the findings in Anderson et al. (2021), who show that global banks cut back in arbitrage positions, rather than loan provision, in response to wholesale funding dry-ups as a result of the U.S. MMF reform implemented in 2016. Unlike the unsecured wholesale funding, we focus on secured core deposit funding, but the results of banks t cutting no credits in response to a deposit loss due to FinTech competition are similar. This might be due to the fact that the average yield from loan provision services is higher than the investment in liquid assets and financial instruments most of the time. Given that the fundamentals of borrowers are not affected by YEB MMF, more banks prefer to keep the bank-firm relationships to generate more profits.

[Table 4 here]

This finding also has important implications for the debate about CBDC. A prominent argument against CBDC and neo-bank entrants is that CBDC will guide depositors to shift money from bank deposits to digital cash. As a result, those deposits no longer fund bank loans, reducing banks' lending (Bank of International Settlements, 2020). In some sense, the YEB MMF can be regarded as a form of digital currency that pays interest provided by big-tech companies.

## 5.2 Impact of FinTech on Banking: Evidence from 2015-2018

The FinTech deposit-like product crowds out bank deposits due mainly to the fact that it provides liquidity service value and marketized yield much higher than bank deposit rates. From 2012 to 2014, the rise in the Yu'ebao yield shifted the deposit demand curve (from the depositors' perspective) to the left. As long as the ceiling rate is in effect, banks could not respond directly by raising the deposit rates.[27] As a result, deposits at banks declined, which is confirmed in Section 5.1 before. However, the official deposit rate ceiling was removed in October 2015, after which banks became able to adjust their deposit rates more flexibly.[28] The removal of the official deposit rate ceiling, coupled with other measures to promote the interest rate liberalization by China's government, such as the introduction of large-denomination certificates of deposits to individuals and companies starting in June 2015, allows commercial banks to better respond to FinTech competition.

[27] There has long been a huge gap between the YEB yield and the deposit rate ceiling, as shown in Figure 1.
[28] Although deposit rates are still largely constrained by the regulator's window guidance and the market interest rate pricing self-regulation mechanism, banks have a higher degree of freedom to adjust their deposit rates, and they can also engage in regulatory arbitrage to circumvent the implicit deposit rate ceiling.

How do banks respond to FinTech competition after 2015? Does the impact of FinTech on banks after 2015 remain the same as from 2012 to 2014? If not, how can the change in the equilibrium outcome be explained? In this subsection, we explore the influence of FinTech competition on banks from 2015 to 2018. We regress changes in bank outcome variables from 2015 to 2018 on FinTech exposure as of the end of 2015 and 2013, following the equation (5). The estimation results are presented in Table 5.

[Table 5 here]

The columns (3), (5), and (7) report results for the household deposits. Assuming that banks remain unchanged in the deposit supply side, as in the case from 2012 to 2014, a crowding-out effect of FinTech on household deposits, as shown in Table 2, should also be expected. However, we find that all the coefficients on YEB exposure turn out to be positive, though insignificant in panel A and significant in panel B. It is suggested that, unlike the case before 2015, more FinTech exposure does not result in more household deposit outflows after 2015. In contrast, results in panel B show that banks more exposed to FinTech at the end of 2016 or 2013 experienced significantly higher household deposit growth from 2016 to 2018, mainly driven by the rise in household time deposit growth.

To assess the economic magnitude, we use the estimate in column (8) of panel B as an illustration. A positive one standard deviation increase in FinTech exposure (0.674), measured as of 2013, predicts a 2.15% increase in the average household deposit growth from 2016 to 2018, which is economically significant compared to the mean value of 11.59%. Recall that in Table 2 the same magnitude of FinTech exposure led to a reduction in household deposits by 3.53% from 2012 to 2014. The surprisingly reversed effects of FinTech on household deposits are suggestive of banks' endogenous responses to FinTech competition, which changes the equilibrium outcome.

How about the responses of firm deposits that YEB MMF does not directly compete with? We find another surprising result that more exposed banks experienced a higher firm deposit growth, driven by both firm time deposits and demand deposits, according to columns (9) to (14) in Table 5. Considering the impact of FinTech on household and firm deposits together, columns (1) and (2) show that growth rates of total deposits are also positively correlated with FinTech exposure. Specifically, a one-standard-deviation increase in the ln(expYEB_13) predicts a 1.52% (2.71%) rise in the average annualized deposit growth rate from 2015 (2016) to 2018, which is economically sizable relative to the mean value of 12.24% (10.60%). More deposit fundings also lead to a higher loan growth rate, as evidenced in columns (15) and (16).

In summary, FinTech competition had crowded out bank deposits from 2012 to 2014, but it induced more deposit inflows and thus higher loan growth rates after the official deposit rate ceiling was removed in 2015. This result complements the work by Buchak et al. (2021), who examine the same FinTech product−YEB MMF but focus on the period before 2015. They argue that the unprecedented size (of YEB) could bring significant liquidity but systematic risks that have yet to materialize. Given these concerns, regulators in China have begun to enhance regulations on MMFs, for example, by restricting the use of T+0 redemption and limiting the size of any single MMF. The impact of FinTech products in their early stages could be considerably different from the impact in their mature stages. By examining the long-term impact of FinTech, we show that more FinTech competition induces higher deposit and loan growth in the longer term, e.g., from 2015 to 2018, compared to its impact in the beginning.

Furthermore, our findings are consistent with the model predictions in Chiu et al. (2023), who find that, if the CBDC rate is not too high, CBDC would cause more bank intermediation by lowering banks' market power in the deposit market. The YEB MMF plays a similar role to CBDC because it can be regarded as an interest-bearing digital currency that substitutes for cash and bank deposits.[29] Therefore, YEB also threatens banks' market power in the deposit market, as CBDC does in their paper. In line with their findings, we show that YEB competition leads to more deposit and loan growth. In other words, FinTech crowds in bank intermediation in the long term, which also alleviates the concern of many regulators, e.g., Largarde (2018), who worry that FinTech may make banks less relevant in providing financial services, i.e., financial disintermediation.

## 5.3 How to Understand the Reversed Effects after 2015?

How to understand the reversed effects of FinTech on bank deposits after 2015? Theoretically, this can result from a shift of the deposit demand curve to the right or a shift of the deposit supply curve to the right, i.e., an expanding deposit supply. In this subsection, we provide evidence consistent with these two forces. We show that more exposed banks are more likely to roll out innovative deposit products and raise deposit interest rates after the removal of the official deposit

[29] we regard the YEB MMF as a near-safe instrument although the money in YEB is not actually under deposit insurance.

rate ceiling. Consequently, more exposed banks experienced a higher deposit growth rate, primarily in firm deposits and household time deposits, relative to the less exposed ones. In addition, more stringent regulations on YEB MMF after 2015 reduced depositors' demand for YEB and thus made it easier for banks to attract depositors.

### 5.3.1 Banks roll out products similar to YEB to defend

First, more exposed banks are likely to take measures to defend themselves. Buchak et al. (2021) show that banks more exposed to YEB competition are more likely to offer their own YEB-like products with market interest rates, while less exposed banks are less willing to do so, as shown in Figure A1 in Appendix. These products are usually wealth management products (WMPs), e.g., T+0 MMF, and are recorded off the balance sheet. However, the introduction of such competing products contributes to a rise in demand deposits since investors need to deposit their money at banks first before their money gets transferred to WMPs and, when they withdraw money from these WMPs, the money goes back to demand deposit accounts. This can shift the supply curve of deposits to the right, offsetting the original impact of YEB MMF.

Second, in addition to offsetting the loss of depositors influenced by YEB, banks attract other depositors that were not impacted by YEB in the first place, which contributes to a net deposit inflow. For example, we find a rise in the growth rate of firm demand deposits (likely attracted by WMPs in banks but not affected by YEB before) and household time deposits (likely attracted by smart deposits and structured deposits that pay higher interest rates than common term deposits with a similar maturity). The rise in firm demand deposits can be attributed to the improvement in deposit quality. Note that Bao-like products offered by more exposed banks are not only open to retail depositors but also available to firms. Given the improvement in the quality of firm deposits, the supply curve of deposits shifts rightwards, outweighing the original shift to the left due to YEB competition and resulting in deposit inflows.[30]

### 5.3.2 Banks raise deposit rates higher and engage in regulatory arbitrage

On top of the improvement in deposit quality by introducing innovative time deposit products, the rise in firm and household time deposits could also arise from an increase in deposit rates. Table 6 presents the empirical results of the panel-data estimation by regressing the deposit and

[30] One way to improve the quality of firm demand deposit is to link deposit accounts to a MMF with T+0 redemption option provided by a fund company that corporates with a bank.

loan interest rates on FinTech exposure. After controlling the bank-level, bank-city-level characteristics, and bank and year-quarter fixed effects, the result with the IV approach in column (2) shows that a one-standard-deviation (0.9) increase in the FinTech exposure raises the average total deposit rate by 27 bps, more than one half of the standard deviation of the average total deposit rate, i.e., 49.75 bps. As the demand deposit rates barely vary over time for all banks (see Figure 5), the rise in average deposit rates for more exposed banks is primarily driven by increased interest rates on time deposits. In contrast, columns (3) and (4) show that more exposed banks lower their loan interest rates, rather than transferring the increased funding costs to borrowers. This can be explained by more intense competition in the loan market after the removal of the 75% cap on the loan to deposit ratio (LDR) in June 2015. Another possible explanation is that more exposed banks become more prudent when issuing loans with a rising funding cost and roll-over risk in the deposit market (Acharya et al., 2021). Figure A2 in the Appendix shows that LDR for the whole banking system keeps increasing after 2015 and surpasses 75% after 2019. With the removal of the 75% cap, banks have incentives to issue more loans and take more deposits. We find that more exposed banks take more deposits by raising the deposit rates and issuing more loans with lower loan interest rates.

[Table 6 here]

Increased credit supply justifies the willingness to raise the deposit rate for more exposed banks. However, one may still wonder how banks are able to raise the time deposit rate under the implicit deposit rate ceiling imposed by the self-regulatory mechanism. Next, we show that more exposed banks can actually circumvent the implicit rate ceiling by engaging in regulatory arbitrage and offering innovative time deposit products to attract more depositors.

For instance, many banks in China have rolled out "smart deposits" products, which are fixed-term deposits for 1-5 years that permit withdrawal in advance by investors, while still providing high returns calculated based on tiered annual rates (i.e., higher interest rates are provided for lengthier deposit periods). Moreover, an increasing number of banks are using structured deposits (SDs) improperly as a covert means of providing higher returns to clients.[31] The SDs working as time deposits are reported as wealth-management products subject to no implicit restriction on the

[31] Indeed, many SDs are "fake" SDs with unrealistic features. For example, the product introduction of one SD in China Minsheng Bank states: "In the next 6 months, the yield rate will be 3.7% if the price of gold does not change by more than $500 compared to the current price; otherwise, the yield rate will be 1.55%."

deposit rates.[32] Figure A3 shows the ratio of the SDs to total deposits from 2011 to 2019.[33] The ratio rises tremendously after 2017, especially for SMBs.[34] Although these regulatory arbitrage activities in the deposit market after 2015 have caught the attention of the CBIRC, banks more exposed to FinTech competition are still allowed to expand their deposit supply by offering deposit rates that are even higher than the upper limit imposed by the self-discipline mechanism.[35]

Another piece of evidence in support of the rising interest rates relates to the deposit rate ceiling for 1-year time deposits.[36] Figure 5 shows that the average household time deposit rate traces the ceiling of the 1-year time deposit rate quite closely before 2015. However, it exceeds the implicit ceiling imposed by the self-regulatory mechanism and becomes closer to the R007 after 2015. This is suggestive of an overall increase in household time deposit rate after 2015, even under the implicit deposit rate ceiling, probably due to the innovative deposit products discussed above.

Finally, the two groups of depositors that banks lose to YEB and attract after they catch up may not be very alike. When the YEB yield is much higher than bank deposit rates in the beginning, it is possible that younger and less risk-averse depositors shift more money from banks to YEB since they prefer online shopping with digital payments. However, as banks provide higher term deposit rates and better time deposit products, they start to attract more conservative depositors who trust banks more and care not only about returns but also risks. Therefore, for banks more exposed to FinTech, although they lose some younger depositors to YEB, they could still attract more conservative depositors who shift money from other assets, e.g., the stock market, to bank time deposits because of the risk-return trade-off, resulting in net deposit inflows for banks more exposed to FinTech competition.

[32] An investment in a SD is composed of two parts, one risk-free part, which is counted as a term deposit, while the other part, linked to the price of stocks, commodities, etc., is not considered as a deposit due to the risk-bearing nature.
[33] Unfortunately, most banks do not report the amount of SDs explicitly in financial reports; therefore, we cannot formally test how FinTech affects the growth of SDs. Here, we show overall time-series evidence for large banks and SMBs.
[34] In unreported results, we show that FinTech promotes the growth rate of time deposits more for SMBs relative to big banks from 2015 to 2018.
[35] See the news from Reuters, May 2019, "China cracks down on high-interest rate deposit schemes: sources" (https://www.reuters.com/article/us-china-banks-idINKCN1SS0I6) and Moody's analytics, Oct 2019, "CBIRC notice on regulating structured deposit business of banks" (https://www.moodysanalytics.com/regulatory-news/oct-18-19-cbirc-notice-on-regulating-structured-deposit-business-of-banks).
[36] The ceiling after Oct 2015 is the self-regulatory upper limit of 1 year time deposit imposed by the self-regulatory mechanism.

### 5.3.3 More stringent regulations on the money market fund

The empirical results in the previous subsection 5.3.2 suggest that more exposed banks expand deposit supply to compete with YEB MMF. In addition to the expansion of deposit supply, the demand curve of banks' deposits could also shift rightward due to several regulatory changes, compared to the case before 2015 after the introduction of YEB. For example, in October 2017, Chinas Securities Regulatory Commission (CSRC) issued regulations requiring MMFs to be unavailable to any single borrower and assets with lower credit ratings: "Chinese MMFs must not hold cash deposits, bonds or other assets from a single bank worth more than 10% of that bank's net assets, and assets from a single institution must not exceed 2% of an MMF's net assets".[37]These regulations forced YEB MMF to lower yields and thus reduced the attractiveness of YEB relative to bank deposits.

In addition, in 2018, CSRC set rules to limit instant redemptions of withdrawals, which lets individual investors get cash no more than 10,000 yuan ($1,560) from a single money market fund on the same day.[38] This regulation aims to curb the feverish growth of China's MMF market, prevent liquidity risks in extreme market conditions, and eliminate the threats to cause systemic instability. As YEB was the largest MMF in China, the rule lowered YEB's liquidity service value. Overall, the regulations mentioned above shifted banks' deposit demand curve to the right by reducing YEB's yield and liquidity value, although they targeted the whole MMF industry. Combined with the expansion of deposit supply, the rightward shift in deposit demand makes it easier for more exposed banks to attract depositors, compared to the case before 2015.

## 6. Impact of FinTech on Monetary Policy Transmission: Evidence

In the previous Section 5, we showed that FinTech competition in the deposit market had crowded out bank deposits in the beginning but induced more deposit inflows since the official deposit rate ceiling was removed in 2015. This section continues to explore how FinTech competition impacts MPT in bank lending.

[37] See "China regulators target 'systemic risk' from money-market funds" reported by Financial Times, Sep 4. 2017. Link: https://www.ft.com/content/c145a75a-9136-11e7-a9e6-11d2f0ebb7f0

[38] See "China steps up regulation of fast-growing money market funds" reported by Thomson Reuters, June 1, 2018. Link: https://www.reuters.com/article/us-china-funds-moneymarket/china-steps-up-regulation-of-fast-growing-money-market-funds-idUSKCN1IX4FZ

We propose two possible hypotheses relating to two opposite scenarios. Firstly, according to the deposit channel (Drechsler et al., 2017), the competition from FinTech/YEB could strengthen deposit outflows in periods of monetary tightening since liquid deposits become relatively less attractive, especially when households can substitute bank deposits for YEB that provides both liquidity value and high yields. If banks cannot completely make up for deposit loss with wholesale funding due to information problems in the market for equity and corporate debt (Bernanke and Blinder, 1992), the banks more exposed to FinTech are expected to contract more of their lending in response to monetary tightening, implying that FinTech strengthens MPT via bank lending.

Second, according to the findings in Section 5.2, more exposed banks endogenously roll out their innovative deposit products and raise deposit rates higher to attract more depositors in response to intense FinTech competition during monetary tightening. These actions can offset the original impact of YEB competition and even attract depositors that are not affected by YEB, e.g., institutional depositors, in the first place. This results in smaller deposit and credit declines in periods of monetary contraction, mitigating the effectiveness of MPT.

To test these two hypotheses, we first analyze how the price and quantity of YEB MMF and commercial bank deposits change with the 7-day repo rate and show that FinTech competition is more intense during monetary tightening. Next, we proceed to examine MPT by estimating the equation (7) and differentiating between periods before and after 2015. The main findings support the second hypothesis, indicating that FinTech mitigates the effectiveness of MPT.

## 6.1 The Substitution Effect of FinTech During Monetary Tightening

[Figure 5 here]

Figure 5 plots the 7-day repo rate, the average bank deposit rate, the average household demand and time deposit rates, and the 7-day annualized yield of the YEB fund over 2005-2019. We find that the spread between the YEB yield and the average deposit interest rate widens in periods of monetary tightening. The effect is economically significant. For example, during the 2016Q1-2018Q2 tightening cycle, the M2 growth rate decreased from 12.7% to 7.9%, the 7-day repo rate increased from 2.47% to 3.42% (95 bps), and the difference between the YEB yield and the deposit rate increased from 0.97% to 1.91% (94 bps). The increases in YEB spreads were larger for household demand deposit rate (120 bps) and smaller for household time deposit rate (78 bps).[39] As the transaction convenience of bank deposits is relatively stable over time, such big changes in relative yields may significantly affect depositors' choice between YEB and bank deposits.

Specifically, we regress YEB spreads for different deposit products on the 7-day repo rate, controlling for macroeconomic variables, such as real GDP growth rates, inflation, bank characteristics, and bank fixed effects. Table 7 presents the relevant empirical results. Consistent with the graphical analysis, a 1% increase in the 7-day repo rate is associated with a 0.9% increase in the difference between YEB yield and the average deposit rates. The spread sensitivity for the difference between YEB yield and household time deposit rates was still high, i.e., 0.64.

[Table 7 here]

Do the widening YEB spreads lead to a stronger crowding-out effect? The top panel of Figure 6 plots R007 and the annual percentage growth rates in the aggregate amounts of total deposits, total demand deposits, and household time deposits. Consistent with conventional wisdom (Drechsler et al., 2017), a higher R007 is associated with a lower growth rate in commercial bank deposits, and the negative correlation between R007 and demand deposit growth rates gets stronger.[40] However, the bottom panel of Figure 6 shows a significant positive correlation ($\rho$=0.53) between the 7-day repo rate and the growth rate of the YEB fund. These results reveal that during monetary tightening, more funds are reallocated from retail deposits (mostly demand deposits) to YEB MMF since the latter provides a higher market-competitive yield than retail deposits, conforming with the substitution of retail deposits for alternative money-like assets (e.g., MMFs) in the US (Choi and Choi, 2021; Xiao, 2020).[41] Also, note that when R007 and the growth rate of YEB fund rise during monetary tightening, the growth rate of household time deposit also rises after 2015 (e.g., from 2016Q1 to 2018Q2). This suggests that, even when more households invest

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[39] The deposit rates are the average deposit rates across all banks in the sample. When computing YEB spreads, to be consistent with the timing of the YEB yield, we lag the deposit rates by two quarters since the average deposit rates are measured over the past year, rather than the deposit rates in the current quarter.

[40] The correlation between 7-day repo rates and growth rates of total deposits (demand deposits) is -0.53 (-0.71) from 2007Q1 to 2019Q4.

[41] Choi and Choi (2021) find that the yield spread between MMFs, and bank deposits increases when the policy rate increases, leading to substitution between money-like assets: funds are reallocated from retail deposits to MMFs during tightening, shifting the supply curve of retail deposits to banks upward.

in YEB MMF after 2015 as R007 increases, the household time deposit also becomes more attractive, reaffirming the evidence provided in Section 5.3.2.[42]

[Figure 6 here]

## 6.2 Impact of FinTech on Monetary Policy Transmission via Bank Lending

Next, we examine the impact of FinTech on MPT. The panel-data estimation results for the equation (7) are illustrated in Table 8. We regress the changes in banks' lending on the FinTech exposure and its interaction with the monetary policy shocks. Columns (1) to (6) show the results when the FinTech exposure is measured by the YEB balance penetration ratio, while columns (7) to (12) display the results with the YEB account penetration ratio. The estimation results using two FinTech measures are similar to each other. Specifically, we find no significant effect of FinTech penetration on banks' loan growth rates in most columns. However, the interaction terms of the monetary policy shock and FinTech exposure are significantly negative in almost all specifications, suggesting a weakening effect of FinTech on MPT via bank lending.

[Table 8 here]

To gain a better understanding of the economic magnitude of these estimates, we focus on the 2SLS estimate in column (12), controlling for various types of fixed effects (e.g., bank fixed effects and year-quarter fixed effects), bank-level and bank-city level characteristics, and the initial level of total loans (to control for mean reversion channel). In response to a one-percentage-point fall in M2 growth, the loan growth rate of a bank at the 75$^{th}$ percentile of YEB account penetration (0.562) is 2.15% (-1%*(-1.949)*1.1035) higher than a bank at the 25$^{th}$ percentile (-0.541). The extra increase or less decline in loan growth associated with FinTech exposure is 1.56% for YEB balance penetration. These numbers are economically meaningful compared to the average loan growth rate across banks, which is 14.7% in the sample period.

**First Stage and Identifying Assumptions.** The first stage of the 2SLS estimations, along with the standard hypothesis testing for over- and under-identifications with multiple endogenous regressors, support the validity of the identifying assumptions. Table A3 reports the first-stage estimation results associated with the specification for bank lending in column (6) of Table 8. As

[42] Before 2015 (e.g., from 2013Q1-2015Q1), the growth rate of household time deposit declined when the YEB spread rose because YEB MMF crowded out household time deposits with the deposit rate ceiling being effective.

one would expect, the coefficients on instrument variables, including interacted instruments, are generally statistically significant. Tests for weak, under, and over-identification are summarized in the bottom panel of Table 8. With multiple endogenous regressors, two separate tests are conducted to detect weak and under-identification. The under-identification refers to a zero correlation between the instruments and the endogenous regressors. Since standard errors are clustered at the bank level, the heteroskedasticity-robust Kleibergen-Paap Lagrange multiplier is the appropriate test statistic for the assessment if the instruments are correlated with the endogenous regressors. The under-identification is rejected at the 1% level. Testing for weak identification is also important as nonzero but weak correlations between the instruments and endogenous regressors could bias the 2SLS estimates significantly towards their OLS analogs. The null hypothesis of this test is that the maximal bias due to instrument weakness exceeds 10%. Results in Table 8 show that Kleibergen-Paap Wald statistic and Cragg-Donald Wald statistic are both larger than the 5% critical values for the CD Wald statistic (Stock and Yogo, 2005), which recommends the rejection of a weak identification at the 5% level. Moreover, the overidentification tests suggest we cannot reject the null hypothesis that all instruments are exogenous. Overall, these tests confirm the validity of these instruments.

## 6.3 Robustness Checks

**Local Banks.** A key challenge in identifying the causal effect of FinTech exposure on lending in response to monetary contraction is disentangling the credit supply expansion from the changes in credit demand. If the economic conditions driving FinTech penetration ratio also impact loan demand, the OLS estimates can be biased. In addition to addressing this concern using an instrumental variables approach, we control city characteristics, such as population, GDP growth rate, and GDP per capita, to capture the local business cycle in the baseline regressions following the literature (Choi and Choi, 2021; Buchak et al., 2021). However, these city-level control variables are aggregated to bank-level weighted by banks' local branch shares. One might still worry that the weighted bank-city controls are less effective, especially for banks operating in multiple cities. To mitigate this concern, we limit our sample to "local" banks that operate mainly in a single city so that our bank-city-level controls better capture the economic environment facing banks. Following Choi and Choi (2021), we define a bank as "local" if more than 70% of its branches are located in one city.[43] Columns (2) and (8) report the estimation results using local banks only and controlling for city characteristics. The estimated coefficients on $logE_{b,t-1}^{YEB} * MP_t$ in the equation (7) are still negative and statistically significant, consistent with the baseline regressions. The banks more exposed to FinTech competition are still found to be increase their loan supply, controlling for time-varying local loan demand.

[Table 9 here]

**Additional Controls.** Columns (4) and (10) in Table 9 add additional controls to baseline regressions. Following Jiménez et al. (2014) and Buchak et al. (2021), in addition to bank size, equity to asset ratio, and liquidity, we also control for other bank attributes, such as profitability (e.g., return on assets), riskiness (e.g., non-performing loan ratio), market power (e.g., branch share), and liability structure (e.g., the ratio of deposit to liability). All control variables are measured as of a year ago to mitigate simultaneity problems. The main results are very robust with additional controls. We further augment the baseline specification by interacting all the bank-level and bank-city-level control variables with the monetary policy shock. Results are displayed in columns (5) and (11) in Table 9. Given the inclusion of these additional interactions, the robustness of the coefficients on the interaction of YEB penetration ratio and the MP shock and their statistical precision suggests that the main results are not spuriously driven by these other determinants of loan growth.

**Other Robustness Checks.** According to Table 9, the results of the baseline models in Table 8 are also robust to (i) using the log level of total loans as the dependent variable (columns 1 and 7); (ii) alternative measurements of IVs, such as the driving distance to Hangzhou (columns 3 and 9); (iii) employing the exogenous M2 growth in the previous year to measure the monetary policy shock as in Chen et al. (2018) (columns 6 and 12).

## 6.4 Heterogeneous Effects

Next, we explore several sample splits to analyze whether baseline results in Table 8 differ across different periods (e.g., before and after 2015) to account for the influence of regulatory changes in

[43] Among 829 banks in the sample, 741 of them (89.4%) are local banks as of 2013Q4 according to this definition.

2015 in the banking system and across bank attributes, such as size and ownership. The main findings regarding heterogeneity are presented below.

**Before and After 2015.** Based on Table 8, we find that more exposed banks experience a smaller credit decline during monetary tightening. This result is consistent with the second hypothesis. However, there might be other possible explanations. If the smaller declines in loans are due mainly to increased deposit fundings for more exposed banks, we should expect muted MPT via bank lending to be significant mainly during periods after 2015, based on the discussion in Section 5.3. To explore the impact of regulatory changes in 2015 on the effect of FinTech on the sensitivity of bank lending to monetary policy shocks, we split the sample into two periods, before and after 2015 periods. Estimation results are presented in panel A of Table 10. We find that the estimated coefficients on $logE_{b,t-1}^{YEB} * MP_t$ remain positive, though insignificant for the period before 2015. This result is consistent with the strengthening effect of FinTech on MPT when FinTech competition facilitates deposit outflows from the banking system through the deposit channel (Drechsler et al., 2017). The insignificant estimate could be due to the finding in Table 4: banks do not cut lending in response to deposit losses. The estimate of $logE_{b,t-1}^{YEB} * MP_t$ turns to be significantly negative for the period after 2015, in line with the baseline results in Table 8. This finding suggests that the regulatory changes in 2015 can play a critical role in generating a muted MPT via bank lending. The second hypothesis still holds that banks' endogenous responses to deal with FinTech competition attract more deposits lead to a smaller credit decline in the periods of monetary contraction.

[Table 10 here]

**Banks in YEB's Whitelist.** Note that some of the retail deposit outflows to YEB MMF re-enter the banking sector as wholesale funding and negotiable term deposits.[44] If banks more exposed to YEB penetration are those into which the YEB fund manager invests most of the money, the overall effect of YEB on banking and banks' responses to monetary policy shocks can be distorted. To address this concern, we split the sample based on whether a bank is on YEB's "whitelist" and repeat the baseline regression for two subsamples, respectively. How to identify banks on the

[44] As of 2019Q4, according to the annual report of Tianhong Yu'ebao MMF, nearly 60% of YEB funds are invested in so-called negotiable term deposits, meaning the money returns to the banking system, while other 40% of funds are invested in the wholesale funding market and bond market. See: http://pdf.dfcfw.com/pdf/H2_AN202004241378540578_1.pdf

whitelist? Dengfeng Wang, the manager of the YEB fund at Tianhong Asset Management Co., stated in some interviews that: "I've created a whitelist of banks we feel comfortable to lend money to, based on their sizes, financial indicators, reputation, etc. … the 29 banks on the white list approved by the regulatory authorities, including big state-owned banks and a dozen large joint-stock banks. We don't consider small- and medium-sized city commercial banks and rural commercial banks." I, therefore, define a whitelist of banks as those with the top 29 asset levels as of 2013Q4.[45] Panel E of Table 10 presents the estimation results. We find that muted MPT is significant for banks not on the whitelist, and, thus, it is not driven by banks that can obtain more funding when money in the YEB fund re-enters the financial system.

**Bank Ownership and Size.** One distinctive characteristic of China's banking system is the division between state-owned and non-state-owned commercial banks. There are six state-owned banks (SOBs) controlled and protected directly by the central government.[46] The remaining commercial banks are nonstate banks (nSOBs), including twelve joint-stock commercial banks (JSCBs), 133 city commercial banks (CCBs), and more than 3,800 rural banks (e.g., rural commercial banks, village banks, rural cooperative banks, and rural credit cooperatives).[47] Nonstate banks as a whole represent half the size of the entire banking system. Due to their reputation and well-developed branch network across the entire country, SOBs have gained a significant market power in the deposit market, and they might be less sensitive to FinTech competition during monetary tightening. In contrast, small- and medium-sized local banks, such as a majority of city and rural commercial banks, could be more severely impacted by FinTech, especially when they cannot easily get access to wholesale funding in periods of monetary tightening. Therefore, we split the whole sample based on banks' ownership. Specifically, we divide banks into several different subsamples: (1) rural banks versus non-rural banks; (2) SOBs

[45] See https://www.bloombergquint.com/china/china-s-biggest-money-fund-is-bracing-for-more-liquidity-shocks and https://m.yicai.com/news/3556559.html for related news.
[46] The six big state-owned banks include Industrial and Commercial Bank of China, the Bank of China, the Construction Bank of China, the Agricultural Bank of China, the Bank of Communications and Postal Savings Bank of China.
[47] The calculation is based on the list of financial institutions in the banking industry as of 2020Q2 issued by China Banking and Insurance Regulary Commission. We exclude the foreign banks.

versus non-SOBs; (3) CCBs/rural banks versus SOBs and JSCBs. We also split banks into big banks and small banks according to a bank's asset level.[48]

The estimation results with subsamples are displayed in panels B to E of Table 10. We find that the mitigating effect of FinTech on the sensitivity of bank lending to monetary policy shocks is mainly driven by non-state-owned banks and SMBs, such as city commercial banks and rural banks. We further interact the MP*ln(expYEB) with a time dummy, indicating periods after 2015, to investigate whether these heterogenous effects would be influenced by regulatory changes in 2015. Results summarized in panel G reveal that, for those banks more sensitive to FinTech exposure during monetary tightening, e.g., rural and city commercial banks, non-SOBs, and SMBs, the negative impacts of FinTech on MPT are significant only after 2015. On the contrary, for the periods before 2015, the estimated coefficients of MP*ln(expYEB) in all columns in panel G are positive and are statistically significant for rural banks (column 1) and risky banks (column 6).[49]

Overall, these results suggest that, in response to FinTech exposure, banks had shown a tendency to cut their credit supply before 2015 but increase it after 2015 in periods of monetary tightening. This reversal could be related to important regulatory changes in the banking system in 2015 and was more pronounced for non-state-owned banks, such as city commercial banks and rural banks, SMBs, and riskier banks.

## 6.5 Aggregate Effects at the City Level

Does FinTech affect the monetary policy transmission in the aggregate? we answer this question by investigating the impact of FinTech on the responses of real GDP growth and bank loan growth to monetary policy shocks. Specifically, we consider a simple panel-data regression and regress the year-over-year growth rates of real GDP and bank loans on contemporaneous monetary policy shocks at the city level.[50] Results presented in panel A of Table 11 show that the responses of the real GDP growth (bank loan growth) on contemporaneous monetary policy shocks for more exposed cities are about one-third (two-third) of that for less exposed cities, which is consistent with the muted MPT due to FinTech competition documented with bank-level evidence. Then, we

[48] A big bank is defined as a bank with assets of more than CNY 4 trillion (US$ 615 billion) according to the classification standards for financial institutions issued by the National Bureau of Statistics in China in 2015.
[49] A risky bank is defined as a bank with a non-performing loan ratio higher than the sample median as of 2013Q4, following Berger et. al. (2017).
[50] we also include lags of MP shocks in this panel-data regression and find that the results, which are unreported here, remain qualitatively robust.

divide the sample of more and less exposed banks further based on the cut-off year, i.e., the year 2015, and find that the muted responses of bank loan growth to monetary policy shocks are mainly driven by more exposed cities after 2015 (see the column 1 in panel B of Table 11). This city-level finding is consistent with the fact that FinTech started to crowd in bank intermediation only after 2015. Overall, the city-level results confirm that the muted MPT due to FinTech competition at the bank level is also significant in aggregate.

[Table 11 here]

## 7. FinTech and Monetary Policy Transmission: Mechanisms

In section 6, we document a causal relationship between FinTech competition and the sensitivity of bank lending to monetary policy shocks. We find a mitigated monetary policy transmission to bank lending when banks are under competitive pressure from FinTech penetration. In this section, we comprehensively investigate potential mechanisms behind this causal relationship.

### 7.1 Evidence for "Catfish Effect" Channel

The first possible channel through which FinTech exposure can affect the sensitivity of bank lending to monetary policy shocks is related to the second hypothesis proposed in Section 6. There are several distinctive features of this channel. First, in response to more intense FinTech competition in the deposit market during monetary tightening, more exposed banks would endogenously roll out their own innovative deposit products to compete with YEB. Second, they raise deposit rates to a higher level to attract more depositors. In either case, the introduction of innovative products as well as the increased deposit rates not only offset the original impact of YEB but also attract more depositors that were not directly affected by YEB in the first place. This results in smaller deposit and credit declines in periods of monetary contraction, mitigating the effectiveness of MPT. We call this channel the "catfish effect" channel (Zhang et al., 1996), a term used in the literature of human resource management, which suggests that the arrival of a strong competitor encourages "weaker" players to innovate and better themselves.[51] One famous example of the catfish effect is Tesla in the auto sector.

[51] "Catfish effect" comes from an old story in Norway. In old days, sardines were popular, and the alive ones sold at a higher price. However, it was not easy to keep them alive, as they would mostly end up dead while traveling back to a port. A fisherman came up with the idea of keeping a catfish in the sardine tank. While sardines were expected to be eaten, it actually increased their chances of survival to the port as they struggled to live.

Turning to our case, deposit-like FinTech products, such as YEB, become the catfish to banks' sardines, forcing the established financial institutions to engage more in "defensive" innovations, offer innovative products, improve deposit features, and raise interest rates of deposits to avoid losing customers facing their competition. Overall, due to this catfish effect, deposits provided by more exposed banks are more attractive relative to those offered by less exposed ones. Next, we provide more empirical evidence in support of this channel. First, we show that more exposed banks also experience a smaller deposit decline during monetary tightening, and this result is only significant after 2015. Second, in addition to deposit growth, more exposed banks also raise the deposit rates more during monetary tightening.

### 7.1.1 Monetary Policy Transmission via Bank Deposits Growth

We explore the impact of FinTech on the sensitivity of bank deposits to monetary policy shocks by estimating the following equation (8):

$$\Delta\log\,(Deposits)_{bt} = \beta_0 + \beta_1 MP_t + \beta_2 logE^{YEB}_{b,t-1} + \beta_3 logE^{YEB}_{b,t-1} * MP_t + X'_{b,t-1}\beta + K_b + \mu_t + \varepsilon_{bt}, \quad (8)$$

where the dependent variables are the year-over-year growth rates of various types of deposits in bank b in year t. The coefficient of interest is $\beta_3$. In response to a drop in demand for deposits, if banks remain inactive on the deposit supply side, we expect $\beta_3$ to be positive in response to contractionary monetary policy shocks that raise the YEB yield and shift the deposit demand curve downward further. On the contrary, a negative estimate of $\beta_3$ could be indicative of an expanding supply of deposits.

[Table 12 here]

Column 1 in panel A of Table 12 presents the estimation results of the equation (8) for the growth rate of total deposits. We find that the estimate of $\beta_3$ is negative and statistically significant. For a 1% fall in M2 growth, a bank at the 75$^{th}$ percentile of YEB account penetration experiences a 4% larger increase in deposit growth relative to a bank at the 25$^{th}$ percentile. This number is economically significant in comparison to the average deposit growth rate across banks, which is 12.7% during the sample period. As shown in column (10), this result is robust if we restrict the sample to local banks to better control the local business cycle.

Furthermore, we split the entire sample into two periods, i.e., before and after 2015, to explore the impact of regulatory changes. Results displayed in column (1) of panels B and C show that the increased deposit growth during monetary tightening was significant only after 2015 for more exposed banks. Before 2015, the estimated coefficient of $\beta_3$ was positive, though not statistically significant.[52] These results suggest that FinTech competition tended to promote deposit outflows from the banking system before 2015 but induced banks to supply more deposits to depositors after 2015. The reversal in the effect of FinTech on the sensitivity of banks' deposit-taking to monetary policy changes is consistent with the reversed MPT via bank lending, as shown in Section 6.4.

We also explore the heterogeneous effects across different types of deposit products. Columns (2) to (9) in panel A of Table 12 report the estimation results for the full sample period. Several interesting results merit a discussion. First, banks more exposed to FinTech competition significantly increase their supply for time deposits, especially the household time deposits. Second, on top of the direct impact of YEB on household deposits, we find an indirect effect of YEB penetration on the response of firm deposits to monetary policy shocks. Columns (7) to (9) in Table 12 indicate that more exposed banks experience a higher growth rate in firm deposits, due primarily to the firm demand deposits during monetary tightening. Third, the mitigating effects of FinTech on the responses of deposits to contractionary monetary policy shocks are significant only after 2015, suggesting an important role of regulatory changes in 2015 in shaping banks' incentives to supply deposits. Table A4 in the Appendix reports the results of robustness checks when the FinTech exposure is measured by YEB balance penetration. All results are similar to those in Table 12. In column (6) of panel B, the estimate of $\beta_3$ is significantly positive, which is consistent with a stronger substitution effect of YEB for household demand deposits in response to monetary contraction.

In Section 6.4, we show that the mitigating effect of FinTech on the sensitivity of bank lending to monetary policy shocks is mainly driven by non-SOBs, SMBs, and banks not on the whitelist. If the rise in the level of credit supply during monetary tightening results from the deposit supply expansion for more exposed banks, a similar heterogeneous pattern for deposit growth should be observed. Indeed, we find that this is the case. Panel D in Table 12 presents results of similar heterogeneity tests as in Table 10. Consistent with the main findings regarding bank lending, the weakened effect of monetary tightening on deposit outflows exists only in non-SOBs, CCBs and rural banks, SMBs, and banks not on the white list.

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[52] The insignificant estimate of $\beta$ is probably due to the limited sample size before 2015.

### 7.1.2 Monetary Policy Transmission via Bank Deposits Rates

The above results indicate that muted MPT via bank lending on the asset side is closely related to muted MPT via bank deposits on the liability side. To further justify the catfish effect from the perspective of the deposit's price, we investigate how FinTech affects the responses of deposit rates to monetary policy shocks by estimating the following equation:

$$\Delta Deposit\ Rate_{bt} = \beta_0 + \beta_1 MP_t + \beta_2 logE^{YEB}_{b,t-1} + \beta_3 logE^{YEB}_{b,t-1} * MP_t + X'_{b,t-1}\beta + K_b + \mu_t + \varepsilon_{bt}, \quad (9)$$

where the dependent variable is the year-over-year change in the average deposit rate. We estimate the equation for the rates of total deposits, time deposits, and demand deposits. The estimation results are presented in Table 13. According to column (1), for a 1% fall in M2 growth, a bank at the 75th percentile of YEB account penetration experiences an additional 6.8 bps increase in the change of the average deposit rate relative to a bank at the 25th percentile, making up a one-quarter of one standard deviation of $\Delta Deposit\ Rate_{bt}$ over the entire sample, which is 29 bps. The additional increase in the deposit rate through a similar calculation for the time deposit (demand deposit) is 13.65 bps (2.9 bps), much larger (smaller) than that of the total deposits. This marginal effect of YEB penetration on the deposit rate change for time deposit is equivalent to a drop of M2 by 2%, according to column (4).

As a robustness test, we also consider the change in the 7-day repo rate as a measure of monetary policy shocks and conduct a similar regression.[53] Columns (7) and (8) show that a 1% increase in the 7-day repo rate is associated with a 32.8 bps increase in the average deposit rate and that a bank at the 75th percentile of YEB penetration experiences an additional 5.1 bps increase in the change of the average deposit rate relative to a bank at the 25th percentile, which is about 15.5% of the increase in the deposit rate due to a 1% rise in R007. Overall, these results imply that the average deposit rate rises more for more exposed banks during monetary tightening.

[Table 13 here]

How does the impact of FinTech on the sensitivity of deposit rate changes to monetary policy shocks vary across different deposit products and periods? Table A5 reports the regression results of the equation (9) for the firm and household deposits and for periods before and after 2015.

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[53] The estimate of $\beta_3$ in this regression could be biased because the change in the 7-day repo rate may be endogenous. To mitigate this concern, we also use the exogenous M2 growth rate as an instrument for the change in R007 and find very similar results. The estimates of $\beta_1$ and $\beta_3$ are 4.44 and 32.39, repectively, and are both statistically significant.

Consistent with the results in Table 13, panel A shows that the rise in deposit rate for more exposed banks during monetary tightening relative to less exposed ones is mainly driven by the increase in the firm demand deposit rate and the household time deposit rate. In addition, panel B reveals that the positive impacts of FinTech penetration on banks' deposit rates during monetary tightening are large and significant only after 2015, suggesting that more exposed banks only raise their deposit rates after the removal of the explicit deposit rate ceiling in 2015.

Considering the results regarding the deposit quantity and the deposit rate together, we show that, in periods of monetary contraction, both the deposit growth rate and the change in the deposit rate rise more for more exposed banks relative to less exposed ones. The fact that deposit prices (inversely correlated with the deposit rate) and quantities move in opposite directions indicates that, during monetary tightening, greater exposure to FinTech leads banks to shift the deposit supply curve downward (i.e., increase deposit supply). This finding is consistent with the result not conditional on monetary policy changes (e.g., results in Tables 5 and 6). Overall, the direct impacts of FinTech on bank loans and deposits are similar to those conditional on monetary contraction. It is due to the fact that the competition from YEB (i.e., the large positive YEB spread) exists during monetary tightening (see Figure 5) and that all the effects we discuss in Section 5.3 just become more pronounced during monetary contraction. More exposed banks, in response to FinTech competition, attract more deposits that generate a smaller credit decline in periods of monetary tightening, mitigating the effectiveness of MPT.

## 7.2 Evidence against Alternative Causal Channels

Next, we present evidence against three possible causal mechanisms from the literature that can also lead to a muted MPT for banks more exposed to FinTech competition. The tables that present the relevant results and further discussions are provided in the Appendix.

A first alternative explanation is that increased competition due to FinTech exposure may erode bank franchise value and increase the moral hazard behavior, such as excessive risk-taking, due to risk-shifting incentives (Keeley, 1990; Hellmann et al., 2000). As the crowding-out effect of YEB on deposits gets stronger during monetary tightening, more exposed banks may lend more and lend to riskier borrowers, mitigating the tightening effect of monetary contraction on bank lending. We present three pieces of evidence suggesting that this mechanism cannot explain our main findings. First, using a panel-data regression at the bank-year level, we explore the impact of FinTech on banks' franchise value measured by the market to book asset ratio (Keeley, 1990) for all publicly listed banks in China before 2019.[54] Results presented in Table A6 show that FinTech competition decreases banks' franchise value according to OLS estimates. However, when evaluated with the 2SLS estimates, this effect becomes statistically insignificant, even conditional on monetary policy changes. This might be the case that there were only 45 listed banks in China before 2019, and most of them were big SOB and JSCB (e.g., banks in YEB's whitelist) that are less affected by YEB MMF.

As the second piece of evidence against the risk-shifting story, we show that greater FinTech competition does not induce banks to take more risks. For this, we measure three aspects: loan portfolio risk, default risk, and leverage risk. Following Shim (2013) and Berger et al. (2014), NPL ratios and Z-scores are used as a proxy for loan portfolio risks and default risks, respectively.[55] Tables A7 and A8 in the Appendix show no evidence that FinTech exposure would predict a higher NPL ratio for the subsequent 1 to 3 years. If any, we find that a higher FinTech exposure before 2015 predicts a lower NPL ratio from 2015 to 2018.[56] Results summarized in Table A9 suggest no significant influence of FinTech on banks' default risk, either for the full sample or periods after 2015. Finally, Table A10 reveals that FinTech competition does not contribute to more leverage risk, defined as the book value of liabilities over the market value of assets (Gropp and Vesala, 2004).

Thirdly, a lower franchise value might incentivize banks to invest more in risky projects. If so, banks should prefer high-risk investment opportunities that generate higher expected returns over lower-risk and safer financial instruments. Yet, we find that more exposed banks not only expanded their credit supply after 2015 but also increased their investments in liquid assets, such as cash and reserve (Refer to Table A11). This risk-balance behavior does not agree with the potential risk-taking incentives, providing further evidence against the risk-taking story.

A second alternative explanation for our finding is the possible presence of funding substitution, especially during monetary tightening. For example, Choi and Choi (2021) suggest that banks could mitigate the effectiveness of monetary policy through the lending channel by replacing deposit outflows with wholesale funds and that banks with a higher funding composition sensitivity

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[54] The data on stock prices and outstanding shares of listed banks are obtained from CSMAR database.
[55] Z-score for a bank in period t is calculated as $Z - score_{bt} = (ROA_{bt} + CAR_{bt})/\sigma_{ROA_{bt}}$, $CAR_{bt}$ is the ratio of total equity to total assets. $\sigma_{ROA_{bt}}$ is computed by three-year rolling window scale instead of the full sample period to allow time variation of the standard error following Beck et al. (2013).
[56] Consistent with the finding that more exposed banks lower their loan rate, probably due to intense loan competition, a lower NPL ratio implies that they might issue more loans to safer borrowers at a lower rate.

tend to lend more during monetary tightening than those with a lower funding sensitivity. Romer et al. (1990) show that banks can significantly mitigate any direct impact of tightening monetary policy on their lending by issuing certificates of deposit subject to low reserve requirements in response to a decline in the quantity of transactions balances caused by a reduction in reserves. Turning back to our case, FinTech competition crowds out retail deposits and makes a bank's deposit base more volatile because of the rising idiosyncratic withdrawal risk. This could potentially give banks an incentive to seek other sources of funds with low costs in terms of the reserve, e.g., wholesale funding, and engage more actively in funding substitution, especially during monetary tightening, thus mitigating MPT via bank lending.

To test this alternative channel, we investigate the influence of FinTech on banks' wholesale funding (WSF). Results are presented in Table A12. Overall, we find no direct impacts of FinTech competition on the growth rate of WSF for the full sample, periods before 2015 and periods after 2015. The effects remain insignificant conditional on monetary policy changes. The only significant impacts are found from the sample periods after 2015, as shown in columns (3) and (4) in panel B. Greater FinTech exposure before 2015 predicts a lower WSF to liability ratio afterward. This result implies that, instead of substituting WSF for deposits as suggested by Choi and Choi (2021), more exposed banks increase their demand for deposits and decrease demand for WSF, generating a lower WSF to liability ratio relative to less exposed ones.[57]

A further alternative explanation of our results is that FinTech exposure of banks in the deposit market in this paper may capture, at least to some extent, banks' exposure to FinTech in the loan market. For example, a city where the YEB penetration rate is higher might also be a city where households are more likely to adopt FinTech, leading to a higher local penetration rate of FinTech credits, e.g., small loan companies. If this is the case, then muted MPT might be due to the competition between FinTech credits and bank loans (Hansan et al., 2020), especially when FinTech credits substitute for bank lending, as evidenced by Buchak et al. (2020). However, the lending competition channel cannot explain the reversed effect of FinTech on bank lending after 2015. Specifically, the first small-loan company and the first internet small-loan company (Ali Small Loan) were established in 2005 and 2010 in China, respectively, both before the introduction

[57] The average wholesale funding interest rate is 3.66% between 2015 to 2018 for our sample, larger than the average time deposit rate, which is 2.85% and the average total deposit rate, which is 1.94%. On average, deposit funding is much cheaper compared to wholesale funding.

of the YEB fund in 2013. Moreover, the loan rate liberalization was put into effect in July 2013. Therefore, if muted MPT via bank lending is due to FinTech competition with bank credits, we should observe a similar result for the periods before 2015. However, we find this is not the case based on the results in panel A of Table 10.

## 8. Conclusion

This is the first study that provides empirical findings on FinTech's role in banking and MPT by focusing on the competition between FinTech companies and banks in the deposit market. The results regarding the impact of FinTech on banking suggest that, in the short-run, i.e., from 2012 to 2014, banks more exposed to FinTech competition experienced a more severe deposit outflow due to negative deposit demand shocks from the household deposit market. In response, more exposed banks chose not to cut lending but instead reduce the liquid assets and financial investments and issue more bonds, in an attempt to mitigate the impact of deposit losses. After the removal of the official deposit rate ceiling in 2015, more exposed banks witnessed higher deposit and loan growth rates from 2015 to 2018, mainly driven by the growth of firm deposits and household time deposits.

We provide detailed explanations to interpret the reversed effects of FinTech on banks after 2015. Specifically, we show that more exposed banks are more likely to offer innovative deposit products and raise deposit interest rates more to avoid losing customers facing competition. These actions not only offset the original impact of YEB MMF but also attract more depositors that are not directly affected by YEB in the first place, giving rise to deposit inflows for more exposed banks.

Next, we explore the effect of FinTech on MPT. We find a mitigated impact of FinTech on MPT via bank lending. Overall, the effects of FinTech on banks conditional on monetary tightening are similar to the direct impacts of FinTech because contractionary monetary policy shocks intensify the FinTech competition by raising the YEB spread. We show that, for the full sample period, more exposed banks experienced a higher loan growth rate during monetary tightening. This mitigating effect on the MPT was significant after 2015 and for SMBs and non-SOBs, such as city commercial banks and rural banks. The city-level results also confirm that the muted MPT due to FinTech competition is significant in aggregate.

To further examine these novel findings, we propose a catfish effect channel, wherein a stronger competitor makes the weak better themselves. In addition to the improvement of deposit quality, e.g., more innovative deposit products, we provide two more pieces of evidence in support of this channel. For banks more exposed to FinTech competition, we first show that they witness a higher deposit growth rate, driven primarily by household time deposits and firm demand deposits in periods of monetary tightening. Second, we find that they raise deposit interest rates more than less exposed banks during monetary tightening. These two pieces of evidence suggest that more exposed banks increase the deposit supply in the face of intense FinTech competition. It is the increased deposit funding that allow banks to expand their credit supply during monetary contraction. In the end, we rule out several other alternative channels that could also explain muted MPT when banks are under competitive pressure from FinTech companies, such as the risk-shifting channel, the funding substitution channel, and the lending competition channel.

The findings in this study have important implications for monetary policymaking and financial regulation. In a broader sense, monetary policymakers need to account for the rapid development of the FinTech industry when evaluating the effect of monetary policy and adequately adjust financial sector regulation accordingly. Our findings confirm that FinTech competition outside the traditional financial sector can significantly influence the whole banking industry and the effectiveness of the MPT. On the one hand, it could generate welfare redistribution in which more benefits from banks are transferred to depositors and borrowers. This redistribution, however, may erode banks' profitability, especially for SMBs, CCBs, and rural banks. On the other hand, FinTech competition could have an unintended consequence on MPT by mitigating the tightening effect of monetary contraction on bank lending. From the perspective of policymakers, differentiated monetary policies for different types of banks could help alleviate these adverse impacts of FinTech. One example is the PBOC's "structural" monetary policy and policy tools, such as the cut of targeted reserve requirement ratio, which could be more supportive for SMBs and rural banks when the overall monetary policy stance changes.

Our findings also shed light on the discussion about the competition between traditional banks and FinTech and on how the competition would affect MPT. Many policymakers (e.g., Lagarde, 2018) worry that MPT would be less effective if banks were to become less relevant in the new financial world due to competition from FinTech. A precondition for this argument is that FinTech will partially take over the financial service provided by traditional banks in the long term. However, we show that, in response to FinTech competition, banks would catch up endogenously and roll out their own innovative financial products to compete with FinTech competitors outside the banking system. The catfish effect suggests that FinTech could spur competitive innovation and stimulate banks to do a better job in financial intermediation, which means that banks can be more relevant, rather than less relevant in the new financial world.

On top of that, this work also has crucial implications for other countries currently experiencing dramatic FinTech development, such as India, Singapore, South Korea, Australia, etc. For example, India has all essential ingredients for enabling a similar FinTech revolution as China, i.e., a large population of small savers, a gradually rising penetration of smartphones, and digital payments. In the U.S., online banks, deposit-taking FinTech firms and BigTech companies having partnerships with large banks are all threatenning the market power of traditional banks and altering the sensitivity of deposit demand to monetary policy changs. Our findings can, therefore, provide important lessons for monetary policymaking and financial regulation in other countries.

Finally, we flag several limitations in our study. First, we focus on the impact of FinTech on banks and MPT through the banking system and do not clearly identify the aggregate effects of FinTech on the macroeconomy. Based on our results, the catfish effect exists in most SMBs and non-SOBs. As for the big SOBs that dominate half of the banking system, the impact of FinTech competition on total amounts of credits in the economy and the responses of macroeconomic variables (e.g., GDP growth rates, inflation, investment, and unemployment rates) to monetary policy shocks can be less significant. Second, more direct empirical evidence and a well-established theoretical framework are needed to better understand the reversed effects of FinTech after 2015. Overall, this study is the first attempt to understand the role of FinTech in the banking industry and MPT. How to construct an equilibrium structure model to analyze the competition between traditional banks and FinTech companies outside the banking system? How will FinTech competition affect banks' off-balance-sheet activities, e.g., shadow banking? What is the aggregate effect of FinTech on the macroeconomy and social welfare? we will relegate these questions for future research.

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## Figures and Tables

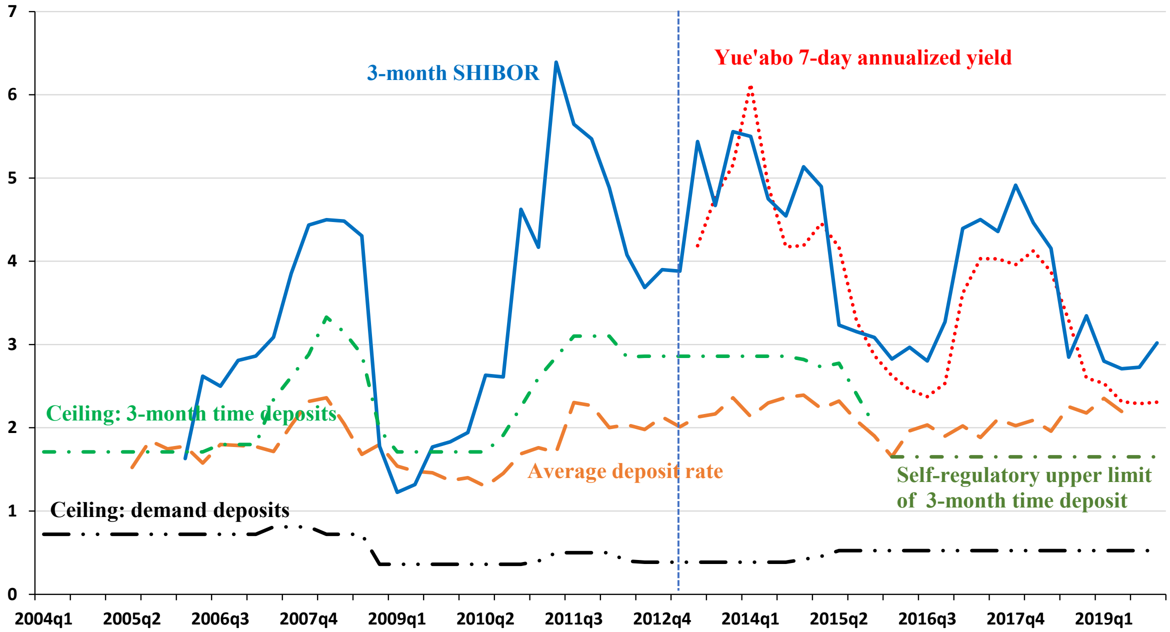
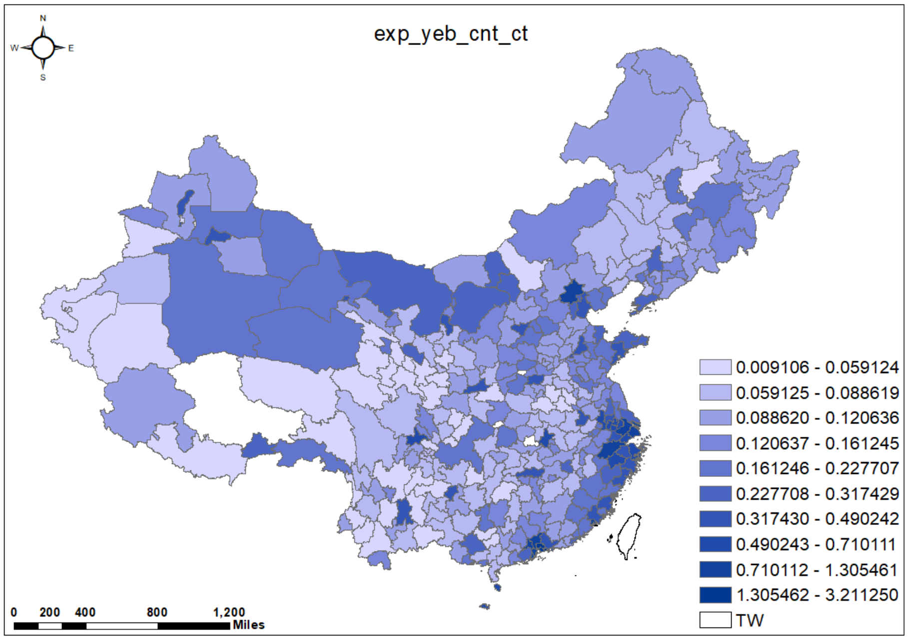



**Figure 1: Dual-track Interest Rates under Deposit Rate Ceiling Regulation**

*Notes:* The blue dashed vertical line represents the introduction of Yu'ebao in Jun 2013. The blue solid line is the 3-month Shanghai Interbank Offered Rate (SHIBOR). The red dotted line is Yu'ebao's seven-day annualized yield. The green dash-dotted line indicates the deposit rate ceiling for 3-month time deposits, while the black dash-dotted line is the interest rate cap on demand deposits (both were lifted in Oct. 2015). The dark green and black dash-dotted lines after 2015 October represent the implicit deposit rate cap imposed by the self-discipline mechanism. The orange dashed line is the average deposit rate across all banks in the sample.

**Panel A: Yu'ebao penetration (2013Q4)**




**Panel B: Alipay penetration (2013Q1)**

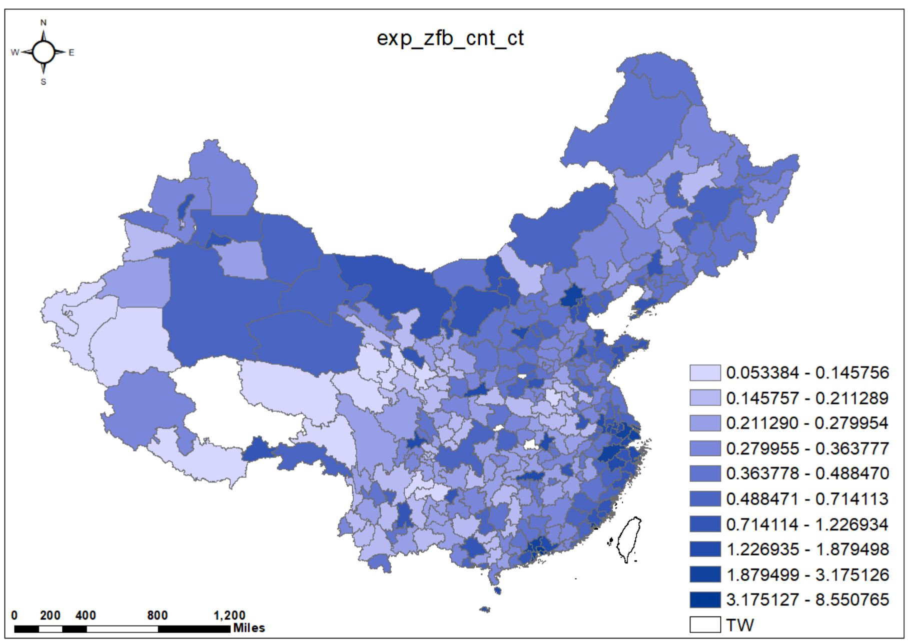



**Figure 2: Yu'ebao Penetration and Alipay Penetration**

*Notes:* The figure plots city-level FinTech penetration rates. Panel A shows the Yu'ebao penetration ratios as of 2013 Q4, defined as the number of active Yu'ebao users divided by the local population. Panel B shows the Alipay penetration ratios as of 2013Q1, defined similarly. Both numerator and denominator are normalized with the mean value of all 336 cities at/above prefecture level across all quarters in the sample periods before calculations. The sample spans from 2012Q2 to 2017Q4 for Alipay and from 2013Q2 to 2018Q4 for Yu'ebao.

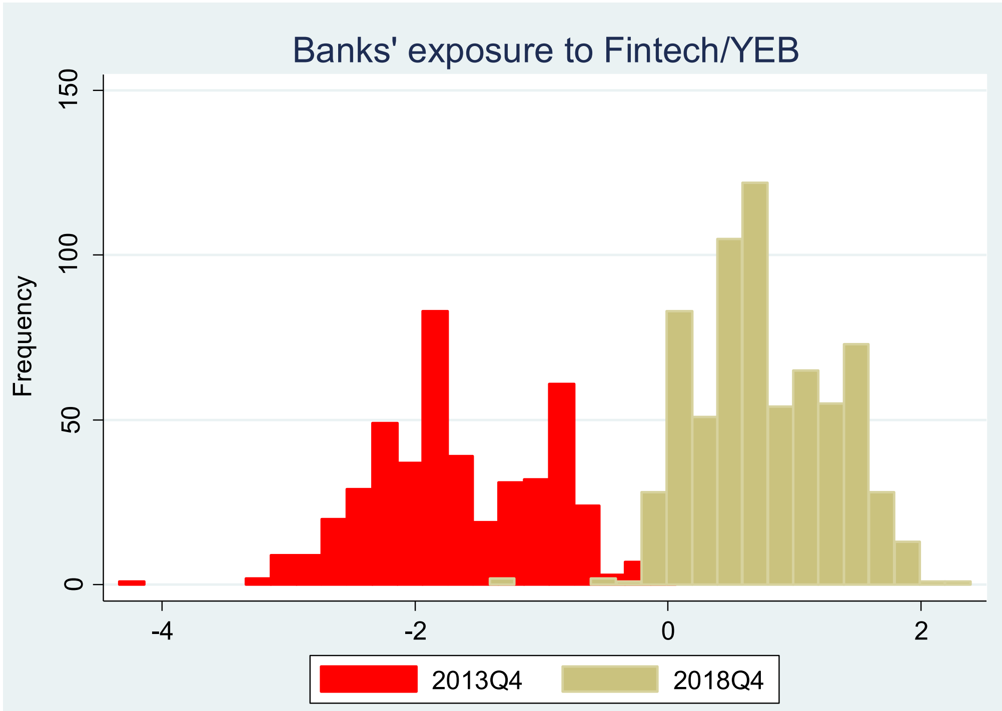
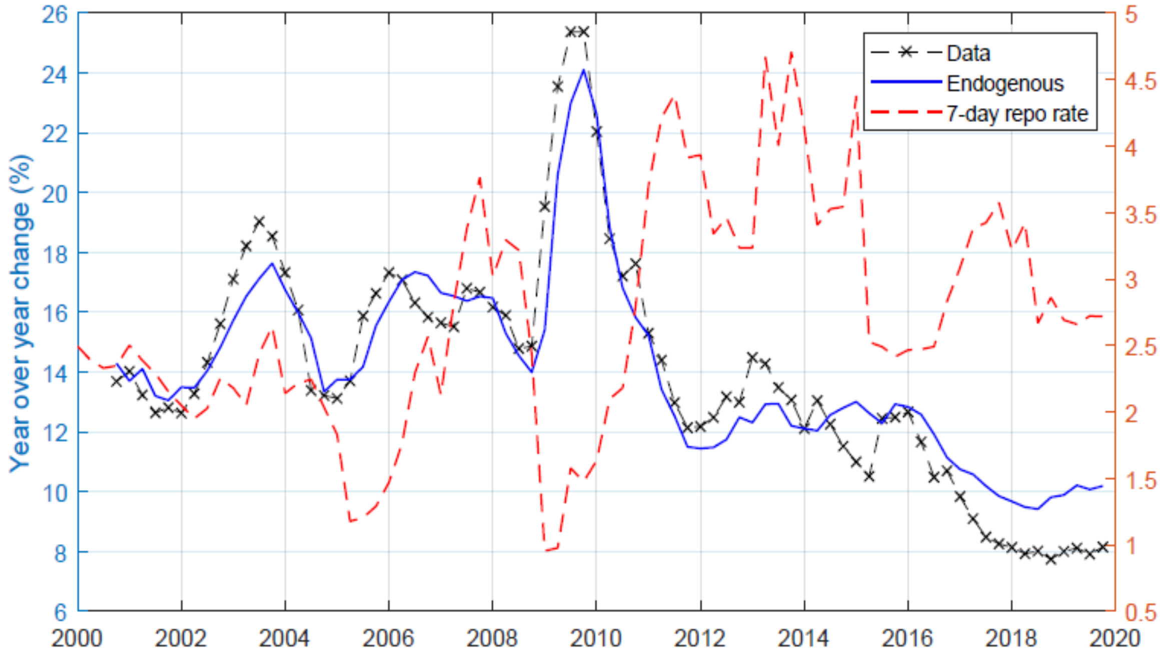


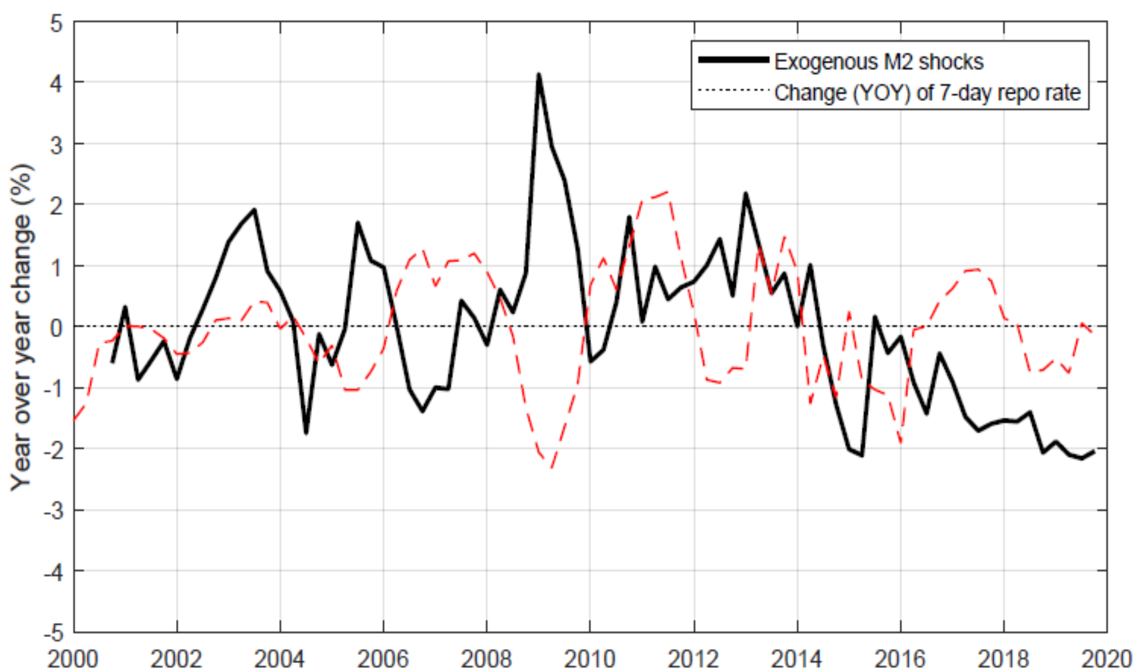

**Figure 3: Banks' Exposure to FinTech/YEB (ln logs)**

*Notes:* The figure plots distributions of bank-level FinTech/YEB account penetration. The left histogram in red shows the frequency distribution of banks' exposure to FinTech (in logs) as of 2013Q4, while the right histogram in gold shows the same distribution as of 2018Q4.

**Panel A: M2 growth rate and 7day repo rate (R007)**




**Panel B: MP shock and %Δ7day repo rate**




## Figure 4: Monetary Policy Shock in China

*Notes*: In panel A, the black dashed line is the year-over-year change (%) of the actual M2 supply, while the solid blue line is the endogenous component of M2 growth estimated with the method in Chen et al. (2018). Their differences, the exogeneous M2 shocks, are plotted as the solid black line in panel B. The red dashed line in panel A is the 7-day repo rate, and the dashed red line in panel B represents the year-over-year change in the 7-day repo rate measured in a quarterly frequency.

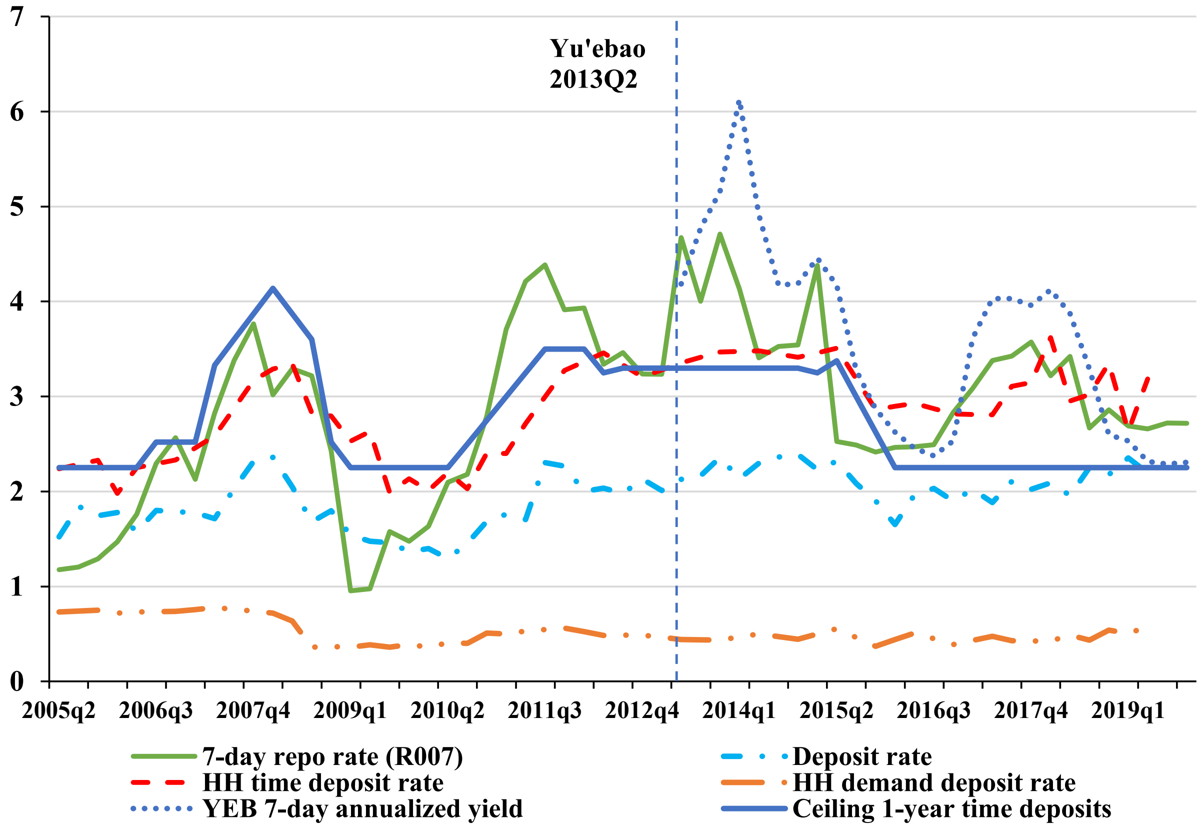
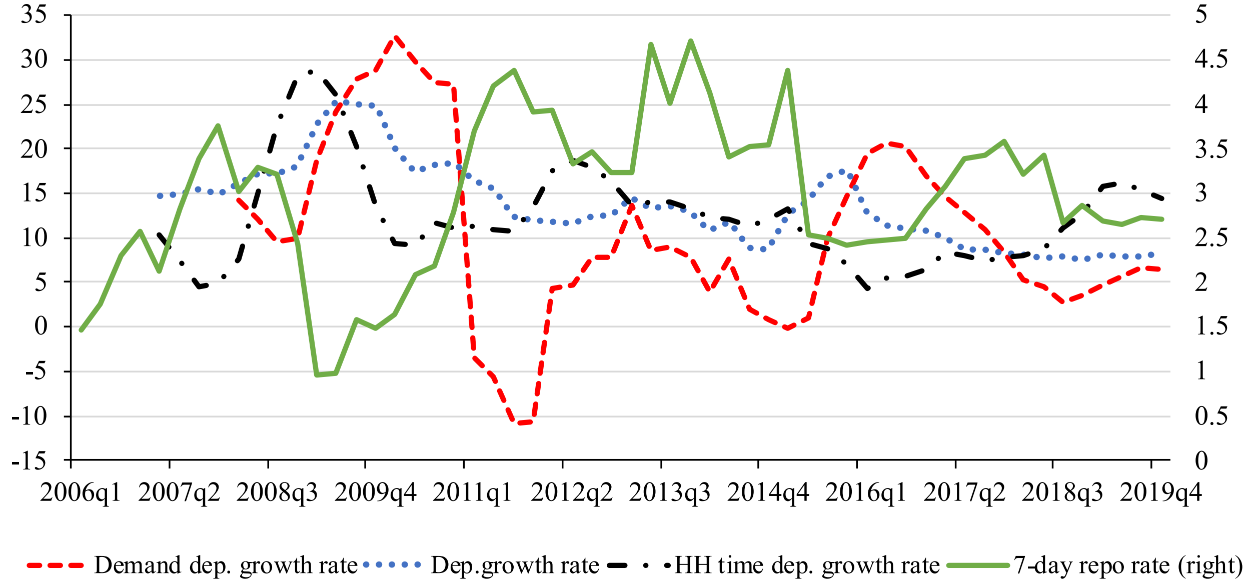



**Figure 5: Deposit Rates, YEB Yield, and 7-day Repo Rate**

*Notes:* The blue dashed vertical line represents the introduction of Yu'ebao in Jun 2013. The dark blue solid line is the deposit rate ceiling on 1-year time deposits. The dark blue dashed line is Yu'ebao's seven-day annualized yield. The solid green line indicates the 7-day repo rate. The red dashed line is the average household time deposit rate across all banks in the sample. The dash-dotted light blue line is the average deposit rate, while the dash-dotted orange line is the household demand deposit rate.

**Panel A: Deposit growth rates and R007**




**Panel B: Yu'ebao growth rate and R007**

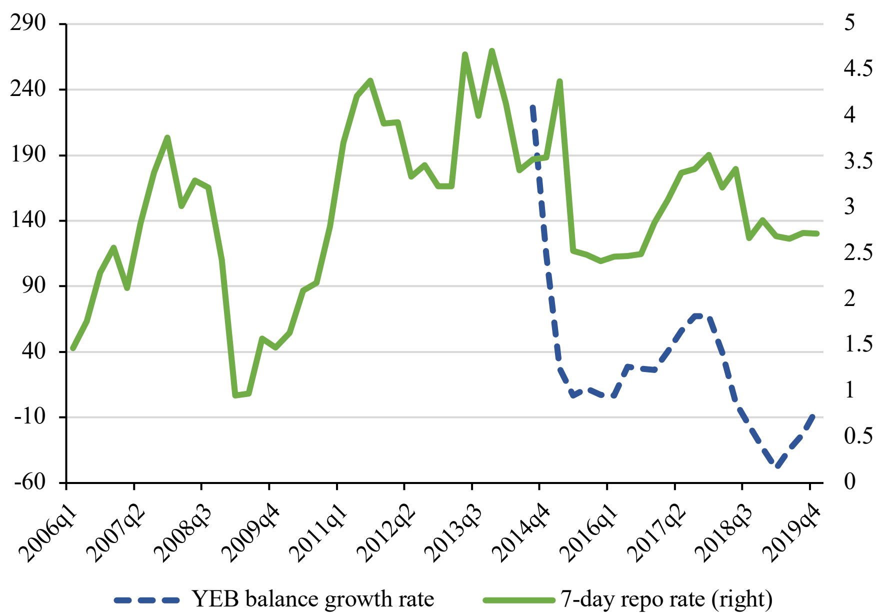



**Figure 6: Deposit Growth Rate, YEB Growth Rate, and 7-day Repo Rate**

*Notes*: The solid green lines in two panels are the 7-day repo rates. The blue dotted line, red dashed line and black dashed line in the upper panel A represent the average growth rates in the total deposit, demand deposit and household time deposit across all banks in the sample period, respectively. The dark blue dashed line in the bottom panel B shows the growth rate of Yu'ebao MMF. All growth rates are measured as the quarterly year-over-year growth rates (in logs).

**Table 1: Summary Statistics**

| | (1) N | (3) p25 | (4) p50 | (5) p75 | (7) mean | (8) sd |
|---|---|---|---|---|---|---|
| **(a) Outcome variables** | | | | | | |
| Δ Total dep. (%) | 330 | 12.200 | 16.480 | 19.990 | 17.020 | 7.055 |
| Δ HH dep. (%) | 250 | 13.090 | 16.910 | 21.660 | 17.690 | 8.537 |
| Δ HH time dep. (%) | 209 | 15.470 | 20.300 | 25.950 | 21.360 | 10.600 |
| Δ HH demand dep. (%) | 209 | 2.686 | 8.918 | 15.540 | 9.882 | 14.370 |
| **(b) Key explanatory and instrumental variables** | | | | | | |
| eyeb_c_13 | 453 | 0.114 | 0.170 | 0.330 | 0.234 | 0.159 |
| ezfb_c_13q1 | 758 | 0.217 | 0.344 | 0.622 | 0.443 | 0.310 |
| disHZ_12q4 | 758 | 407.1 | 757.9 | 1223.0 | 842.5 | 568.2 |
| **(c) Bank control variables** | | | | | | |
| lnsize_12 | 358 | 13.290 | 14.380 | 15.660 | 14.620 | 1.861 |
| capital_ratio_12 | 352 | 0.062 | 0.078 | 0.099 | 0.082 | 0.029 |
| roa_12 | 339 | 0.010 | 0.012 | 0.017 | 0.013 | 0.005 |
| liquid_asset_ratio_12 (%) | 284 | 28.380 | 34.710 | 41.160 | 35.490 | 9.522 |
| npl_ratio_12 (%) | 311 | 0.740 | 1.090 | 1.770 | 1.448 | 1.283 |
| lnbkshare_12 | 446 | -4.251 | -3.822 | -3.320 | -3.738 | 1.243 |
| depositIBL_12 (%) | 350 | 79.530 | 91.150 | 95.980 | 86.620 | 12.220 |
| **(d) Bank-city control variables** | | | | | | |
| lnngdppc_12 | 453 | 10.370 | 10.770 | 11.070 | 10.740 | 0.541 |
| grngdppc_12 | 453 | 0.090 | 0.108 | 0.123 | 0.106 | 0.033 |
| lnpop_12 | 453 | 5.797 | 6.253 | 6.638 | 6.204 | 0.616 |

**(A) Bank-level summary stats: cross-sectional 2012-2014**

| | (1) N | (3) p25 | (4) p50 | (5) p75 | (7) mean | (8) sd |
|---|---|---|---|---|---|---|
| **(a) Outcome variables** | | | | | | |
| Δ Total loan (%) | 483 | 9.555 | 12.960 | 17.190 | 13.920 | 7.284 |
| Δ Total dep. (%) | 483 | 8.810 | 11.510 | 14.530 | 12.240 | 6.175 |
| Δ Total time dep. (%) | 319 | 6.899 | 10.950 | 14.650 | 11.620 | 7.524 |
| Δ Total demand dep. (%) | 319 | 8.478 | 13.290 | 19.050 | 13.380 | 10.920 |
| Δ Total firm dep. (%) | 358 | 7.606 | 13.280 | 19.810 | 13.840 | 11.990 |
| Δ HH dep. (%) | 358 | 7.055 | 11.050 | 16.180 | 12.090 | 9.969 |
| Δ HH time dep. (%) | 319 | 7.407 | 11.190 | 16.940 | 13.130 | 9.101 |
| Δ HH demand dep. (%) | 317 | 4.151 | 9.290 | 16.920 | 9.454 | 19.920 |
| **(b) Key explanatory and instrumental variables** | | | | | | |
| eyeb_c_15 | 609 | 0.639 | 0.894 | 1.596 | 1.128 | 0.686 |
| ezfb_c_15 | 609 | 0.693 | 0.947 | 1.662 | 1.186 | 0.689 |
| disHZ_15 | 689 | 407.1 | 734.6 | 1141.0 | 821.6 | 564.4 |
| **(c) Bank control variables** | | | | | | |
| lnsize_15 | 593 | 13.450 | 14.260 | 15.470 | 14.470 | 1.917 |
| capital_ratio_15 | 593 | 0.068 | 0.082 | 0.100 | 0.094 | 0.054 |
| roa_15 | 575 | 0.007 | 0.010 | 0.013 | 0.010 | 0.006 |
| liquid_asset_ratio_15 (%) | 450 | 18.920 | 25.120 | 34.440 | 27.890 | 11.390 |
| npl_ratio_15 (%) | 516 | 1.420 | 1.930 | 2.480 | 2.154 | 1.238 |
| lnbkshare_15 | 680 | -4.463 | -4.018 | -3.426 | -3.975 | 1.310 |
| depositIBL_15 (%) | 565 | 74.130 | 87.800 | 94.500 | 83.230 | 13.900 |
| **(d) Bank-city control variables** | | | | | | |
| lnngdppc_15 | 689 | 10.370 | 10.860 | 11.250 | 10.820 | 0.568 |
| grngdppc_15 | 689 | 0.046 | 0.060 | 0.078 | 0.057 | 0.047 |
| lnpop_15 | 689 | 5.855 | 6.247 | 6.627 | 6.193 | 0.605 |

**(B) Bank-level summary stats: cross-sectional 2015-2018**

| | (1) | (3) | (4) | (5) | (7) | (8) |
|---|---|---|---|---|---|---|
| | N | p25 | p50 | p75 | mean | sd |
| **(a) Outcome variables** | | | | | | |
| Δ Total loans | 3,758 | 0.094 | 0.134 | 0.184 | 0.147 | 0.094 |
| Δ Total deposits | 3,771 | 0.071 | 0.115 | 0.164 | 0.127 | 0.099 |
| Δ Time deposits | 2,047 | 0.068 | 0.121 | 0.195 | 0.142 | 0.144 |
| Δ Demand deposits | 2,048 | 0.018 | 0.105 | 0.210 | 0.115 | 0.197 |
| Δ Firm deposits | 2,320 | 0.036 | 0.128 | 0.228 | 0.137 | 0.198 |
| Δ Firm time deposits | 2,016 | -0.008 | 0.126 | 0.297 | 0.150 | 0.444 |
| Δ Firm demand deposits | 2,027 | 0.013 | 0.125 | 0.253 | 0.136 | 0.225 |
| Δ HH deposits | 2,330 | 0.065 | 0.111 | 0.175 | 0.128 | 0.140 |
| Δ HH time deposits | 2,038 | 0.070 | 0.120 | 0.192 | 0.143 | 0.150 |
| Δ HH demand deposits | 2,031 | -0.015 | 0.078 | 0.161 | 0.083 | 0.280 |
| Avg. deposit rates (%) | 1,459 | 1.699 | 2.009 | 2.390 | 2.060 | 0.508 |
| Avg. time deposit rates (%) | 492 | 2.628 | 3.023 | 3.398 | 3.054 | 0.536 |
| Avg. demand dep. rates (%) | 491 | 0.518 | 0.615 | 0.722 | 0.637 | 0.196 |
| (YEB yield - dep. Rate) | 1,459 | 0.577 | 1.116 | 1.979 | 1.225 | 0.856 |
| **(b) Key explanatory and instrumental variables** | | | | | | |
| disHZ_lg1y | 5,470 | 351.1 | 765.6 | 1102.0 | 803.7 | 547.3 |
| eyeb_c_lg1y | 5,512 | 0.569 | 1.020 | 1.719 | 1.259 | 0.952 |
| eyeb_b_lg1y | 5,512 | 0.538 | 0.858 | 1.406 | 1.067 | 0.783 |
| ezfb_c_lg1y | 5,431 | 0.736 | 1.168 | 1.814 | 1.400 | 0.895 |
| ezfb_b_lg1y | 5,431 | 0.546 | 1.069 | 2.041 | 1.604 | 1.794 |
| MP | 5,512 | -0.016 | -0.014 | -0.004 | -0.012 | 0.007 |
| 7-day repo rate | 5,512 | 0.027 | 0.029 | 0.035 | 0.030 | 0.005 |
| **(c) Bank control variables** | | | | | | |
| lnsize_lg1y | 5,072 | 9.356 | 10.240 | 11.660 | 10.590 | 2.036 |
| cap_ratio_lg1y | 5,060 | 0.064 | 0.076 | 0.090 | 0.081 | 0.030 |
| roa_lg1y | 4,951 | 0.007 | 0.009 | 0.012 | 0.010 | 0.005 |
| liq_ar_lg1y (%) | 4,405 | 17.750 | 23.270 | 31.810 | 25.760 | 10.360 |
| npl_ratio_lg1y | 4,657 | 1.270 | 1.740 | 2.390 | 2.014 | 1.338 |
| lnbkshare_lg1y | 5,425 | -4.276 | -3.778 | -3.047 | -3.593 | 1.470 |
| depositIBL (%) | 4,777 | 70.950 | 83.810 | 93.200 | 81.190 | 13.330 |
| **(d) Bank-city control variables** | | | | | | |
| lnngdppc_lg1y | 5,470 | 10.580 | 10.990 | 11.380 | 10.950 | 0.549 |
| grngdppc_lg1y | 5,470 | 0.057 | 0.077 | 0.096 | 0.071 | 0.065 |
| lnpop_lg1y | 5,470 | 5.919 | 6.311 | 6.669 | 6.250 | 0.607 |

**(C) Bank-level summary stats: panel-data 2014-2018**

*Notes:* This table shows the summary statistics of the bank-level cross-section date from 2012-2014 and 2015-2018, as well as panel data from 2014Q1-2018Q4. eyeb_c, eyeb_b, ezfb_c, ezfb_b stand for YEB account penetration, YEB balance penetration, Alipay account penetration, and Alipay balance penetration. lg1y means the variable is measured with the value at the end of the previous year. Δ represent the year-over-year growth rate in logs.

**Table 2: Household Deposit Growth (2012-2014)**

| | Δ HH demand deposits | | | Δ HH time deposits | | | Δ HH total deposits | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | No controls | w/controls | IV both | No controls | w/controls | IV both | No controls | w/controls | IV both |
| ln(expYEB) | -3.227* | -7.132*** | -7.221*** | -5.676*** | -5.520*** | -5.223** | -5.111*** | -4.888*** | -4.618*** |
| | (1.787) | (2.612) | (2.579) | (1.204) | (2.010) | (2.038) | (0.893) | (1.735) | (1.773) |
| ln(bank_size) | | 0.947 | 0.946 | | 2.911 | 2.860 | | 0.925 | 0.894 |
| | | (2.280) | (2.280) | | (1.845) | (1.853) | | (1.601) | (1.607) |
| capital ratio | | -0.725 | -0.723 | | -0.589* | -0.594* | | -0.284 | -0.288 |
| | | (0.672) | (0.672) | | (0.314) | (0.315) | | (0.273) | (0.273) |
| roa | | 5.592 | 5.594 | | 5.116** | 5.099** | | 1.594 | 1.576 |
| | | (3.968) | (3.968) | | (2.217) | (2.221) | | (1.902) | (1.896) |
| liquid asset ratio | | 0.097 | 0.097 | | 0.108 | 0.108 | | 0.103 | 0.103 |
| | | (0.134) | (0.135) | | (0.092) | (0.092) | | (0.074) | (0.074) |
| npl ratio | | -1.074 | -1.066 | | 0.219 | 0.196 | | 0.093 | 0.073 |
| | | (1.463) | (1.458) | | (0.778) | (0.787) | | (0.689) | (0.697) |
| ln(branchshare) | | -0.808 | -0.820 | | -0.317 | -0.334 | | -2.844* | -2.853* |
| | | (2.863) | (2.856) | | (1.436) | (1.438) | | (1.520) | (1.520) |
| deposit/liability | | -0.102 | -0.102 | | 0.033 | 0.033 | | -0.040 | -0.039 |
| | | (0.121) | (0.121) | | (0.088) | (0.088) | | (0.073) | (0.073) |
| bank_lnngdppc | | 7.962** | 8.048** | | 4.651* | 4.360 | | 2.517 | 2.275 |
| | | (3.767) | (3.776) | | (2.597) | (2.649) | | (2.406) | (2.449) |
| bank_grngdppc | | 0.336 | 0.336 | | 0.037 | 0.040 | | 0.181 | 0.185 |
| | | (0.349) | (0.348) | | (0.219) | (0.218) | | (0.168) | (0.167) |
| bank_lnpop | | -0.284 | -0.263 | | -1.321 | -1.391 | | -0.379 | -0.439 |
| | | (1.878) | (1.874) | | (1.436) | (1.420) | | (0.941) | (0.929) |
| ln(outcome_2012) | | -1.151 | -1.136 | | -4.959** | -4.905** | | -0.216 | -0.190 |
| | | (3.553) | (3.542) | | (2.181) | (2.189) | | (2.232) | (2.234) |
| 1st-stage $F$ Statistic | | | 1819 | | | 2219.5 | | | 2047.6 |
| Overidentification $p$-value | | | 0.800 | | | 0.814 | | | 0.859 |
| Obs. | 207 | 179 | 179 | 208 | 179 | 179 | 249 | 195 | 195 |
| Adjusted $R^2$ | 0.015 | 0.047 | 0.047 | 0.110 | 0.258 | 0.258 | 0.127 | 0.217 | 0.216 |

*Notes*: This table shows the results for household deposit growth. Columns (1), (4), and (7) show the results of OLS regressions with no controls. Columns (2), (5), and (8) show results of baseline OLS regression with all controls. Columns (3), (6), and (9) show IV regressions using Alipay exposure and Hangzhou distance as instruments for Yu'ebao exposure. Ln(outcome_2012) represents the log value of the outcome variable in the corresponding regression as of 2012Q4. The numbers in the parentheses show robust standard errors, adjusted for a small sample. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 3: Total Deposit Growth and Firm Deposit Growth (2012-2014)**

| | Δ Total deposits | | Δ Firm deposits | | Δ Firm time deposits | | Δ Firm demand deposits | |
|---|---|---|---|---|---|---|---|---|
| | (1) w/controls | (2) IV both | (3) w/controls | (4) IV both | (5) w/controls | (6) IV both | (7) w/controls | (8) IV both |
| ln(expYEBc_13) | -2.628** | -2.051* | 1.335 | 1.379 | -1.093 | 0.162 | 2.587 | 1.868 |
| | (1.108) | (1.108) | (2.302) | (2.290) | (5.067) | (5.236) | (2.571) | (2.585) |
| ln(bank_size) | 41.756** | 41.291** | -0.879 | -0.877 | 19.749*** | 19.816*** | -1.084 | -1.047 |
| | (17.733) | (17.745) | (3.406) | (3.407) | (5.553) | (5.563) | (3.659) | (3.669) |
| capital ratio | -0.259 | -0.259 | 0.460 | 0.459 | 1.765 | 1.736 | -0.149 | -0.135 |
| | (0.389) | (0.392) | (0.517) | (0.518) | (1.147) | (1.146) | (0.629) | (0.631) |
| roa | -1.399 | -1.431 | -1.558 | -1.564 | -8.724 | -8.834 | 1.560 | 1.609 |
| | (1.132) | (1.129) | (2.258) | (2.252) | (5.420) | (5.425) | (2.754) | (2.746) |
| liquid asset ratio | -0.007 | -0.008 | 0.113 | 0.113 | -0.054 | -0.057 | 0.156 | 0.158 |
| | (0.059) | (0.059) | (0.100) | (0.100) | (0.215) | (0.215) | (0.114) | (0.114) |
| npl ratio | -0.967** | -1.006** | -0.570 | -0.574 | 0.075 | -0.043 | -0.362 | -0.303 |
| | (0.466) | (0.466) | (1.080) | (1.084) | (3.028) | (3.054) | (1.201) | (1.199) |
| ln(branchshare) | 0.105 | 0.100 | 0.584 | 0.584 | -6.460* | -6.481* | 1.894 | 1.875 |
| | (0.736) | (0.731) | (1.652) | (1.651) | (3.727) | (3.727) | (1.662) | (1.664) |
| deposit/liability | 0.448* | 0.446* | -0.165* | -0.164* | -0.069 | -0.063 | -0.201* | -0.204* |
| | (0.236) | (0.236) | (0.099) | (0.099) | (0.211) | (0.209) | (0.105) | (0.105) |
| bank_lnngdppc | 0.324 | -0.190 | -4.865 | -4.906* | -5.686 | -6.865 | -4.475 | -3.790 |
| | (1.360) | (1.352) | (3.005) | (2.945) | (6.240) | (6.353) | (3.373) | (3.323) |
| bank_grngdppc | 0.171 | 0.177 | 0.245 | 0.245 | 0.285 | 0.290 | 0.165 | 0.161 |
| | (0.150) | (0.148) | (0.242) | (0.243) | (0.636) | (0.633) | (0.279) | (0.280) |
| bank_lnpop | 2.827*** | 2.677*** | 4.320*** | 4.311*** | 0.602 | 0.307 | 4.625*** | 4.787*** |
| | (0.718) | (0.711) | (1.502) | (1.506) | (3.290) | (3.280) | (1.757) | (1.768) |
| ln(outcome_2012) | -43.206** | -42.765** | -0.823 | -0.826 | -13.674*** | -13.772*** | -2.034 | -2.020 |
| | (17.575) | (17.585) | (2.090) | (2.096) | (3.185) | (3.210) | (2.556) | (2.563) |
| Obs | 234 | 234 | 194 | 194 | 179 | 179 | 178 | 178 |
| Adjusted R2 | 0.189 | 0.189 | 0.071 | 0.071 | 0.199 | 0.198 | 0.068 | 0.068 |

*Notes*: This table shows the results for total and firm deposit growth. Columns (1), (3), (5), and (7) show the results of OLS regressions with all control variables. Columns (2), (4), (6), and (8) show IV regressions using Alipay exposure and Hangzhou distance as instruments for Yu'ebao exposure. Ln(outcome_2012) represents the level value of the outcome variable in the corresponding regression as of 2012Q4. The numbers in the parentheses show robust standard errors, adjusted for a small sample. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 4: Total Loan Growth and Other Assets (2012-2014)**

| | Δ Total loans | | Δ Liquid assets | | Δ Fin. investment | | Δ Bond payable | |
|---|---|---|---|---|---|---|---|---|
| | (1) w/controls | (2) IV both | (3) w/controls | (4) IV both | (5) w/controls | (6) IV both | (7) w/controls | (8) IV both |
| ln(expYEBc_13) | -0.460 | -0.227 | -5.429** | -4.462* | -9.525* | -10.263* | 39.339*** | 43.392*** |
| | (1.179) | (1.202) | (2.475) | (2.488) | (4.977) | (5.205) | (13.514) | (14.878) |
| ln(bank_size) | 16.842*** | 16.886*** | 52.101** | 52.225** | 18.516*** | 18.524*** | 26.042 | 25.645 |
| | (2.681) | (2.688) | (20.174) | (20.269) | (5.288) | (5.294) | (16.231) | (16.251) |
| capital ratio | 0.374 | 0.372 | -0.178 | -0.188 | -0.537 | -0.516 | 5.603 | 5.702 |
| | (0.280) | (0.279) | (0.485) | (0.485) | (1.023) | (1.024) | (6.547) | (6.500) |
| roa | -0.322 | -0.333 | 0.718 | 0.669 | -0.762 | -0.783 | -26.133 | -27.071 |
| | (1.429) | (1.424) | (2.438) | (2.434) | (7.068) | (7.074) | (19.866) | (19.818) |
| liquid asset ratio | -0.025 | -0.026 | 1.098* | 1.101* | -0.124 | -0.120 | 0.845 | 0.846 |
| | (0.049) | (0.049) | (0.597) | (0.599) | (0.338) | (0.339) | (0.776) | (0.778) |
| npl ratio | 0.204 | 0.190 | -0.765 | -0.831 | -4.231 | -4.129 | -32.020** | -34.436** |
| | (0.433) | (0.435) | (1.143) | (1.152) | (4.855) | (4.865) | (13.629) | (13.664) |
| ln(branchshare) | -0.410 | -0.411 | 3.094* | 3.083* | -0.599 | -0.612 | -6.986 | -6.021 |
| | (0.721) | (0.718) | (1.747) | (1.742) | (3.926) | (3.940) | (9.908) | (9.803) |
| deposit/liability | 0.155*** | 0.157*** | 0.087 | 0.093 | 0.200 | 0.196 | 0.137 | 0.164 |
| | (0.051) | (0.052) | (0.107) | (0.106) | (0.295) | (0.294) | (0.873) | (0.882) |
| bank_lnngdppc | -1.661 | -1.867 | 2.264 | 1.402 | 11.687* | 12.276** | -28.810 | -31.843 |
| | (1.374) | (1.382) | (3.382) | (3.394) | (6.086) | (6.105) | (27.024) | (27.975) |
| bank_grngdppc | 0.079 | 0.082 | 0.380 | 0.391 | -0.896 | -0.909 | 0.260 | 0.314 |
| | (0.125) | (0.124) | (0.273) | (0.274) | (0.690) | (0.694) | (1.835) | (1.839) |
| bank_lnpop | -0.288 | -0.346 | 6.808*** | 6.561*** | 1.318 | 1.508 | -5.218 | -6.381 |
| | (0.812) | (0.811) | (1.751) | (1.727) | (4.512) | (4.565) | (8.183) | (8.136) |
| ln(outcome_2012) | -17.505*** | -17.559*** | -56.835*** | -56.995*** | -19.673*** | -19.630*** | -22.670** | -23.181*** |
| | (2.614) | (2.624) | (20.007) | (20.114) | (5.222) | (5.230) | (8.496) | (8.571) |
| Obs | 234 | 234 | 194 | 194 | 179 | 179 | 178 | 178 |
| Adjusted R2 | 0.189 | 0.189 | 0.071 | 0.071 | 0.199 | 0.198 | 0.068 | 0.068 |

*Notes*: This table shows the results for total loans, liquid assets, financial investment, and bond payable. Columns (1), (3), (5), and (7) show the results of OLS regressions with all control variables. Columns (2), (4), (6), and (8) show IV regressions using Alipay exposure and Hangzhou distance as instruments for Yu'ebao exposure. Ln(outcome_2012) represents the level value of the outcome variable in the corresponding regression as of 2012Q4. The numbers in the parentheses show robust standard errors, adjusted for a small sample. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 5: The Impact of FinTech on Banks from 2015 to 2018**

| | ΔTotal deposits (2015-2018) | | ΔHH. demand dep. (2015-2018) | | ΔHH time dep. (2015-2018) | | ΔHH. Deposits (2015-2018) | | ΔFirm demand dep. (2015-2018) | | ΔFirm time dep. (2015-2018) | | ΔFirm deposits (2015-2018) | | ΔTotal loans (2015-2018) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Panel A: 2015-2018 | | | | | | | | | | | | | | | | |
| ln(expYEB_15) | 3.118*** | | 5.894* | | 2.406 | | 1.922 | | 5.467** | | 17.323*** | | 6.757*** | | 3.214** | |
| | (1.158) | | (3.552) | | (1.793) | | (1.863) | | (2.379) | | (4.725) | | (2.291) | | (1.289) | |
| ln(expYEB_13) | | 2.255*** | | 3.290 | | 2.148 | | 1.808 | | 5.394*** | | 12.192*** | | 5.457*** | | 1.979** |
| | | (0.831) | | (2.963) | | (1.560) | | (1.452) | | (2.012) | | (3.725) | | (1.782) | | (0.907) |
| Observations | 357 | 315 | 291 | 266 | 293 | 268 | 311 | 283 | 285 | 264 | 286 | 265 | 311 | 282 | 357 | 315 |
| R-squared | 0.186 | 0.187 | 0.126 | 0.135 | 0.335 | 0.341 | 0.292 | 0.318 | 0.309 | 0.280 | 0.164 | 0.124 | 0.320 | 0.283 | 0.315 | 0.441 |
| | ΔTotal deposits (2016-2018) | | ΔHH. demand dep. (2016-2018) | | ΔHH time dep. (2016-2018) | | ΔHH. Deposits (2016-2018) | | ΔFirm demand dep. (2016-2018) | | ΔFirm time dep. (2016-2018) | | ΔFirm deposits (2016-2018) | | ΔTotal loans (2016-2018) | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Panel B: 2016-2018 | | | | | | | | | | | | | | | | |
| ln(expYEB_16) | 4.593*** | | 8.875** | | 3.538** | | 2.939* | | 9.857*** | | 19.734*** | | 10.001*** | | 4.298*** | |
| | (1.186) | | (4.127) | | (1.702) | | (1.608) | | (3.021) | | (5.879) | | (2.711) | | (1.207) | |
| ln(expYEB_13) | | 4.018*** | | 6.440 | | 3.011* | | 3.185** | | 9.225*** | | 16.383*** | | 8.733*** | | 3.786*** |
| | | (1.058) | | (3.935) | | (1.729) | | (1.403) | | (2.521) | | (4.969) | | (2.440) | | (0.968) |
| Observations | 451 | 337 | 357 | 275 | 358 | 276 | 381 | 293 | 354 | 276 | 355 | 277 | 382 | 293 | 451 | 337 |
| R-squared | 0.177 | 0.127 | 0.101 | 0.105 | 0.328 | 0.335 | 0.304 | 0.318 | 0.232 | 0.271 | 0.253 | 0.183 | 0.249 | 0.275 | 0.276 | 0.408 |

*Notes*: This table shows the estimates of the cross-sectional regressions from 2015-2018 (panel A) and 2016-2018 (panel B). Odd columns show results estimated with the key explanatory variable (ln(expYEB)) measured as of the end of 2015 (panel A) and the end of 2016 (panel B). Even columns show results estimated with ln(expYEB) measured as of the end of 2013. Every regression is estimated using Alipay exposure and Hangzhou distance as instruments for Yu'ebao exposure. Every regression includes all bank-level and bank-city level controls. The numbers in the parentheses show robust standard errors, adjusted for a small sample. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 6: The Impact of FinTech on Deposit and Loan Rates**

| | Total deposit interest rate (1) | Total deposit interest rate (2) | Loan interest rate (3) | Loan interest rate (4) |
|---|---|---|---|---|
| ln(expYEB) | 0.337** | 0.298* | -0.805** | -0.810** |
| | (0.144) | (0.164) | (0.372) | (0.384) |
| Bank f.e. | Y | Y | Y | Y |
| Bank-level controls | Y | Y | Y | Y |
| Bank-city controls | Y | Y | Y | Y |
| Year-quarter f.e. | Y | Y | Y | Y |
| Method | OLS | IV | OLS | IV |
| Observations | 943 | 910 | 856 | 818 |
| R-squared | 0.552 | 0.141 | 0.614 | 0.088 |

*Notes*: The dependent variables are the quarterly levels of deposit and loan rates. These rates are forwarded by 2 quarters because the average rate measured in quarter t reflects the average rate from t-4 to t by definition. FinTech exposure is measured by the YEB account penetration ratio. Columns (2) and (4) are estimated with 2SLS using Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. Standard errors shown in the parentheses are clustered by bank. The sample period is 2014Q1 to 2019Q4. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 7: YEB Spread and 7-day Repo Rate**

| | YEB yield – overall deposit rate (1) | YEB yield - time dep. rate (2) | YEB yield - demand dep. rate (3) | YEB yield - firm time dep. rate (4) | YEB yield - firm demand dep. rate (5) | YEB yield -HH time dep. rate (6) | YEB yield - HH demand dep. rate (7) |
|---|---|---|---|---|---|---|---|
| Panel A: Pooled OLS | | | | | | | |
| 7-day repo rate | 1.335*** | 1.179*** | 1.249*** | 1.149*** | 1.262*** | 1.245*** | 1.262*** |
| | (0.022) | (0.043) | (0.037) | (0.057) | (0.038) | (0.044) | (0.040) |
| Observations | 2007 | 677 | 676 | 671 | 672 | 671 | 672 |
| R-squared | 0.649 | 0.553 | 0.643 | 0.378 | 0.633 | 0.561 | 0.598 |
| Panel B: FE | | | | | | | |
| 7-day repo rate | 0.901*** | 0.639** | 0.848*** | 0.690** | 0.847*** | 0.660** | 0.833*** |
| | (0.223) | (0.264) | (0.287) | (0.269) | (0.289) | (0.270) | (0.293) |
| Macro controls | Y | Y | Y | Y | Y | Y | Y |
| Bank f.e. | Y | Y | Y | Y | Y | Y | Y |
| Bank-level controls | Y | Y | Y | Y | Y | Y | Y |
| Bank-city controls | Y | Y | Y | Y | Y | Y | Y |
| Observations | 1888 | 631 | 631 | 624 | 626 | 624 | 624 |
| R-squared | 0.840 | 0.769 | 0.806 | 0.629 | 0.803 | 0.779 | 0.781 |

*Notes*: This table presents regressions of YEB spreads (the difference between YEB 7-day annualized yield and banks' deposit rates) on the 7-day repo rate. The deposit rate is the average deposit rate. Macro controls include the GDP deflator inflation rate and the real GDP growth rate. Bank-level controls include bank size (log), capital ratio, liquid asset ratio, ROA, non-performing loan ratio, bank branch share, deposit to liability ratio. Bank-city controls include city-level population (log), NGDP per capita (log), and growth rate of NGDP per capita, all aggregated to the bank level using banks' branch shares as weights. The numbers in the parentheses show robust standard errors, two-way clustered by bank and year-quarter. The sample period is 2013Q2 to 2019Q4. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 8: FinTech and Monetary Policy Transmission - Growth Rate of Total Loans**

| | ln(expYEB)=ln(expYEBb) | | | | | | ln(expYEB)=ln(expYEBc) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| L4.log(Total loans) | -0.185*** | -0.186*** | -0.228*** | -0.227*** | -0.224*** | -0.224*** | -0.181*** | -0.188*** | -0.244*** | -0.231*** | -0.243*** | -0.224*** |
| | (0.025) | (0.025) | (0.050) | (0.050) | (0.049) | (0.048) | (0.020) | (0.026) | (0.045) | (0.050) | (0.045) | (0.048) |
| ln(expYEB) | -0.009 | 0.018 | 0.003 | 0.017 | -0.020 | -0.023 | -0.008 | 0.055 | -0.042** | 0.067 | -0.039** | -0.002 |
| | (0.014) | (0.031) | (0.015) | (0.027) | (0.013) | (0.030) | (0.021) | (0.045) | (0.018) | (0.061) | (0.019) | (0.046) |
| MP*ln(expYEB) | -0.772* | -1.132** | -0.811 | -1.284** | -1.075** | -1.574*** | -0.918** | -1.332* | -1.008** | -1.453* | -1.145** | -1.949*** |
| | (0.467) | (0.518) | (0.513) | (0.566) | (0.493) | (0.551) | (0.435) | (0.701) | (0.468) | (0.787) | (0.467) | (0.740) |
| lnpop_lg1y | -0.060* | -0.056* | | | -0.023 | -0.023 | -0.043 | -0.046 | | | -0.027 | -0.024 |
| | (0.031) | (0.031) | | | (0.034) | (0.034) | (0.028) | (0.034) | | | (0.032) | (0.034) |
| lnngdppc_lg1y | -0.129*** | -0.110*** | | | -0.126*** | -0.128*** | -0.099*** | -0.132*** | | | -0.099*** | -0.119*** |
| | (0.038) | (0.043) | | | (0.036) | (0.041) | (0.038) | (0.040) | | | (0.035) | (0.037) |
| grngdppc_lg1y | 0.075** | 0.052 | | | 0.089*** | 0.086** | 0.068** | 0.095*** | | | 0.079** | 0.091** |
| | (0.030) | (0.034) | | | (0.033) | (0.037) | (0.031) | (0.034) | | | (0.034) | (0.036) |
| ln_asset_lg1y | | | 0.130*** | 0.129*** | 0.127*** | 0.127*** | | | 0.171*** | 0.127*** | 0.170*** | 0.128*** |
| | | | (0.038) | (0.038) | (0.037) | (0.037) | | | (0.036) | (0.038) | (0.035) | (0.037) |
| capital_ratio_lg1y | | | 1.216*** | 1.226*** | 1.205*** | 1.203*** | | | 1.083*** | 1.188*** | 1.108*** | 1.207*** |
| | | | (0.222) | (0.222) | (0.219) | (0.220) | | | (0.194) | (0.224) | (0.192) | (0.220) |
| liquid_ar_lg1y | | | 0.001 | 0.001 | 0.001* | 0.001* | | | 0.000 | 0.001 | 0.001* | 0.001* |
| | | | (0.000) | (0.000) | (0.000) | (0.000) | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Bank f.e. | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year-quarter f.e. | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Instruments | N | Y | N | Y | N | Y | N | Y | N | Y | N | Y |
| KPaap LM statistic | | 105.46 | | 91.18 | | 87.44 | | 124.38 | | 96.48 | | 101.12 |
| p-value | | 0.00 | | 0.00 | | 0.00 | | 0.00 | | 0.00 | | 0.00 |
| CD Wald statistic | | 257.82 | | 349.33 | | 244.14 | | 331.06 | | 173.35 | | 292.80 |
| KP Wald statistic | | 50.76 | | 62.17 | | 47.30 | | 64.32 | | 48.45 | | 55.73 |
| Hansen J (p-value) | | 0.32 | | 0.23 | | 0.31 | | 0.29 | | 0.17 | | 0.24 |
| Observations | 3720 | 3625 | 3247 | 3166 | 3247 | 3166 | 4826 | 3625 | 4275 | 3166 | 4275 | 3166 |
| R-squared | 0.182 | 0.140 | 0.213 | 0.177 | 0.224 | 0.189 | 0.162 | 0.141 | 0.212 | 0.167 | 0.221 | 0.185 |

*Notes*: The dependent variable is the quarterly year-over-year growth rate (in logs) of total loans. Columns (1) to (6) ((7)-(12)) show the results when expYEB is measured by YEB balance penetration (account penetration). IV regressions use Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. KPaap LM statistic (p-value) is the Kleibergen-Paap rk LM statistic (p-value) for the under-identification test. CD Wald and KP Wald statistics are Cragg-Donald Wald F statistic and Kleibergen-Paap rk Wald F statistic for the weak identification test. The 5%, 10%, and 20% critical values for the CD Wald statistic are 11.04, 7.56, and 5.57 (respectively) Stock and Yogo (2005). Critical values for KP Wald statistics are not tabulated as they vary across applications. Standard practice is to compare the statistic to the associated CD Wald critical value even though the implied p-value is not asymptotically correct (Bazzi and Clemens, 2013). Hansen J statistic and p-value show result for the overidentification test of all instruments. The sample period is 2014Q1 to 2018Q4. Standard errors shown in the parentheses are clustered by the bank. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 9: Robustness Tests for FinTech and Monetary Policy Transmission**

| | ln(expYEB)=ln(expYEBb) | | | | | | ln(expYEB)=ln(expYEBc) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Log (Loans) | Local bank | Dis_d_HZ | Additional controls | MP*Controls | MP=MP_lg1y | Log (loans) | Local bank | Dis_d_HZ | Additional controls | Mp*Controls | MP=MP_lg1y |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| L4.log(Loans) | | -0.217*** | -0.224*** | -0.220*** | -0.222*** | -0.217*** | | -0.216*** | -0.224*** | -0.220*** | -0.222*** | -0.219*** |
| | | (0.053) | (0.048) | (0.051) | (0.053) | (0.051) | | (0.053) | (0.048) | (0.051) | (0.053) | (0.051) |
| ln(expYEB) | 0.036 | 0.041 | -0.001 | -0.012 | -0.081 | 0.005 | -0.013 | 0.006 | -0.023 | -0.026 | -0.054 | -0.009 |
| | (0.114) | (0.064) | (0.046) | (0.045) | (0.058) | (0.055) | (0.073) | (0.046) | (0.030) | (0.031) | (0.039) | (0.033) |
| MP*ln(expYEB) | -2.627** | -1.713* | -1.960*** | -1.780** | -2.809*** | -1.620* | -1.813** | -1.474** | -1.578*** | -1.404** | -2.024*** | -1.164* |
| | (1.036) | (0.875) | (0.740) | (0.763) | (1.036) | (0.839) | (0.771) | (0.659) | (0.550) | (0.563) | (0.630) | (0.596) |
| ln_asset_lg1y | 0.547*** | 0.102** | 0.128*** | 0.117*** | 0.108*** | 0.117*** | 0.548*** | 0.102** | 0.127*** | 0.115*** | 0.107*** | 0.115*** |
| | (0.042) | (0.040) | (0.037) | (0.038) | (0.037) | (0.038) | (0.040) | (0.040) | (0.037) | (0.038) | (0.037) | (0.038) |
| cap_ratio_lg1y | 2.240*** | 1.095*** | 1.207*** | 0.919*** | 1.083*** | 0.940*** | 2.247*** | 1.115*** | 1.203*** | 0.915*** | 1.054*** | 0.936*** |
| | (0.373) | (0.222) | (0.220) | (0.270) | (0.323) | (0.271) | (0.370) | (0.221) | (0.220) | (0.271) | (0.322) | (0.272) |
| liq_ar_lg1y | -0.002*** | 0.001*** | 0.001* | 0.001* | 0.001* | 0.001** | -0.002*** | 0.001** | 0.001* | 0.001** | 0.001* | 0.001** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| roa_lg1y | | | | 1.744* | 1.513 | 1.832* | | | | 1.730 | 1.265 | 1.736* |
| | | | | (1.053) | (1.517) | (1.053) | | | | (1.057) | (1.520) | (1.052) |
| npl_ratio_lg1y | | | | -0.001 | -0.003 | -0.001 | | | | -0.001 | -0.004 | -0.001 |
| | | | | (0.003) | (0.007) | (0.003) | | | | (0.003) | (0.007) | (0.003) |
| lnbkshare_lg1y | | | | 0.031* | 0.039** | 0.030* | | | | 0.031* | 0.037** | 0.031* |
| | | | | (0.018) | (0.018) | (0.018) | | | | (0.018) | (0.019) | (0.018) |
| dep/liability_lg1y | | | | -0.001 | -0.001 | -0.001 | | | | -0.001 | -0.001 | -0.001 |
| | | | | (0.000) | (0.000) | (0.000) | | | | (0.000) | (0.000) | (0.000) |
| lnpop_lg1y | 0.027 | -0.028 | -0.024 | -0.028 | -0.024 | -0.026 | 0.020 | -0.040 | -0.023 | -0.026 | -0.014 | -0.024 |
| | (0.065) | (0.050) | (0.034) | (0.035) | (0.038) | (0.035) | (0.061) | (0.046) | (0.034) | (0.035) | (0.037) | (0.035) |
| lnngdppc_lg1y | -0.020 | -0.130*** | -0.119*** | -0.113*** | -0.064 | -0.116*** | -0.014 | -0.114* | -0.128*** | -0.126*** | -0.117*** | -0.121*** |
| | (0.072) | (0.042) | (0.037) | (0.038) | (0.045) | (0.039) | (0.093) | (0.060) | (0.041) | (0.044) | (0.045) | (0.043) |
| grngdppc_lg1y | 0.108* | 0.112*** | 0.091** | 0.081** | 0.154* | 0.084** | 0.080 | 0.075 | 0.086** | 0.083** | 0.222** | 0.080** |
| | (0.065) | (0.040) | (0.036) | (0.038) | (0.090) | (0.041) | (0.088) | (0.046) | (0.037) | (0.039) | (0.088) | (0.039) |
| Bank f.e. | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Year-quarter f.e. | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| MP*Bank controls | N | N | N | N | Y | N | N | N | N | N | Y | N |
| Observations | 3823 | 2348 | 3166 | 2951 | 2951 | 2951 | 3823 | 2348 | 3166 | 2951 | 2951 | 2951 |
| R-squared | 0.216 | 0.201 | 0.185 | 0.179 | 0.189 | 0.174 | 0.217 | 0.203 | 0.189 | 0.184 | 0.187 | 0.187 |

*Notes*: The dependent variable is the quarterly year-over-year growth rate (in logs) of total loans except for columns (1) and (2), in which the dependent variable is the log of total loans. Columns (2) and (8) show results for local banks that have more than 70% of total branches in one city. Columns (3) and (9) use Alipay exposure and the driving distance to Hangzhou as instruments for YEB exposure. Columns (4) and (10) use additional controls. Columns (5) and (11) include the interaction terms of monetary policy shock and bank-level control variables. Columns (6) and (12) use the monetary policy shock in the previous year. Every regression, except for (3) and (9), is estimated with 2SLS using Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. The sample period is 2014Q1 to 2018Q4. Standard errors shown in the parentheses are clustered by the bank. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 10: FinTech and Monetary Policy Transmission - Heterogeneity Tests**

| | Panel A: Time period | | Panel B: Rural banks | | Panel C: SOCB | |
|---|---|---|---|---|---|---|
| | <=2015 | >2015 | YES | NO | YES | NO |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| MP*ln(expYEB) | 4.573 | -2.883*** | -2.220** | 0.310 | 2.401 | -1.786** |
| | (3.513) | (0.985) | (0.994) | (1.018) | (1.621) | (0.771) |
| Observations | 755 | 2133 | 1715 | 1236 | 110 | 2841 |
| R-squared | 0.180 | 0.215 | 0.238 | 0.223 | 0.572 | 0.179 |
| | Panel D: SOCB/JSCB | | Panel E: Big banks | | Panel F: White list | |
| | YES | NO | YES | NO | YES | NO |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| MP*ln(expYEB) | -1.411 | -2.070** | -0.761 | -1.875** | -0.182 | -2.324** |
| | (1.342) | (0.836) | (1.323) | (0.784) | (1.227) | (0.936) |
| Observations | 302 | 2649 | 190 | 2761 | 420 | 2531 |
| R-squared | 0.296 | 0.181 | 0.408 | 0.179 | 0.354 | 0.180 |
| | Panel G: Subsamples before and after 2015 | | | | | |
| | Rural banks | NSOCB | CCB/Rural banks | Small banks | Not White | Risky banks |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| MP*ln(expYEB) | 2.304* | 2.010 | 2.267 | 2.061 | 2.653 | 9.729*** |
| | (1.190) | (1.301) | (1.558) | (1.357) | (2.106) | (3.627) |
| MP*ln(expYEB)*After_15 | -4.634*** | -5.054*** | -5.540*** | -5.209*** | -5.998** | -11.565*** |
| | (1.442) | (1.696) | (1.940) | (1.754) | (2.423) | (3.820) |
| Observations | 2343 | 2841 | 2649 | 2761 | 2531 | 1020 |
| R-squared | 0.245 | 0.174 | 0.174 | 0.173 | 0.174 | 0.259 |

*Notes*: This table presents results for heterogeneity tests. The dependent variable is the quarterly year-over-year growth rate (in logs) of total loans. ExpYEB is measured by the YEB account penetration rate. Every regression is estimated with 2SLS using Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. A big bank is defined as a bank with assets of more than CNY 4 trillion (US$ 615 billion) according to classification standards for financial institutions issued by the National Bureau of Statistics in China in 2015. Banks in the whitelist are banks with the top 29 assets as of 2013Q4. Risky banks are banks whose NPL ratio is higher than the sample median as of 2013Q4. Every regression includes all bank-level and bank-city level controls, year-quarter, and bank fixed effects; Standard errors shown in the parentheses are clustered by bank. The sample period is 2014Q1 to 2018Q4. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 11: Aggregate Impacts of FinTech on Monetary Policy Transmission at the City Level**

| Panel A: | Dependent variable: gr of rgdp (yoy) | | Dependent variable: gr of bank loans (yoy) | |
|---|---|---|---|---|
| | More exposed | Less exposed | More exposed | Less exposed |
| | (1) | (2) | (3) | (4) |
| MP (yoy) | 0.476** | 1.444*** | 1.092*** | 1.868*** |
| | (0.208) | (0.186) | (0.223) | (0.239) |
| City f.e. | Y | Y | Y | Y |
| Observations | 1008 | 1008 | 946 | 795 |
| R-squared | 0.007 | 0.070 | 0.033 | 0.092 |
| Num. of cities | 168 | 168 | 160 | 136 |

| Panel B: | Dependent variable: gr of bank loans (yoy) | | | |
|---|---|---|---|---|
| | More exposed after 2015 | More exposed before 2015 | Less exposed after 2015 | Less exposed before 2015 |
| | (1) | (2) | (3) | (4) |
| MP (yoy) | -0.098 | 0.876*** | 0.878* | 0.740*** |
| | (0.400) | (0.268) | (0.457) | (0.279) |
| City f.e. | Y | Y | Y | Y |
| Observations | 475 | 471 | 400 | 395 |
| R-squared | 0.000 | 0.026 | 0.017 | 0.025 |
| Num. of cities | 160 | 157 | 136 | 132 |

*Notes*: This table presents results of the impacts of FinTech on monetary policy transmission at the city level. The dependent variable in columns (1) and (2) in panel A is the year-over-year growth rate (in logs) of real GDP. The dependent variable in panel B and columns (3) and (4) in panel A is the year-over-year growth rate (in logs) of total bank loans. MP (yoy) is the year-over-year exogeneous growth rate of M2 measured at the Q4 in each year. More (less) exposed cities refer to cities with higher (lower) than median level YEB penetration rate (account penetration rate) as of 2013Q4. Robust standard errors are shown in the parentheses. The sample period is 2012 to 2018. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 12: FinTech and Monetary Policy Transmission − Growth Rates of Deposits**

| Variable | ΔTotal Deposits | Δ Time Deposits | ΔDemand Deposits | ΔHH Deposits | ΔHH Time Deposits | ΔHH Demand Deposits | ΔFirm Deposits | ΔFirm Time Deposits | ΔFirm Demand Deposits | ΔTotal Deposits (local bank) |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Panel A: Full sample | | | | | | | | | | |
| MP*ln(expYEBc) | -3.623*** | -5.000*** | -2.660 | -1.884 | -5.052*** | -1.774 | -6.175*** | -8.142 | -4.718** | -4.323*** |
| | (0.860) | (1.499) | (2.003) | (1.242) | (1.423) | (3.129) | (2.245) | (5.685) | (2.230) | (1.103) |
| Observations | 2956 | 1806 | 1806 | 1974 | 1801 | 1794 | 1967 | 1793 | 1791 | 2150 |
| R-squared | 0.341 | 0.264 | 0.275 | 0.254 | 0.256 | 0.257 | 0.327 | 0.308 | 0.342 | 0.284 |
| Panel B: Before 2015 | | | | | | | | | | |
| MP*ln(expYEBc) | 2.066 | 11.536 | -1.840 | 4.121 | 3.676 | 0.373 | 4.424 | 15.951 | -4.934 | -0.160 |
| | (3.059) | (12.260) | (7.087) | (4.934) | (6.749) | (10.047) | (6.457) | (19.293) | (8.107) | (6.204) |
| Observations | 756 | 550 | 550 | 594 | 547 | 545 | 590 | 543 | 541 | 534 |
| R-squared | 0.166 | 0.141 | 0.502 | 0.362 | 0.308 | 0.478 | 0.494 | 0.586 | 0.450 | 0.315 |
| Panel C: After 2015 | | | | | | | | | | |
| MP*ln(expYEBc) | -4.024*** | -3.615* | -7.454*** | -1.367 | -4.747** | -2.243 | -5.151* | 2.801 | -9.514*** | -4.381*** |
| | (1.167) | (2.038) | (2.834) | (1.570) | (2.003) | (4.543) | (3.019) | (9.092) | (3.135) | (1.327) |
| Observations | 2137 | 1190 | 1190 | 1316 | 1188 | 1184 | 1314 | 1185 | 1186 | 1553 |
| R-squared | 0.420 | 0.356 | 0.465 | 0.400 | 0.360 | 0.409 | 0.411 | 0.284 | 0.459 | 0.375 |
| Panel D: ΔTotal | Rural Banks | | SOCB | | SOCB/JSCB | | Big Bank | | White List Bank | |
| Deposits | YES | NO | YES | NO | YES | NO | YES | NO | YES | NO |
| MP*ln(expYEBc) | -4.473*** | -1.256 | 0.808 | -3.620*** | 1.883* | -4.159*** | 1.565 | -3.755*** | 1.102 | -4.487*** |
| | (1.162) | (1.235) | (1.046) | (0.864) | (1.007) | (0.925) | (1.305) | (0.883) | (1.079) | (1.028) |
| Observations | 1714 | 1242 | 110 | 2846 | 304 | 2652 | 190 | 2766 | 422 | 2534 |
| R-squared | 0.259 | 0.481 | 0.881 | 0.336 | 0.664 | 0.334 | 0.677 | 0.336 | 0.583 | 0.329 |

*Notes*: The dependent variable is the quarterly year-over-year growth rate (in logs) of various types of deposits. FinTech exposure is measured by the YEB account penetration ratio. Every regression is estimated with 22SLS using Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. Every regression includes all bank-level and bank-city level controls, year-quarter, and bank fixed effects. Standard errors shown in the parentheses are clustered by bank. The sample period is 2014Q1 to 2018Q4. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table 13: FinTech and Monetary Policy Transmission − Changes in Deposit Interest Rates**

| | ΔDeposit Rate | | ΔTime Deposit Rate | | ΔDemand Deposit Rate | | ΔDeposit Rate | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| MP*ln(expYEB) | -6.132*** | -4.844*** | -12.372*** | -10.247** | -3.666** | -2.635** | | |
| | (1.699) | (1.515) | (3.912) | (3.215) | (1.625) | (1.256) | | |
| MP | | -1.656 | | -6.870*** | | -2.510*** | | |
| | | (1.244) | | (2.031) | | (0.881) | | |
| ΔR007*ln(expYEB) | | | | | | | 4.502*** | 4.599*** |
| | | | | | | | (1.427) | (1.398) |
| ΔR007 | | | | | | | | 32.819*** |
| | | | | | | | | (12.619) |
| Bank controls/f.e. | Y | Y | Y | Y | Y | Y | Y | Y |
| Year f.e. | N | Y | N | Y | N | Y | N | Y |
| Quarter f.e. | N | Y | N | Y | N | Y | N | Y |
| Year-quarter f.e. | Y | N | Y | N | Y | N | Y | N |
| Observations | 1517 | 1517 | 482 | 482 | 482 | 482 | 1155 | 1155 |
| R-squared | 0.280 | 0.275 | 0.456 | 0.450 | 0.255 | 0.255 | 0.308 | 0.356 |

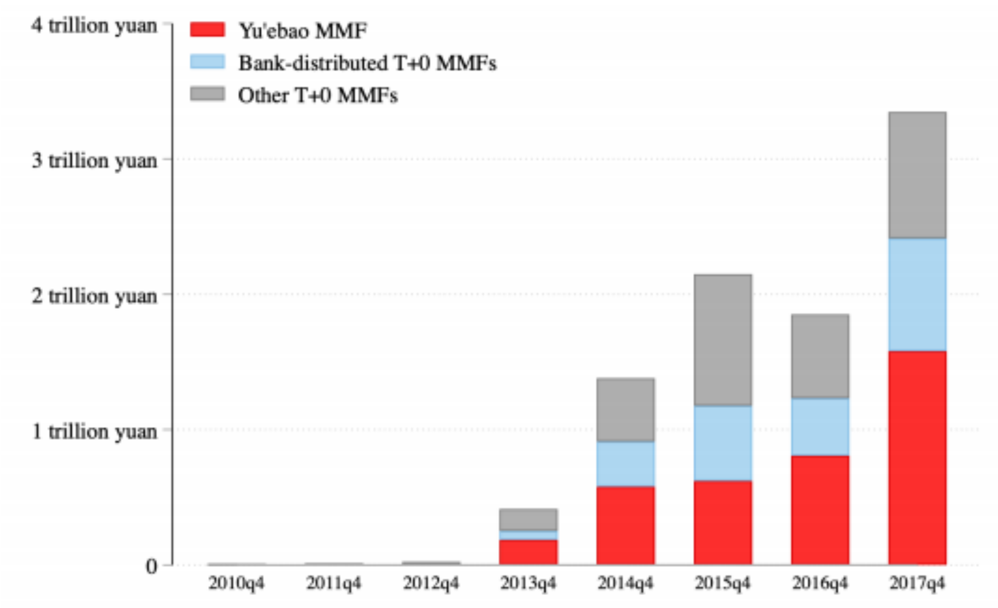
*Notes*: The dependent variables are the quarterly year-over-year change in deposit rates of various types of deposits. FinTech exposure is measured by the YEB account penetration ratio. Regressions (1) – (6) are estimated with 2SLS using Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. Regressions (7) and (8) use the same IVs for YEB exposure and use MP as the IV for ΔR007. ΔR007 is measured with the change of R007 in the previous year because outcome variables measure the average deposit rates in the previous four quarters and because it takes time for the rates on nonzero maturity deposits to reset (Drecheler et al. 2017). Standard errors are clustered by bank. The sample period is 2014Q1 to 2018Q4. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

# Appendix:

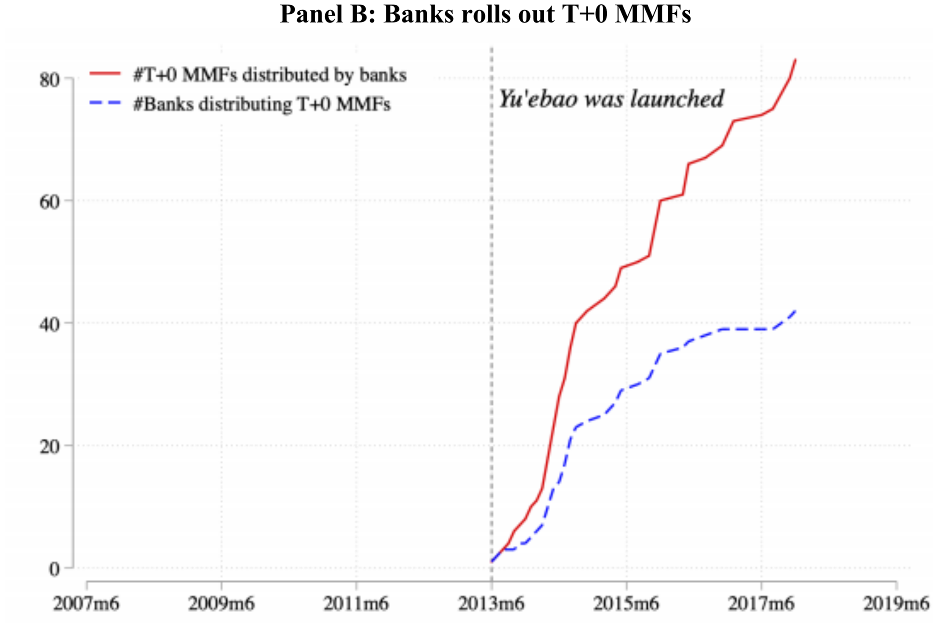
## List of Variables

| | |
|---|---|
| Dependent variables | |
| Δ Total loans | The year-over-year (yoy) log differences of total loans. |
| Δ Total deposits | The year-over-year log differences of total deposits. We also consider growth rates of eight subcategories of deposits (introduced in section 2) calculated similarly. |
| ΔDeposit Rate | The change (yoy) in the average deposit rate is measured by the deposit interest expense divided by total deposits. We also consider changes in the interest rates of eight subcategories of deposits (introduced in section 2) calculated similarly. |
| Yu'ebao Spread | The difference between YEB yield and the average deposit rate. Defined in a similar way for the other eight subcategories of deposits. |
| ΔNIS | The difference (yoy) of net interest spread. |
| ΔNIM | The difference (yoy) of net interest margin. |
| Key explanatory variables and instrumental variables | |
| expYEBc/Alipay_c | A bank's exposure to YEB using the branch-weighted sum of city-level YEB account penetration rate. The exposure to Alipay account penetration is defined similarly. |
| expYEBb/Alipay_b | A bank's exposure to YEB using the branch-weighted sum of city-level YEB balance penetration rate. The exposure to Alipay balance penetration is defined similarly. |
| disHZ | A bank's distance to Hangzhou city using the branch-weighted sum of the city-level distance to Hangzhou. |
| Control variables | |
| bank size | The log value of a bank's total asset |
| liquid asset ratio | The ratio of a bank's liquid asset to total asset |
| capital ratio | The ratio of book equity to total asset |
| ROA | Return on asset, computed as the ratio of total net profit to total asset |
| NPL ratio | Non-performing loan ratio |
| branchshare | A bank's branch share in the national branch network |
| bank_lnngdppc | City-level log of GDP per capita aggregated to bank-level using branch weights. |
| bank_grngdppc | City-level growth rate of GDP per capita aggregated to bank-level with branch weights. |
| bank_lnngdppc | City-level log of population aggregated to bank-level using branch weights. |

**Panel A: Size of money market funds with T+0 feature**




**Panel B: Banks rolls out T+0 MMFs**




## Figure A1: YEB MMF and other T+0 MMFs

*Notes*: Source: Buchak et. al. (2021). Panel A shows the size of MMFs with $T+0$ fast redemption features distributed by Alipay, commercial banks, and other institutions (such as broker-dealers). Panel B shows the number of $T+0$ MMFs distributed by banks (red) and the number of unique banks distributing $T+0$ MMFs (blue).


**Figure A2: Loan to Deposit Ratio in China's Banking System**

Notes: Source: Wind and CICC Research.

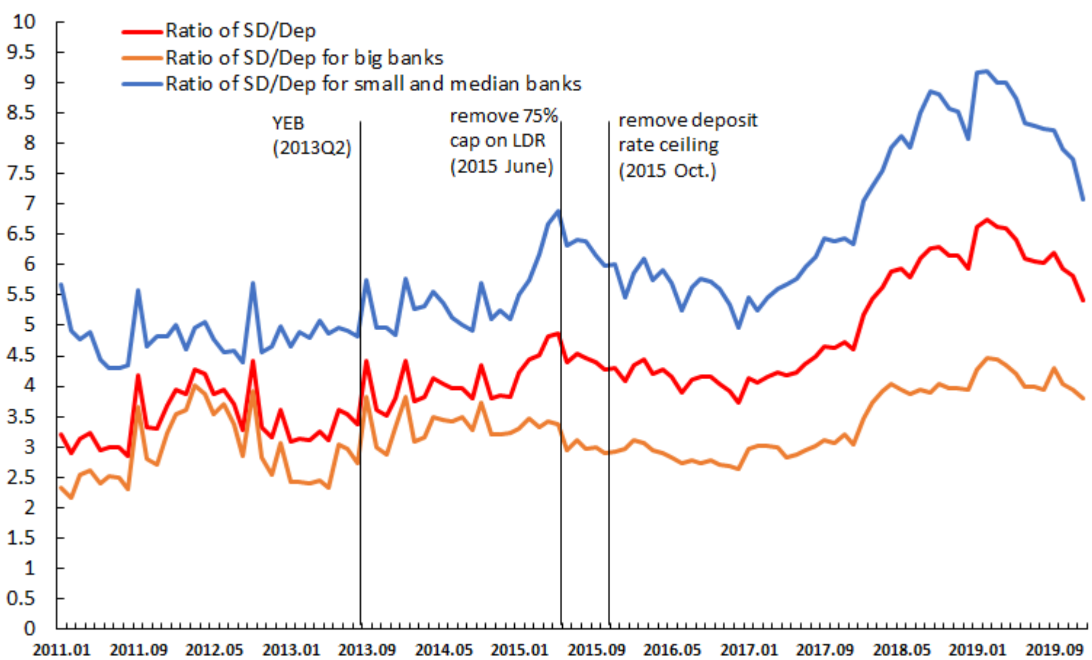



**Figure A3: Ratio of Structured Deposits on Total Deposits (2011-2019)**

*Notes:* Source: People's Bank of China and author's calculation.

**Table A1: First-stage Regressions: Cross-sectional Regressions 2012-2014**

| | ln(exposureYEBc) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| ln_disHZ_12 | -0.083*** | -0.089*** | -0.085*** |
| | (0.006) | (0.006) | (0.005) |
| ln(Alipay_c_2013q1) | 1.091*** | 1.075*** | 1.080*** |
| | (0.020) | (0.018) | (0.016) |
| ln(bank_size) | -0.003 | 0.030*** | 0.028*** |
| | (0.010) | (0.010) | (0.011) |
| capital ratio | 0.002 | 0.001 | 0.001 |
| | (0.003) | (0.003) | (0.003) |
| roa | 0.008 | 0.008 | 0.017 |
| | (0.015) | (0.014) | (0.014) |
| liquid asset ratio | -0.000 | -0.001 | -0.001 |
| | (0.001) | (0.001) | (0.001) |
| npl ratio | 0.005 | 0.003 | 0.002 |
| | (0.007) | (0.007) | (0.007) |
| ln(branchshare) | -0.006 | 0.025** | 0.028** |
| | (0.010) | (0.010) | (0.011) |
| deposit/liability | -0.000 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| bank_lnngdppc | -0.081*** | -0.062*** | -0.059*** |
| | (0.023) | (0.022) | (0.019) |
| bank_grngdppc | -0.005*** | -0.006*** | -0.006*** |
| | (0.001) | (0.001) | (0.001) |
| bank_lnpop | 0.028*** | 0.032*** | 0.029*** |
| | (0.010) | (0.009) | (0.008) |
| lnhdep_d_12 | 0.009 | | |
| | (0.008) | | |
| lnhdep_t_12 | | -0.051*** | |
| | | (0.010) | |
| lnhdep_12 | | | -0.052*** |
| | | | (0.014) |
| Obs | 179 | 179 | 195 |
| Adjusted R2 | 0.992 | 0.993 | 0.992 |

*Notes:* This table presents the results of the first stage regressions for regressions in Table 2. The dependent variable is the bank's exposure to YEB measured by the YEB account penetration ratios. Columns (1), (2), and (3) show first stage results for the growth rates of household demand deposits, household time deposits, and household deposits, respectively. The numbers in the parentheses show robust standard errors, adjusted for a small sample. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table A2: A Placebo Test of Pre-trend Deposit Growths from 2010 to 2012**

| | ΔTotal deposits | ΔFirm deposits | ΔFirm time deposits | ΔFirm demand deposits | ΔHH. deposits | ΔHH. time deposits | ΔHH. demand deposits | ΔTime deposits | ΔDemand deposits |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| ln(expYEBc) | 2.590 | 5.221 | 11.298 | 2.477 | 0.442 | 0.260 | 6.289 | 7.170 | 3.843 |
| | (2.343) | (3.850) | (6.836) | (3.687) | (3.046) | (5.248) | (6.291) | (4.407) | (3.786) |
| lnsize_10 | -28.194 | -6.848 | 12.366** | 4.101 | 7.547*** | 10.106*** | 8.646*** | 7.206** | 8.910 |
| | (44.752) | (5.337) | (5.810) | (4.869) | (1.935) | (3.054) | (2.722) | (3.125) | (5.866) |
| cap_ratio_10 | 0.800 | 0.599 | 0.294 | 0.331 | -0.142 | -0.296 | -0.547 | -0.155 | 0.055 |
| | (0.538) | (0.398) | (1.289) | (0.523) | (0.307) | (0.548) | (0.464) | (0.559) | (0.458) |
| roa_10 | -3.378 | -12.347*** | -25.921*** | -8.622** | 4.067 | 8.180 | 1.618 | -7.134 | -5.915* |
| | (2.380) | (3.506) | (6.411) | (3.514) | (3.005) | (5.481) | (4.844) | (4.647) | (3.270) |
| liq_ar_10 | 0.185** | 0.001 | 0.155 | -0.017 | 0.237 | 0.159 | 0.118 | 0.131 | 0.009 |
| | (0.086) | (0.140) | (0.307) | (0.149) | (0.165) | (0.261) | (0.187) | (0.229) | (0.146) |
| npl_ratio_10 | -1.348*** | -3.835* | -17.163*** | 0.712 | -0.412 | -1.414 | 2.172 | -6.076* | 0.886 |
| | (0.437) | (2.062) | (5.308) | (1.540) | (1.244) | (1.921) | (2.438) | (3.146) | (1.552) |
| lnbkshare_10 | 0.557 | 4.948** | 6.762 | 0.128 | 0.061 | 3.032* | 1.077 | 5.582* | -0.077 |
| | (1.050) | (2.262) | (4.601) | (1.860) | (1.586) | (1.608) | (3.261) | (2.941) | (1.870) |
| depositIBL_10 | -0.533 | -0.178 | -0.014 | 0.060 | 0.140 | 0.163 | 0.222 | -0.053 | 0.162 |
| | (0.573) | (0.128) | (0.275) | (0.127) | (0.144) | (0.238) | (0.148) | (0.202) | (0.127) |
| lnngdppc_10 | -5.418*** | -11.037*** | -15.826** | -7.291* | -0.439 | 3.065 | -6.608 | -5.010 | -8.023** |
| | (1.894) | (3.962) | (7.773) | (3.881) | (3.577) | (6.229) | (8.538) | (4.542) | (3.993) |
| grngdppc_10 | 0.151 | -0.154 | -0.363 | -0.122 | 0.211 | 0.539 | -0.071 | 0.113 | -0.110 |
| | (0.175) | (0.291) | (0.761) | (0.300) | (0.344) | (0.503) | (0.382) | (0.584) | (0.297) |
| lnpop_10 | -0.809 | -0.216 | -4.202 | -0.453 | -0.152 | 1.526 | -3.339 | -1.444 | -1.299 |
| | (1.531) | (2.115) | (4.064) | (1.590) | (1.800) | (2.550) | (2.721) | (3.051) | (1.467) |
| ln(outcome_10) | 26.478 | 1.470 | -19.408*** | -4.527 | -9.204*** | -15.332*** | -9.938*** | -14.370*** | -9.203 |
| | (44.406) | (3.879) | (2.749) | (3.983) | (2.208) | (3.176) | (3.319) | (1.759) | (5.862) |
| Obs | 136 | 96 | 90 | 90 | 97 | 90 | 90 | 91 | 91 |
| Adjusted R2 | 0.288 | 0.212 | 0.562 | -0.004 | 0.335 | 0.489 | 0.030 | 0.488 | 0.003 |

*Notes*: This table shows the placebo test results for various types of deposits indicated in the first row. The dependent variables are annualized average deposit growth rates from 2010 to 2012. Every regression is estimated with 2SLS using Alipay exposure and Hangzhou distance as instruments for Yu'ebao exposure. Ln(outcome_10) represents the level value of the outcome variable in the corresponding regression as of 2010Q4. The numbers in the parentheses show robust standard errors, adjusted for a small sample. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table A3: First Stage Regressions for Table 8**

| | (1) | (2) |
|---|---|---|
| Dependent variable: | ln(expYEBb) | MP*ln(expYEBb) |
| L4.ln of total loan | -0.008 | 0.000 |
| | (0.027) | (0.000) |
| ln_disHZ_lg1y | -0.727* | 0.010*** |
| | (0.418) | (0.003) |
| ln(expAlipay_b) | 0.578*** | -0.003*** |
| | (0.055) | (0.000) |
| MP* ln_disHZ_lg1y | -2.286*** | 0.010 |
| | (0.574) | (0.012) |
| MP*ln(expAlipay_b) | -2.606*** | 0.648*** |
| | (0.682) | (0.020) |
| ln_asset_lg1y | 0.013 | -0.000 |
| | (0.045) | (0.000) |
| cap_ratio_lg1y | -0.968*** | 0.005 |
| | (0.353) | (0.004) |
| liq_ar_lg1y | 0.000 | 0.000 |
| | (0.001) | (0.000) |
| bank_lnpop_lg1y | -0.122 | 0.002 |
| | (0.105) | (0.001) |
| bank_lnngdppc_lg1y | -0.363*** | 0.003*** |
| | (0.088) | (0.001) |
| bank_grngdppc_lg1y | 0.326*** | -0.003*** |
| | (0.083) | (0.001) |
| Bank f.e. | Y | Y |
| Year-quarter f.e. | Y | Y |
| Observations | 3247 | 3247 |
| R-squared | 0.974 | 0.976 |

*Notes*: This table presents the results of the first stage regressions for regressions in Table 8, column (6). The YEB exposure is measured by the YEB balance penetration ratio. The sample period is 2014Q1 to 2018Q4. Standard errors shown in the parentheses are clustered by bank. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table A4: Robustness Checks for the Growth Rate of Deposit**

| Variable | ΔTotal Deposits | Δ Time Deposits | ΔDemand Deposits | ΔHH Deposits | ΔHH Time Deposits | ΔHH Demand Deposits | ΔFirm Deposits | ΔFirm Time Deposits | ΔFirm Demand Deposits |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Panel A: Full sample | | | | | | | | | |
| MP*ln(expYEBb) | -2.853*** | -4.007*** | -2.829* | -1.533 | -3.685*** | -1.631 | -5.976*** | -6.889 | -4.446*** |
| | (0.623) | (1.143) | (1.526) | (0.939) | (1.050) | (2.458) | (1.749) | (4.296) | (1.672) |
| Observations | 2956 | 1806 | 1806 | 1974 | 1801 | 1794 | 1967 | 1793 | 1791 |
| R-squared | 0.359 | 0.274 | 0.280 | 0.254 | 0.260 | 0.258 | 0.348 | 0.311 | 0.358 |
| Panel B: Before 2015 | | | | | | | | | |
| MP*ln(expYEBb) | -1.019 | 2.566 | -1.001 | 2.329 | 2.914 | 22.252* | 5.532 | 28.605 | -7.867 |
| | (1.567) | (7.450) | (7.652) | (5.280) | (5.880) | (11.713) | (8.405) | (22.427) | (8.949) |
| Observations | 756 | 550 | 550 | 594 | 547 | 545 | 590 | 543 | 541 |
| R-squared | 0.313 | 0.302 | 0.502 | 0.384 | 0.343 | 0.461 | 0.489 | 0.545 | 0.421 |
| Panel C: After 2015 | | | | | | | | | |
| MP*ln(expYEBb) | -3.153*** | -2.375 | -7.961*** | -1.227 | -2.931** | -1.644 | -5.376** | 1.695 | -9.125*** |
| | (0.801) | (1.518) | (1.977) | (1.088) | (1.363) | (3.274) | (2.209) | (6.401) | (2.175) |
| Observations | 2137 | 1190 | 1190 | 1316 | 1188 | 1184 | 1314 | 1185 | 1186 |
| R-squared | 0.440 | 0.367 | 0.488 | 0.404 | 0.376 | 0.410 | 0.424 | 0.279 | 0.491 |

*Notes*: The dependent variable is the quarterly year-over-year growth rate (in logs) of various types of deposits. FinTech exposure is measured by expYEBb. Every regression is estimated with 2SLS using Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. Every regression includes all bank-level and bank-city level controls, year-quarter, and bank fixed effects. Standard errors shown in the parentheses are clustered by bank. The sample period is 2014Q1 to 2018Q4. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$

**Table A5: Changes in Deposit Interest Rates of Different Products**

| Variable | ΔFirm Deposit Rate | ΔFirm Time Deposit Rate | ΔFirm Demand Deposit Rate | ΔHH Deposit Rate | ΔHH Time Deposit Rate | ΔHH Demand Deposit Rate |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: | | | | | | |
| MP*ln(expYEB) | -8.216** | 2.624 | -5.187*** | -7.060** | -9.619** | 1.430 |
| | (3.700) | (7.149) | (1.943) | (3.147) | (4.113) | (1.537) |
| Bank controls | Y | Y | Y | Y | Y | Y |
| Bank f.e. | Y | Y | Y | Y | Y | Y |
| Year-quarter f.e. | Y | Y | Y | Y | Y | Y |
| Observations | 563 | 474 | 474 | 565 | 474 | 474 |
| R-squared | 0.419 | 0.573 | 0.315 | 0.313 | 0.388 | 0.144 |
| | ΔTime Deposit Rate | | | ΔDemand Deposit Rate | | |
| Variable | Full | <=2015 | >2015 | Full | <=2015 | >2015 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel B: | | | | | | |
| MP*ln(expYEB) | -12.372*** | -1.058 | -13.420*** | -3.666** | 0.608 | -4.515** |
| | (3.912) | (3.297) | (4.359) | (1.625) | (0.963) | (2.079) |
| Bank controls | Y | Y | Y | Y | Y | Y |
| Bank f.e. | Y | Y | Y | Y | Y | Y |
| Year-quarter f.e. | Y | Y | Y | Y | Y | Y |
| Observations | 482 | 89 | 376 | 482 | 89 | 376 |
| R-squared | 0.456 | 0.809 | 0.436 | 0.255 | 0.655 | 0.274 |

*Notes*: The dependent variables are the quarterly year-over-year change in deposit interest rates of various types of deposits. FinTech exposure is measured by the YEB account penetration ratio. Every regression is estimated with 2SLS using Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. Every regression includes all bank-level and bank-city level controls, year-quarter, and bank fixed effects. Standard errors shown in the parentheses are clustered by bank. The sample period is 2014Q1 to 2018Q4 for panel A. In panel B, columns (2) and (5) use the sample from 2014Q1-2015Q4, while columns (3) and (6) use the sample from 2016Q1-2018Q4. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table A6: FinTech and Franchise Value of Banks**

| | Franchise Value (1) | Franchise Value (2) | Franchise Value (3) | Franchise Value (4) |
|---|---|---|---|---|
| ln(expYEBc) | -0.054*** | -0.034 | -0.053*** | -0.029 |
| | (0.020) | (0.023) | (0.020) | (0.023) |
| MP*ln(expYEBc) | | | -0.117 | -0.195 |
| | | | (0.470) | (0.463) |
| Bank controls | Y | Y | Y | Y |
| Bank f.e. | Y | Y | Y | Y |
| Year-quarter f.e. | Y | Y | Y | Y |
| Method | OLS | 2SLS | OLS | 2SLS |
| Observations | 705 | 705 | 705 | 705 |
| R-squared | 0.467 | 0.103 | 0.467 | 0.103 |

*Notes*: The dependent variable is the bank's franchise value, defined as the market to book asset ratio as in Keeley (1990). FinTech exposure is measured by the YEB account penetration ratio. Standard errors shown in the parentheses are robust standard errors clustered by bank. The sample period is 2014Q1 to 2018Q4. *** for p < 0.01, ** for p < 0.05, and * for p < 0.1.

**Table A7: FinTech and NPL Ratio 2015-2018**

| | ΔNPL ratio (2015-2018) | ΔNPL ratio (2015-2018) | ΔNPL ratio (2015-2018) |
|---|---|---|---|
| Panel A: 2015-2018 | (1) | (2) | (3) |
| ln(expYEBc_15) | -0.365*** | -0.356*** | |
| | (0.126) | (0.129) | |
| ln(expYEBc_13) | | | -0.416*** |
| | | | (0.090) |
| Bank controls (2015) | Y | Y | Y |
| Method | OLS | 22SLS | 22SLS |
| Observations | 344 | 344 | 308 |
| R-squared | 0.133 | 0.133 | 0.178 |
| | ΔNPL ratio (2016-2018) | ΔNPL ratio (2016-2018) | ΔNPL ratio (2016-2018) |
| Panel B: 2016-2018 | (1) | (2) | (3) |
| ln(expYEBc_16) | -0.433*** | -0.503** | |
| | (0.159) | (0.222) | |
| ln(expYEBc_13) | | | -0.562*** |
| | | | (0.126) |
| Bank controls (2015) | Y | Y | Y |
| Method | OLS | 22SLS | 22SLS |
| Observations | 437 | 437 | 330 |
| R-squared | 0.074 | 0.073 | 0.157 |

*Notes*: This table shows the results for NPL ratio with cross-sectional regressions from 2015-2018 (panel A) and 2016-2018 (panel B). Columns (1) and (2) show results estimated with the key explanatory variable (ln(expYEB)) measured as of the end of 2015 (panel A) and the end of 2016 (panel B). Column (3) shows results estimated with ln(expYEB) measured as of the end of 2013. 2SLS estimation uses Alipay exposure and Hangzhou distance as instruments for Yu'ebao exposure. Every regression includes all bank-level and bank-city level controls. The numbers in the parentheses show robust standard errors, adjusted for a small sample. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table A8: Dynamic Impacts on NPL Ratio after 2015**

| | NPL(t) | NPL(t) | NPL(t+4q) | NPL(t+4q) | NPL(t+8q) | NPL(t+8q) |
|---|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) | (6) |
| ln(expYEB)t-1 | 0.083 | 0.005 | 0.657 | 0.983 | -0.035 | 0.328 |
| | (0.701) | (0.783) | (0.791) | (0.854) | (1.069) | (1.219) |
| MPt*ln(expYEB)t-1 | 19.235* | 20.062* | 25.968*** | 24.815** | 5.398 | 5.837 |
| | (10.121) | (10.833) | (9.301) | (9.808) | (9.737) | (9.967) |
| All controls & f.e. | Y | Y | Y | Y | Y | Y |
| Method | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| Observations | 3040 | 2985 | 2034 | 1939 | 1228 | 1106 |
| R-squared | 0.117 | 0.092 | 0.116 | 0.084 | 0.048 | 0.025 |

*Notes*: The dependent variables are NPL ratio in the quarter t, t+4, and t+8. FinTech exposure is measured by the YEB account penetration ratio. Standard errors shown in the parentheses are robust standard errors clustered by bank. The sample period spans from 2016Q1 to 2019Q4. *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table A9: The Impact of FinTech on Banks' Default Risk**

| Variable | Full sample (1) | Full sample (2) | Full sample (3) | Full sample (4) | >2015 (5) | >2015 (6) |
|---|---|---|---|---|---|---|
| ln(expYEBc) | -34.372 | 5.489 | -32.935 | 36.272 | -65.448 | -77.464 |
| | (30.291) | (67.008) | (29.910) | (64.936) | (46.287) | (100.975) |
| MP* ln(expYEBc) | | | -461.788 | -1877.826* | 192.630 | -2318.650 |
| | | | (545.345) | (993.398) | (796.321) | (1605.218) |
| Bank controls | Y | Y | Y | Y | Y | Y |
| Bank f.e. | Y | Y | Y | Y | Y | Y |
| Year-quarter f.e. | Y | Y | Y | Y | Y | Y |
| Method | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
| Observations | 4652 | 3527 | 4652 | 3527 | 3732 | 2601 |
| R-squared | 0.065 | 0.012 | 0.065 | 0.009 | 0.077 | 0.025 |

*Notes*: The dependent variable is the Z-score of banks, defined as $Z - score_{bt} = ROA_{bt} + CAR_{bt}/\sigma_{ROA_{bt}}$. $CAR_{bt}$ is the ratio of total equity to total assets. $\sigma_{ROA_{bt}}$ is computed by a three-year rolling window scale instead of the full sample period to allow time variation of the standard error following Beck et al. (2013). FinTech exposure is measured by the YEB account penetration ratio. 2SLS estimation uses Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. Every regression includes all bank-level and bank-city level controls, year-quarter, and bank fixed effects. Standard errors shown in the parentheses are clustered by bank. The sample period is 2014Q1 to 2019Q4. Columns (5) and (6) use the sample from 2016Q1-2019Q4. *** for p < 0.01, ** for p < 0.05, and * for p < 0.1.

**Table A10: The impact of FinTech on Bank' Leverage Risk**

| Variable | Leverage Risk Full sample (1) | Leverage Risk Full sample (2) | Leverage Risk Full sample (3) | Leverage Risk <=2015 (4) | Leverage Risk >2015 (5) |
|---|---|---|---|---|---|
| ln(expYEBc) | 0.038 | | 0.005 | 0.095*** | 0.068 |
| | (0.043) | | (0.038) | (0.034) | (0.052) |
| ln(expYEBb) | | 0.023 | | | |
| | | (0.025) | | | |
| MP*ln(expYEBc) | | | 0.631* | 0.609*** | 0.125 |
| | | | (0.374) | (0.191) | (0.828) |
| Bank controls | Y | Y | Y | Y | Y |
| Bank f.e. | Y | Y | Y | Y | Y |
| Year-quarter f.e. | Y | Y | Y | Y | Y |
| Observations | 545 | 545 | 545 | 154 | 388 |
| R-squared | 0.153 | 0.154 | 0.139 | 0.456 | 0.158 |

*Notes*: The dependent variable is the leverage risk of banks defined as the book value of liabilities over the market value of assets (Gropp and Vesala, 2004). Every regression is estimated with 2SLS using Alipay exposure and the distance to Hangzhou as instruments for YEB exposure. Every regression includes all bank-level and bank-city level controls, year-quarter, and bank fixed effects. Standard errors shown in the parentheses are clustered by bank. The sample period is 2014Q1 to 2019Q4. Column (4) uses the sample from 2014Q1-2015Q4, while column (5) uses the sample from 2016Q1-2019Q4. *** for p < 0.01, ** for p < 0.05, and * for p < 0.1.

**Table A11: Asset Changes and FinTech**

| Panel A: 2015-2018 | ΔTotal loans (1) | ΔTotal loans (2) | ΔLiquid assets (3) | ΔLiquid assets (4) | ΔFinancial investment (5) | ΔFinancial investment (6) | ΔCash & reserve (7) | ΔCash & reserve (8) |
|---|---|---|---|---|---|---|---|---|
| ln(expYEBc_15) | 3.214** | | 3.274 | | 1.090 | | 4.833** | |
| | (1.289) | | (2.506) | | (5.500) | | (1.920) | |
| ln(expYEBc_13) | | 1.979** | | 3.282 | | -3.982 | | 4.441*** |
| | | (0.907) | | (2.048) | | (4.343) | | (1.484) |
| Observations | 357 | 315 | 345 | 306 | 299 | 271 | 345 | 306 |
| R-squared | 0.315 | 0.441 | 0.369 | 0.381 | 0.357 | 0.324 | 0.170 | 0.138 |
| Panel B: 2016-2018 | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ln(expYEBc_16) | 4.298*** | | 6.246** | | 10.752* | | 8.943*** | |
| | (1.207) | | (2.786) | | (5.819) | | (2.193) | |
| ln(expYEBc_13) | | 3.786*** | | 5.460** | | 8.594 | | 7.152*** |
| | | (0.968) | | (2.503) | | (5.778) | | (1.762) |
| Observations | 451 | 337 | 438 | 327 | 390 | 296 | 437 | 327 |
| R-squared | 0.276 | 0.408 | 0.331 | 0.359 | 0.269 | 0.260 | 0.177 | 0.179 |

*Notes*: This table shows the results for cross-sectional regressions from 2015-2018 (panel A) and 2016-2018 (panel B). The dependent variables are the average annual growth rate of different types of bank assets. Odd columns show results estimated with the key explanatory variable (ln(expYEB)) measured as of the end of 2015 (panel A) and the end of 2016 (panel B). Even columns show results estimated with ln(expYEB) measured as of the end of 2013. Every regression is estimated using Alipay exposure and Hangzhou distance as instruments for Yu'ebao exposure. Every regression includes all bank-level and bank-city level controls. The numbers in the parentheses show robust standard errors, adjusted for a small sample. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

**Table A12: FinTech and Wholesale Funding**

| Panel A: 2012-2014 | ΔWSF (12-14) (1) | ΔWSF (12-14) (2) | ΔWSF/Liability (12-14) (3) | ΔWSF/Liability (12-14) (4) |
|---|---|---|---|---|
| ln(expYEBc_13) | -16.151 | -17.554 | -1.026 | -1.116 |
| | (12.200) | (12.264) | (0.756) | (0.777) |
| Bank controls (2012) | Y | Y | Y | Y |
| Method | OLS | 22SLS | OLS | 22SLS |
| Observations | 211 | 211 | 211 | 211 |
| R-squared | 0.336 | 0.336 | 0.229 | 0.229 |
| **Panel B: 2015-2018** | **ΔWSF (15-18) (1)** | **ΔWSF (15-18) (2)** | **ΔWSF/Liability (15-18) (3)** | **ΔWSF/Liability (15-18) (4)** |
| ln(expYEBc_15) | -6.062 | | -1.159* | |
| | (7.460) | | (0.689) | |
| ln(expYEBc_13) | | -7.331 | | -1.005* |
| | | (6.454) | | (0.512) |
| Bank controls (2015) | Y | Y | Y | Y |
| Method | 22SLS | 2SLS | 2SLS | 22SLS |
| Observations | 322 | 289 | 322 | 289 |
| R-squared | 0.536 | 0.480 | 0.482 | 0.459 |
| **Panel C: Full Sample** | **ΔWSF (1)** | **ΔWSF/deposit (2)** | **ΔWSF/liability (3)** | **ΔWSF Rate (4)** |
| ln(expYEBc) | 0.705 | -3.456 | -0.744 | -1.028 |
| | (0.499) | (4.724) | (2.982) | (1.881) |
| MP*ln(expYEBc) | -12.474 | -46.922 | -33.421 | -0.802 |
| | (8.150) | (59.649) | (36.524) | (28.140) |
| Bank controls | Y | Y | Y | Y |
| Bank f.e. & Y-Q f.e. | Y | Y | Y | Y |
| Observations | 2760 | 3356 | 3356 | 910 |
| R-squared | 0.609 | 0.575 | 0.491 | 0.511 |

*Notes*: The dependent variables are the average annual growth rate of banks' wholesale funding, the first difference in the WSF to liability ratio, the change in WSF to deposit ratio, and the change in the average WSF rates. Panel A shows the cross-sectional regression results with the sample from 2012-2014. Panel B shows the cross-sectional results with the sample from 2015-2018. Panel C shows the panel estimation results with the sample from 2014Q1-2018Q4. YEB exposure is measured by the YEB account penetration ratio. 2SLS estimation uses Alipay exposure and Hangzhou distance as instruments for Yu'ebao exposure. Every regression includes all bank-level and bank-city level controls. Regressions in panel C also include bank fixed-effects and year-quarter fixed effects. The numbers in the parentheses show robust standard errors, adjusted for a small sample for panels A and B and clustered by bank for panel C. The levels of statistical significance are denoted by the asterisks: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.