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Abstract

This study investigates whether and how financial technologies (FinTech) influence the effectiveness of monetary policy transmission. We use an interacted panel vector autoregression model to explore how the effects of monetary policy shocks change with regional-level FinTech adoption. Results indicate that FinTech adoption generally mitigates the transmission of monetary policy to real GDP, consumer prices, bank loans, and housing prices, with the most significant impact observed in the weakened transmission to bank loan growth. The relaxed financial constraints, regulatory arbitrage, and intensified competition are the possible mechanisms underlying the mitigated transmission.

Keywords: financial technology, interacted panel VAR, monetary policy

JEL classification: C32, E52, G21, G23

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1 Introduction

The rise of financial technology (FinTech) has been a major phenomenon in economies across the globe. Spanning from mobile payments, money transfers, and online lending to blockchain, cryptocurrencies, and robo-investing, the broad concept of FinTech revolves around adopting new technologies in financial services.[1] The FinTech revolution in recent years is distinct from the financial innovations that took place in prior decades due to the unprecedented speed, data abundance, and disruptions to the traditional financial sector brought about by big technology (BigTech) firms and digital platforms outside the financial industry (Goldstein et al. 2019, Boot et al. 2021).

As the potential impact of FinTech on the economy increases, so do its implications for monetary policy transmission. As stated in Philippon (2016) and Lagarde (2018), FinTech brings a "brave new world" for monetary policymakers and imposes strong regulatory challenges. However, despite the growing number of studies on how FinTech affects traditional financial services, little is known about the impact of FinTech on monetary policy transmission. Conceptually, predicting this impact is ambiguous. On the one hand, FinTech could mitigate monetary policy transmission in several ways. If tighter financial constraints are associated with stronger responses to monetary policy, according to the classic financial accelerator theory (Gertler and Gilchrist 1994, Kiyotaki and Moore 1997, Bernanke et al. 1999) and recent empirical evidence (Cloyne et al. 2023, Durante et al. 2022), FinTech could mitigate the overall transmission of monetary policy by loosening credit constraints and leading to a higher share of financially-unconstrained firms. FinTech could also dampen monetary policy transmission via regulatory arbitrage when it functions similarly to shadow banks by shifting credit supply from banks to less-

[1] There is a wide variety of interpretations of the term "FinTech". The Financial Stability Board (FSB) provides a definition that was adopted by the Basel Committee on Banking Supervision (BCBS): "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)

regulated nonbanks (Buchak et al. 2018, Elliott et al. 2020, Chen et al. 2018), or offsetting reductions in bank deposits (Xiao 2020) in response to monetary policy tightening. Additionally, the competition of financial services provided by FinTech and banks could possibly dampen market concentration and the associated strong responses to monetary policy (Drechsler et al. 2017). On the other hand, FinTech could enhance transmission through several channels. For instance, by easing frictions that have weakened the transmission, such as the failure of households to optimally refinance mortgages and the capacity constraints of mortgage lenders, FinTech is seen as an amplifier of monetary policy in the mortgage market (Zhou 2022). Moreover, the interest rate channel can be stronger for FinTech lenders compared to traditional banks since the latter try to build long-term relationships with borrowers, dampening the effect of interest rate changes (Bolton et al. 2016), while the direct credit supply from the former is more responsive to borrowers' change in business conditions (Gambacorta et al. 2023, Buchak et al. 2021). Finally, using similar arguments for nonbanks, the risk-taking channel could be stronger if their risk appetite is more sensitive to changes in monetary policy (Stein 2013, Rajan 2006, IMF 2016). Therefore, the role of FinTech in monetary policy transmission remains an empirical question.

This study provides new evidence on whether and how adopting FinTech influences the effectiveness of monetary policy transmission. Specifically, we adopt an interacted panel vector autoregression (IPVAR) method and examine how responses to monetary policy shocks vary with the degree of FinTech adoption. Our analysis employs a parsimonious IPVAR specification, incorporating real GDP, consumer prices, bank loans, and housing prices as endogenous variables in response to exogenous monetary policy shocks, while also considering the interaction with FinTech adoption. Overall, our findings suggest a transmission-mitigating role of FinTech adoption. Regions with higher FinTech adoption exhibit weaker impulse responses to the same monetary policy shock compared to those with lower FinTech adoption.

There are two major challenges in answering our research questions and implementing the IPVAR estimation. The first challenge involves measuring FinTech adoption in a way that suits the examination of its role in monetary policy transmission. A notable issue is the lack of consistent and comparable data on FinTech development, encompassing both credit and non-credit financial businesses driven by new technologies. While recent efforts have been made to construct cross-country FinTech credit databases (Demirgüç-Kunt et al. 2020, Cornelli et al. 2023), their annual frequency and cross-country structure make them less suitable for studying monetary policy transmission. This is due to the more frequent occurrence of monetary shocks and the rarity of cross-country consistency in monetary frameworks and policy-making procedures. To effectively analyze the transmission of monetary policy, we require a national-level dataset that provides cross-sectional variation in FinTech measurements. Solely relying on time variation would make it difficult to distinguish the effects stemming from monetary policy shocks and those attributed to FinTech development. The second challenge pertains to the endogeneity concern regarding the mutual feedback between FinTech and the outcome variables of economic performance. For instance, more developed areas might exhibit higher financing needs, leading to higher FinTech adoption to fulfill those demands. On the other hand, it could be the reverse, where less developed regions adopt FinTech more due to higher financial constraints or diminished market power of traditional financial services. In either case, the estimates of FinTech's effects on economic growth could be biased.

We address these challenges by utilizing a novel dataset and employing an instrumental variable (IV) approach to identify the role of FinTech adoption. First, to tackle the issue of data availability, we exploit a granular measurement of regional FinTech adoption in China (Guo et al. 2020). This allows us to have cross-sectional variation in FinTech while keeping the same monetary policy shocks consistent across regions. With this data structure, we adopt an IPVAR model to examine the different impulse responses to monetary policy shocks based on different levels of FinTech adoption. Specifically, the FinTech measurement used in this study captures the aggregate usage of FinTech services, including digital payments, credits, insurance, money market activities, investment, and credit evaluation within a representative and dominant BigTech company, Ant Financial, for each province in China. China is the undisputed leader and the largest market for FinTech globally, with Ant Financial being a major player in both the Chinese and global financial markets.[2] Furthermore, while the policy measurement is unique to China, the analysis and findings of monetary policy transmission in this study have broader implications for evaluating FinTech development worldwide. Recent studies, such as Chen et al. (2018) and Kamber and Mohanty (2018), demonstrate that the transmission of monetary policy impulses to the rest of the economy in China is similar to the transmission process observed in advanced economies.

Second, to mitigate the endogeneity concerns, we utilize instrumental variables for FinTech adoption. In our baseline analysis, we employ the geographical distance to Hangzhou, the FinTech hub city where the headquarters of Ant Financial is located, as our instrumental variable. The rationale behind this choice is that the dissemination of new FinTech products and services is likely to be uneven, benefiting from interpersonal communication and exchange of user experience. As a result, regions closer to the originating hub city are expected to have higher FinTech adoption levels. In our robustness check, we also explore alternative instrumental variables, including the travel time to Hangzhou and the distance to technology-focused universities. The reason for considering these instruments is that technology-focused universities can influence the diffusion

[2]According to estimates by Cornelli et al. (2023), the top five countries in terms of total alternative credits in 2019 were China ($626.72 billion), United States ($78.45 billion), Japan ($27.87 billion), South Korea ($14.67 billion), and United Kingdom ($11.59 billion). Additionally, China ranked first in terms of alternative credit per capita ($447.64), followed by South Korea ($283.77), United States ($238.86), Japan ($220.83), and United Kingdom ($173.31).

of technical knowledge and potentially influence residents to adopt FinTech services. The geographical locations are plausibly exogenous with respect to most factors that affect the efficiency of monetary policy transmission in each region. In addition, the first stage estimates show that these instrumental variables are valid, as they exhibit a significant association with FinTech adoption. In other words, regions closer to the FinTech hub city and technology-focused universities tend to have higher levels of FinTech adoption. Moreover, the results do not indicate any weak instrument issues.

Next, to examine the mechanisms, we propose three possible channels through which FinTech mitigates monetary policy transmission and scrutinize whether our empirical evidence supports them: the financial constraint, regulatory arbitrage, and competition channels. First, increased FinTech adoption alleviates financial constraints, enabling more borrowers to become financially unconstrained and dampening the effects of the financial accelerator, thereby leading to mitigated monetary policy transmission. Second, when FinTech adoption is primarily driven by regulatory arbitrage, it makes monetary policy less effective by offsetting the responses in the highly-regulated bank sector. Third, when FinTech fiercely competes for the same segment of the financial market already served by banks, FinTech adoption could lower market concentration, which is associated with more pronounced responses to monetary policy, thus hindering the transmission. To investigate each of these possible channels, we construct variables to proxy for them. Specifically, we use the density of young and small firms and the share of short-term loans to capture the financial constraint mechanism. For the regulatory arbitrage mechanism, we use shadow banking size, loan-to-deposit ratio, and non-performing loan ratio. Lastly, for the competition mechanism, we use bank branch intensity and the share of deposits in non-state-owned banks. We then divide the dataset into subsamples based on the median value of these channel variables and re-estimate the IPVAR model for each subsample. Our findings indicate that the transmission-mitigating role of FinTech adoption is stronger in regions with more pronounced financial constraints, regulatory arbitrage, and intense competition, thus providing support for these channels.

This study mainly contributes to two strands of literature. First, we relate to the broad discussions on the transformative changes in the financial landscape brought about by FinTech. Examples in this thriving field include Buchak et al. (2018), Fuster et al. (2019), Berg et al. (2020), and Di Maggio and Yao (2021). A comprehensive survey of the existing literature can be found in Boot et al. (2021) and Allen et al. (2021). Although the potential influence of FinTech on the effectiveness of monetary policy transmission is acknowledged in both policy-making and academic discussions, direct evidence is still scarce. On one hand, current policy debates primarily focus on the impact of digital currency on monetary policy. While digital currency as "hardware" could indeed reshape the entire monetary economy, we emphasize that technological innovations in saving, borrowing, payments, and other financial services within the existing monetary system, which represent a change in the "software", are equally important in influencing the effectiveness of monetary policy transmission. Moreover, this impact is likely to be more universal and pressing. On the other hand, existing studies on FinTech tend to concentrate on comparisons with traditional financial intermediation and often lack a broader perspective of its interaction with monetary policy. This limitation might be attributed to data constraints. Focusing on the exceptional times of the COVID-19 crisis, there is evidence suggesting that FinTech helped to meet the increased demand for financial services and facilitate the distribution of government-guaranteed credit, thus supporting monetary policy (Kwan et al. 2023, Core and De Marco 2023, Branzoli et al. 2023). However, such evidence is limited to the short crisis period and the efficiency of banking systems, rather than exploring the transmission of monetary policy.

Recently, there has been increasing attention given to the relationship between FinTech and monetary policy transmission. For example, Hasan et al. (2021) examine the impact of banks' in-house technology development on the lending channel of monetary policy, De Fiore et al. (2023) model the role of BigTech in increasing the matching efficiency between sellers and buyers on the platform and demonstrate that BigTech credit could mitigate the transmission of monetary policy due to the lower sensitivity of "network collateral" compared to physical collateral, and Huang et al. (2022) utilize micro-level data to investigate the different responses to monetary policy changes in lending behaviors between BigTech lenders and traditional banks. In this study, the availability of granular regional-level FinTech development data provides an excellent opportunity to examine its macroeconomic impact on monetary policy transmission. We differ from other studies in that we offer evidence on the overall and general transmission, including the effects on real GDP growth, inflation, bank loans, and housing prices.

Second, we contribute to the literature concerning macroeconomic factors influencing monetary policy transmission. Castelnuovo and Pellegrino (2018) investigate how economic uncertainty interacts with monetary policy and find that monetary policy shocks have a less pronounced impact on economic activity when uncertainty is high. Lo and Piger (2005) find that monetary policy is more influential during recessions compared to periods of economic booms, while Tenreyro and Thwaites (2016) and Caggiano et al. (2014) demonstrate that monetary policy is less effective in recessions. In our study, we identify FinTech adoption as another critical factor interacting with monetary policy, thereby extending the discussion of transmission mechanisms. There is a growing body of research examining the role of nonbanks and shadow banks in monetary policy transmission, as these intermediaries outside the banking sector are gaining significance in the total credit landscape (Elliott et al. 2020, Buchak et al. 2022, Xiao 2020, Chen et al. 2018). Our paper aligns with this direction but specifically emphasizes the role of FinTech penetration, which arises from BigTech companies outside the finance sector and are distinguished by the use of digital platforms, big data, and credit assessment technologies in offering financial services.

The findings of this study carry significant implications for monetary policy and financial regulation. Given the rapid growth of FinTech, monetary policymakers need to consider the interplay between technology and finance when making adjustments to monetary policy. Furthermore, the similarity between the financial services offered by banks and FinTech companies aligns with the argument made in Lagarde (2018), emphasizing that regulators need to broaden their focus from financial entities to encompass financial activities. FinTech's emergence is likely to bring about substantial changes in both monetary policy transmission mechanisms and regulatory challenges. We view this paper as an initial step in addressing this increasingly important research area.

The remainder of the paper is structured as follows. Section 2 describes the data and variables used in this study. Section 3 presents the methodology of the interacted panel vector autoregression. Section 4 reports the baseline empirical results and robustness checks. Section 5 explores the underlying mechanisms of the findings. Finally, Section 6 concludes the paper.

2 Data

2.1 Monetary Policy Shocks

Specification of the monetary policy rule and identification of its shock are crucial for investigating the transmission of monetary policy to the economy. We adopt the method used in Chen et al. (2018) to measure monetary policy shocks in China. According to their description, the primary goal of China's monetary policy is to achieve an annual GDP growth target, rather than an inflation target, and the growth rate of the money supply (M2) is the most important intermediate target of China's monetary policy. Despite the recent interest rate liberalization, which remains incomplete and unfinished, the importance of credit quantity targets is still significant in China. Starting in 1994, the State Council's Annual Report on the Work of Government specified M2 growth targets until 2018. The M2 growth target holds great significance as a monetary indicator in the annual report, ranking second only to the overall GDP growth target. Both of these targets are delivered by the Premier and are considered to guide the government's economic work for the following year. Chen et al. (2018) capture the monetary policy decision process in China as follows: the People's Bank of China (PBC) adjusts M2 growth rates on a quarterly basis in response to inflation and GDP growth in the previous quarter, with the GDP growth target acting as a lower bound for monetary policy.[3] They estimate the monetary policy rule for the period 2001Q1-2016Q2, and we extend the estimation to cover 2001Q1-2019Q2 using the same method but with an extended sample.[4]

Specifically, the monetary policy rule is estimated as an endogenous quarterly M2 growth, which is a function of the gaps between actual and target inflation and between actual and target GDP growth:

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

where $\epsilon_{m,t}$ is an independent random shock that follows a normal distribution with a mean of zero and a time-varying standard deviation $\sigma_{m,t}$. $g_{m,t}$ is the M2 growth rate, π_t is the CPI inflation rate, $g_{x,t}$ is the GDP growth rate, and π^* and $g^*_{x,t}$ are the growth

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

[4]The underlying macroeconomic data for the estimation is available for a longer period, including the years 2020 and 2021; however, we stop at the year 2019 to exclude the period affected by the coronavirus disease (COVID-19). On one hand, the first human cases of COVID-19 were identified in Wuhan, China, on December 27, 2019, and the World Health Organization declared the COVID-19 outbreak a Public Health Emergency of International Concern on 30 January 2020, and a pandemic on 11 March 2020. Thus, the economic impact of COVID-19 is not a concern as of mid-2019. On the other hand, starting from 2020, COVID-19 became associated with huge economic uncertainty and significant growth gaps. For instance, the State Council did not specify a GDP growth target for the year 2020 due to the extreme uncertainty in the domestic and global economy, making the only exception since 1992. Moreover, it is hardly plausible to assume that the central bank stuck with the usual systematic monetary policy in response to the strike of the pandemic.

targets for inflation and GDP, respectively.[5] The data on real GDP, CPI, and M2 levels are sourced from China's macroeconomic database published by the Federal Reserve Bank of Atlanta, which is consistent with the data used in Chen et al. (2018) and Chang et al. (2016), and we calculate their growth rates by taking the difference of natural logs. Notably, the GDP growth target acts as a lower bound for monetary policy, resulting in time-varying coefficients for the output $\gamma_{x,t}$ and the standard deviation $\sigma_{m,t}$, with the following forms:

$$\gamma_{x,t} = \begin{cases} \gamma_{x,a} & \text{if } g_{x,t-1} - g^*_{x,t-1} \geq 0 \\ \gamma_{x,b} & \text{if } g_{x,t-1} - g^*_{x,t-1} < 0 \end{cases} \tag{2} \qquad \sigma_{m,t} = \begin{cases} \sigma_{m,a} & \text{if } g_{x,t-1} - g^*_{x,t-1} \geq 0 \\ \sigma_{m,b} & \text{if } g_{x,t-1} - g^*_{x,t-1} < 0 \end{cases} \tag{3}$$

where a and b indicate the two states of being above and below the target, respectively. Same as Chen et al. (2018), we expect $\gamma_{x,a}$ to be positive and $\gamma_{x,b}$ to be negative to reflect the fact that economic growth is the overriding priority of the Chinese government, and M2 growth increases to accommodate above-the-target output growth as long as inflation is not a serious threat. Table 1 presents the estimates of the parameters, which are consistent and very close to those reported in Chen et al. (2018). The estimated M2 growth rate ($\hat{g_{m,t}}$) is the endogenous M2 growth, and the monetary policy shock, i.e., the exogenous M2 growth, is calculated as the difference between the actual and endogenous M2 growth.

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

Table 1: Estimated Results for the Endogenously Switching Monetary Policy Rule

Coefficient	Estimate	Standard Error	p-value
γ_m	0.519	0.086	0.000
γ_π	-0.395	0.122	0.001
$\gamma_{x,a}$	0.209	0.059	0.000
$\gamma_{x,b}$	-1.290	0.449	0.004
$\sigma_{m,a}$	0.005	0.001	0.000
$\sigma_{m,b}$	0.009	0.001	0.000

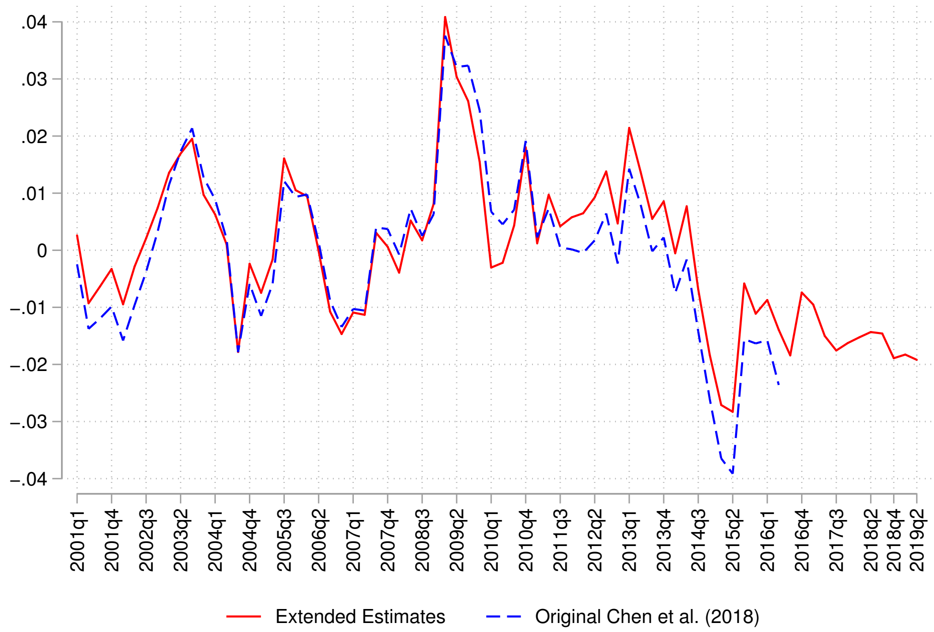
Notes: This table presents the results obtained from estimating the monetary policy rule using extended data covering the period 2000Q1-2019Q2.

Figure 1 presents the quarterly year-over-year change in the monetary policy shock, estimated using both the extended data covering 2001Q1-2019Q2 and the original data covering 2001Q1-2016Q2 obtained from Chen et al. (2018).[6] The figure shows a high correlation between our extended estimates and the original ones by Chen et al. (2018), with a correlation coefficient of 0.95. For the overlapped period 2001Q1-2016Q2, there are some discrepancies between these estimates, and the sources of the discrepancies are data revisions and the extended period (2016Q3-2019Q2). Between them, it is the extended additional data points rather than data revisions that drive the gaps between the original and our extended shock series.[7] Moreover, we report in Table A2 in the appendix that our estimates of the M2-based monetary policy shock are consistent and highly correlated with changes in various interest rates.

[6] The year-over-year change is calculated as the sum of the quarter-over-quarter changes in the last four quarters. Therefore, the year-over-year estimates start from 2001Q1 even though the sample begins from 2000Q1. We replicate the original shock series using the data and codes provided by Chen et al. (2018) and obtained exactly the same results.

[7] Vintages of the real GDP, CPI, and M2 data used in both Chen et al. (2018) and this study are published in the Center for Quantitative Economic Research of the Federal Reserve Bank of Atlanta. Readers can easily observe the data revisions between versions published at different times. Additionally, we report the estimates using the extended data but stopped at 2016Q2 in the appendix. From Figure A1 and Table A1, we can see that the shock estimates using the sample 2001Q1-2016Q2 of the extended data that cover 2001Q1-2019Q2 are very close to the original estimates in Chen et al. (2018), and their correlation coefficient is 0.99.

Figure 1: Monetary Policy Shocks in China



Notes: The solid line indicates the M2-based measurement of monetary policy shocks (in decimal) estimated by authors using the extended data covering 2001Q1-2019Q2. The blue dashed line indicates the original estimates from Chen et al. (2018), which stop in 2016Q2. The correlation coefficient between our extended estimates and the original estimates is 0.95, and it is statistically significant at the 1% level. An increase in the M2-based shock denotes an expansionary monetary policy.

From both estimates, we observe significant variations in monetary policy shocks over the sample period. A positive value indicates an expansionary shock, while a negative value indicates a contractionary one. We see that the most substantial shock occurred in 2009Q2 when the central bank aggressively eased its policy to stimulate the economy in response to the 2008 global financial crisis. Following the crisis, there was a continuous tightening period from 2009 to 2015, and the largest tightening shock occurred in 2015Q2, coinciding with the turning point of the stock market turbulence in 2015. The sample period in this study is 2011Q1-2018Q4 due to the availability of FinTech measurements, as described below.

2.2 FinTech Adoption

FinTech adoption is a broad concept that poses challenges for measurement. As summarized in Thakor (2020) and Stulz (2019), it generally encompasses four main areas: credit, payments, investment, and insurance.[8] We employ a dataset that offers measures of FinTech adoption in these specific areas of financial services. Moreover, it is available at the province level, providing crucial cross-sectional variation to study its role in monetary policy transmission.

The construction of the dataset is based on individual-level usage of various financial services in Alipay, a third-party mobile and online payment platform that accounted for 55.32% of the third-party payment market in mainland China in 2018. Alipay is the largest mobile payment platform in the world, and its parent company, Ant Financial, is among the dominant BigTech companies both domestically and internationally.[9] This dataset was developed by Guo et al. (2020) and launched by the Institute of Digital Finance of Peking University. It has been increasingly used in recent studies, such as Ding et al. (2022) and Hong et al. (2022). Specifically, the FinTech usage is constructed based on the nondimensionalization of 20 indicators, as shown in Table A3 in the appendix. The aggregated FinTech adoption indicator covers the usage of online payment services, online enrollment of insurance policies, access to internet loans, purchase of money market funds, online wealth management and investment, and credit evaluation. It is available for 30 provinces from 2011Q1 to 2018Q4.[10]

[8]Stulz (2019) also specifies the area of blockchain, which is related to cryptocurrency but not the primary focus of this study. Studies exploring the relationship between cryptocurrencies, especially central bank digital currency, and monetary policy are increasing; see Bordo and Levin (2017), He (2018), and a literature review in Beniak (2019).

[9]In this paper, we do not strictly distinguish between FinTech and BigTech. Since our FinTech adoption measurement is constructed using data from a BigTech company, and the mechanisms discussed in Section 5 apply to both FinTech and BigTech, our results are relevant for the monetary policy implications from BigTech credit as well.

[10](i) The 30 "provinces" in our dataset include 22 provinces (Anhui, Fujian, Gansu, Guangdong, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Qinghai, Shaanxi, Shandong, Shanxi, Sichuan, Yunnan, and Zhejiang), 4 autonomous regions (Guangxi, Inner

There are two concerns associated with using the raw FinTech usage index. First, there is a strong time trend in FinTech development during the sampled periods, and the implementation of an interacted panel VAR model requires stationarity of the interaction term. The raw indicators exhibit a clear time trend for each province, with an annual growth rate exceeding 40%, reflecting the robust momentum of FinTech development in China.[11] Second, it is a concern that FinTech adoption might be endogenously correlated with economic and financial developments. Specifically, FinTech adoption shows a significant positive correlation with GDP per capita, with a correlation coefficient of 0.51. This indicates that regions with more developed economies are more likely to adopt FinTech services. The presence of such a strong time trend and correlation with other economic variables in the raw FinTech adoption measurement raises concerns about non-stationarity and endogeneity in the subsequent estimation of its role in monetary policy transmission. We proceed with the following methods to mitigate these concerns.

First, to address the trend issue, we divide the raw index by the national average for each period, thus constructing the relative FinTech adoption indicator.[12] With this measurement, a value larger than 1 indicates that the province's FinTech usage is above the national average, while a value smaller than 1 indicates that the province is lagging behind in FinTech adoption. In this way, we are able to eliminate the strong time trend

Mongolia, Ningxia, and Xinjiang), and 4 municipalities (Beijing, Chongqing, Shanghai, and Tianjin). All of these regions belong to the same administrative hierarchy. Tibet, Hong Kong, and Macau are excluded from the analysis due to their special political and economic characteristics, and data on Taiwan is not available. (ii) The original FinTech adoption data is available at an annual frequency, and we use piecewise cubic Hermite interpolation to construct quarterly data. As we show below, as long as the relative rank and variation between provinces are maintained, and since we use the relative ratio of FinTech adoption in the analysis, the accuracy of the interpolated values does not raise major concerns in this study. Furthermore, we have conducted robustness tests using different interpolation methods, such as linear, cubic, and spline, and our results remain consistent.

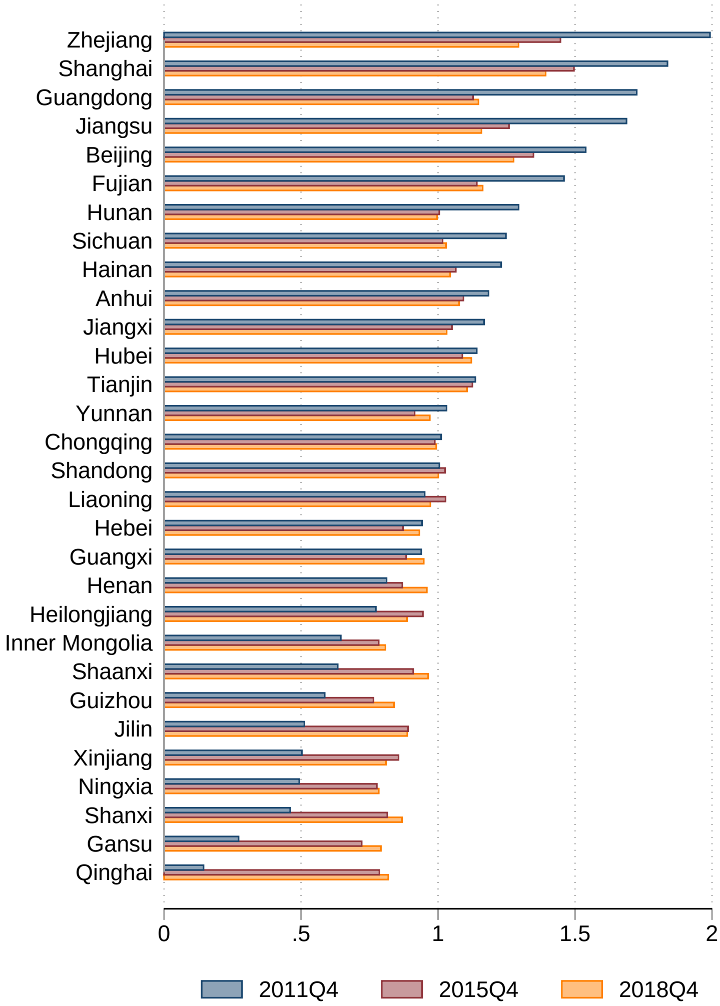
[11] In the appendix, we show the raw FinTech index for each province in 2011, 2015, and 2018 in Figure A2. This clearly demonstrates the strong time trend and momentum in FinTech adoption across all provinces.

[12] Using the FinTech growth rate as an alternative to control for time trends is not suitable, as a higher growth rate of FinTech may not imply a higher FinTech adoption level in a province but could instead capture a low initial FinTech level, given that there is a convergence in FinTech adoption across provinces over time.

while preserving the relative rank. Figure 2 shows the development of the relative FinTech ratios in 2011Q4, 2015Q4, and 2018Q4 for each province. We rank the provinces based on their relative FinTech adoption in 2011Q4. Observations from the figure are as follows. First, Zhejiang province, home of Ant Financial's headquarter, was the first to adopt FinTech in 2011, followed by the coastal provinces of Shanghai, Guangdong, and Jiangsu, and then the capital city of Beijing. Landlocked provinces, such as Qinghai, Gansu, Shanxi, and Ningxia, lag behind in adopting FinTech in financial services. Second, although the regional difference did not change substantially, the deviation and gap between provinces significantly decreased. The bars representing 2015Q4 and 2018Q4 are more concentrated around the value of one than those representing 2011Q4, indicating convergence in FinTech adoption across the country. Third, the ranks demonstrate variations over time. For instance, Shanghai replaced Zhejiang in FinTech adoption in 2015 and maintained its first place in 2018, while Yunnan and Chongqing dropped from the above-average group in the initial year to the below-average group in the later years. In summary, these rich variations over time and across provinces help with identifying the role played by FinTech adoption in the subsequent interacted panel VAR analysis.

Second, to address the potential endogeneity concern, we employ the geographical distance to Hangzhou, the capital city in Zhejiang province and the headquarters of Ant Financial, as the instrumental variable (IV) for FinTech adoption. Table A4 presents the distances from the capital city of each province to Hangzhou. The same IV has been used in Hong et al. (2022) and Ding et al. (2022) for FinTech development, and it is based on the observation that Alipay's financial services expansion centers around its headquarters city and then gradually penetrates nearby areas and distant provinces. Additionally, the geographic distance can be considered exogenous and does not exert a direct effect on the regional economy's response to monetary policy. We present the first stage estimates in Section 3 and conduct several robustness checks by using alternative IVs in Section 4.2.

Figure 2: Relative FinTech Adoption Across Provinces



Notes: The figure shows the relative FinTech adoption for each province in 2011Q4 (in navy bars), 2015Q4 (in maroon bars), and 2018Q4 (in orange bars). The provinces are ranked according to the indicators in 2011Q4. The relative FinTech adoption index is calculated by dividing the raw index by the national average in each period. A value higher than one indicates that FinTech adoption in this province is above the national average, while a value lower than one indicates the opposite.

2.3 Economic Outcome

We include four key macro and financial variables in our IPVAR model to capture the real, nominal, financial, and housing markets: real GDP growth, CPI inflation, bank loan growth, and housing price growth. The reasons for considering real GDP growth and inflation are obvious. Bank loan growth is included because Kashyap and Stein (2000) demonstrate the significance of the bank lending channel in monetary policy transmission, and Bruno and Shin (2015) suggest that the banking sector's leverage can be a channel for transmitting monetary policy to domestic and international variables. Housing prices represent one of the key mechanisms of monetary policy transmission, as emphasized by Mishkin (1995, 2007). They have been widely incorporated as endogenous variables in vector autoregression frameworks to study monetary policy transmission, as seen in studies such as Del Negro and Otrok (2007), Jarociński and Smets (2008), and Paul (2020).

We obtain province-quarter-level data from the CEIC database and use quarterly year-over-year growth rates in our estimation to control for stochastic trends and varying seasonality in the raw time series. Here's how we processed each variable. For the GDP growth rate, the original data consists of year-to-date accumulated GDP values for each province-quarter, released by the National Bureau of Statistics (NBS). We first calculate the change in year-to-date GDP in each quarter compared to the previous quarter and then calculate the year-over-year growth rate for each quarter. For inflation, the original data includes monthly CPI indices for key cities from the NBS. We keep the quarter-end months and use the CPI index of the capital city in each province as a proxy for the price index at the province level. Then we calculate its year-over-year change as the inflation rate. We subtract the inflation rate from the nominal GDP growth rate to obtain the real GDP growth rate. For bank loans, we obtain the monthly outstanding loans data for each province from the PBC. We keep the quarter-end months and calculate the year-over-year growth rate. For housing prices, the original data contains the cumulative average sales price (per square meter) of commercial residential buildings in each province, sourced from the NBS. We then simply calculate its year-over-year growth rate. Table A5 in the appendix presents the summary statistics of each variable by province.

3 Methodology: Interacted Panel VAR

Various VAR models have been widely used for analyzing how monetary policy is transmitted to the economy through different channels over time and across countries. Among many others, see the seminal papers by Sims (1992), Bernanke and Gertler (1995), Leeper et al. (1996), and Baumeister and Hamilton (2018). In this work, we adopt an interacted panel VAR (IPVAR) model to analyze monetary policy transmission to different provinces in China. This approach allows us to examine how their responses to monetary policy shocks may vary based on provincial FinTech adoption levels.

In contrast to stochastically time-varying coefficient VARs in a time series model, which typically postulates a random walk process for the law of motion of the VAR parameters, our IPVAR specification captures additional cross-sectional variation and incorporates functional coefficients to investigate varying responses of the economy to a monetary policy shock. IPVAR method has been employed in previous studies such as Sá et al. (2014) and Towbin and Weber (2013) to study the role of financial structure in affecting the relationship between capital inflows and housing booms, and the role of foreign currency debt and import structure in limiting the impact of floating exchange rates on insulating output from real shocks, respectively. In our IPVAR analyses, our primary focus is on the different impulse responses of the real variable, price level, and financial and housing market variables to a monetary policy shock, contingent on the level of FinTech adoption.

Specifically, for our baseline estimation, we consider an IPVAR model as follows:

$$A_{0,it}Y_{i,t} = \gamma\delta_{it} + \sum_{l=1}^{L} A_l Y_{i,t-l} + B_{0,it} mp_t + U_{it} \tag{4}$$

where $Y_{i,t}$ includes four endogenous variables: the growth rates of real GDP, consumer prices, bank loans, and house prices of province i in quarter t. mp_t is a national-level

M2-based monetary policy shock, which is considered an exogenous variable common to all provinces. δ_{it} is a vector including province-specific intercepts and control variables, and $U_{i,t}$ is a vector of uncorrelated $i.i.d$ shocks. We consider lagged working-age population share as a control variable in δ_{it} in the baseline estimation, and lagged educated population share as an alternative control variable in the robustness check. To select the number of lags L, we rely on the Hannan-Quinn information criterion (HQC) and use two lags for the main analysis. Additionally, we report results based on the Akaike information criterion (AIC) and four lags in the appendix. The confidence intervals of the impulse responses are obtained from 500 bootstrapped samples.

The matrix A_0 captures the responses of economic variables to a monetary policy shock at impact, through the evolution of endogenous variables in response to the shock. B_0 is a vector of parameters representing the contemporaneous responses of endogenous variables to a monetary policy shock. Both matrices are specified with time-varying coefficients as a function of FinTech adoption, $FinTech_{i,t}$, to model its role in monetary policy transmission in the short run. To maintain a parsimonious model specification, we impose recursive assumptions on the A_0 matrix in the order of real GDP, consumer prices, bank loans, and house prices. This ordering is broadly following the categorization of slow-moving variables (real GDP and inflation) and fast-moving variables (loan and housing markets), as suggested by Bernanke et al. (2005). We note that recursive restrictions in VAR models may potentially mislead inferences of the model as discussed in Canova and Pina (2005). Despite this, given an exogenous monetary policy shock, a specific ordering of endogenous variables may not be critical to the estimation and inference of our model. The baseline results are robust to different specifications of the A_0 matrix, including alternative (block) recursive orderings and the identity matrix form. The coefficient matrices $A_{l,it}$ capture dynamics of monetary policy transmission.

To analyze how responses vary with province-specific FinTech adoption, we specify the coefficients in equation (4) as follows:

$$\begin{cases} A_{0,it} &= A_{0,1} + A_{0,2}FinTech_{i,t}, \\ B_{0,it} &= B_{0,1} + B_{0,2}FinTech_{i,t}, \end{cases} \tag{5}$$

where $FinTech_{i,t}$ denotes the measurement of FinTech adoption. If we disregard the second term in coefficient matrices (5), our specification simplifies to a conventional panel VAR model with exogenous monetary policy shocks. We report the impulse responses from the panel VAR estimation in the appendix Figure A3, which shows that the monetary policy operates conventionally in China, with an expansionary shock inducing positive responses in real GDP, inflation, bank loan, and housing price. The inclusion of the second term allows the impulse responses of outcome variables to vary depending on the interaction variable and captures the marginal impact of FinTech adoption on monetary policy transmission.

As a robustness check for the IPVAR model specification, we explore several alternative specifications. These include considering both contemporaneous and lagged macro variables in the interaction term[13], using lagged instead of current FinTech adoption in the interaction term, using four lags based on the Akaike information criterion (AIC), and specifying A_0 as an identity matrix. We obtain consistent results across these different specifications. We show results from these alternative specifications in Table A6 in the appendix.

In our model, one of the key identification assumptions is that the quarterly monetary policy shock is exogenously given to individual provinces in period t. This means that the province-level outcome variables and the FinTech adoption indicators do not con-

[13]We haven't chosen this specification as our baseline due to concerns about limited degrees of freedom, given our relatively small sample size. Furthermore, including interaction coefficients on lagged macro variables results in broader confidence intervals, as these estimates are statistically insignificant or only marginally significant.

temporaneously affect the national-level monetary policy shock. Regarding the timing of the central bank's policy decision, as described in Chen et al. (2018), it is reasonable to treat our measure of the monetary policy as an exogenous component of M2 growth at the beginning of each quarter, as the systematic reactions anticipated by previous economic conditions have been removed. Focusing on the exogeneity of the monetary policy shock, one can label our model specification as an IPVAR with an exogenous variable (IPVARX).

The other identification assumption concerns the exogeneity of FinTech adoption, which is unlikely to hold. As described in the previous section, we address the endogeneity issue by adopting an instrumental variable approach. Specially, we consider the geographical distance from the capital city of each province to Hangzhou, the FinTech hub city and the headquarters of the Ant Financial Group, as an instrument in the first stage regression. We then use the predicted values obtained from this first stage as a measure of FinTech adoption in the second stage estimation. In both stages, we include the lagged macro-finance variables and the ratio of working-age population as control variables, thus keeping the same δ_{it} and $Y_{i,t-l}$. The distance to Hangzhou is arguably exogenous, and it is reasonable to assume that our choice of IV satisfies the exclusion restriction (Hong et al. 2022, Ding et al. 2022).[14]

Table 2 shows the results of the first stage regression, and we consider the specification in column (5) for the baseline estimation. First, it shows that the instrumental variable, distance to Hangzhou, is significantly associated with FinTech adoption. Provinces closer to the headquarter of Alibaba exhibit stronger levels of FinTech adoption. Additionally, the adjusted R-square statistics indicate that we explain a large fraction of the variation

[14]We treat Fintech adoption as an exogenous conditioning variable in our specification. By endogenizing the evolution of FinTech adoption within the IPVAR system, we can investigate the feedback mechanism between economic variables and FinTech in monetary policy transmission. A self-exciting interacted panel VAR (SEIPVAR) model can be considered to model the endogeneity of conditioning variables explicitly. We leave this extension for future research.

in FinTech adoption in the first stage. Second, the presence of a weak instrument problem is not likely. We report the F-statistics calculated following Stock and Watson (2012), and they comfortably exceed the threshold of 10, which is often used as a rule of thumb to identify potential weak instrument issues. Therefore, these results suggest a satisfactory performance of the IV in the first stage, enabling us to proceed with the estimation in the second stage.

Table 2: First Stage Regression for Baseline

DepVar: FinTech Usage	(1)	(2)	(3)	(4)	(5)
Distance to Hangzhou	-0.171***	-0.171***	-0.171***	-0.147***	-0.145***
	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Working-age Population		2.161***	2.291***	1.627***	1.631***
		(0.155)	(0.160)	(0.178)	(0.192)
Constant	1.232***	-0.359***	0.000	0.213	-0.001
	(0.012)	(0.114)	(0.005)	(0.137)	(0.006)
Lagged Macro Variables	No	No	No	Yes	Yes
Time Fixed Effect	No	No	Yes	No	Yes
Adjusted R-squared	0.371	0.487	0.492	0.526	0.529
F-statistics	512.79	411.60	420.47	83.48	84.62

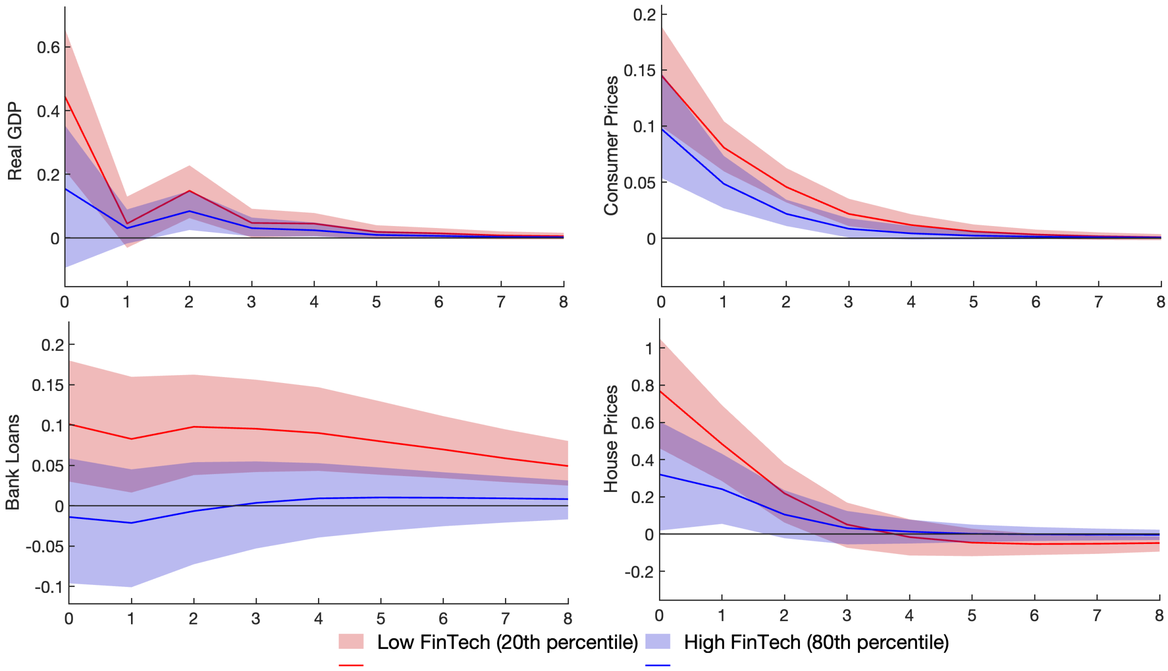
Notes: The table reports the results from the first stage estimation, using the geographical distance to Hangzhou as an instrumental variable for FinTech adoption. We control for lagged working-age population ratio and macro-finance variables. Standard errors are reported in parentheses. *, **, and *** denote significance levels for 10%, 5%, and 1%, respectively.

4 Empirical Evidence

4.1 Baseline Results

As shown in equations (4) and (5), the FinTech adoption variable is not only interacted with the monetary policy shock but also with endogenous variables in $Y_{i,t}$. Therefore, solely examining the coefficient in the interaction term between FinTech adoption and the monetary policy shock is insufficient to assess its role in the IPVAR setting. We follow the literature and illustrate the full impulse responses to monetary policy shocks with values of the variable of key interest at a low and high level, respectively. Specifically, we plot the impulse responses to a one-unit expansionary monetary policy shock when the value of FinTech adoption is at its 20th percentile (low FinTech) and 80th percentile (high FinTech).[15]

Figure 3: Baseline Results: FinTech and Monetary Policy Transmission



Notes: The subfigures present responses of growths of real GDP, consumer prices, bank loans, and house prices to an expansionary monetary policy shock. The x-axis represents the quarters after the shock, and the y-axis denotes the values of the impulse responses (in percentage points of the year-over-year growth rate) to a positive one-unit M2 shock. The red (blue) solid lines and shading represent impulse responses and 90% confidence intervals at the 20th (80th) percentile of FinTech adoption, respectively.

Figures 3 shows the baseline results, where the solid lines indicate the point estimates and the shaded areas correspond to the 90% confidence intervals of impulse responses obtained from 500 bootstrap replications.[16] The different patterns and magnitudes of the

[15]Note that we use the continuous FinTech variable, instead of employing high and low dichotomy variables, in the IPVAR estimation. The high and low FinTech adoption values are used solely for facilitating the visualization of the results. Alternatively, we can estimate a different IPVAR model by using a dummy variable that takes a value of 1 when FinTech adoption is greater than the 50th percentile. We perform this alternative estimation as a robustness check and report the estimates in panel (e) of Table A6 in the appendix, and the results are qualitatively consistent.

[16]We acknowledge the potential generated regressor problem arising from the estimated monetary policy shock. However, a standard two-step bootstrapping procedure to address this issue is not applicable to our model specification.

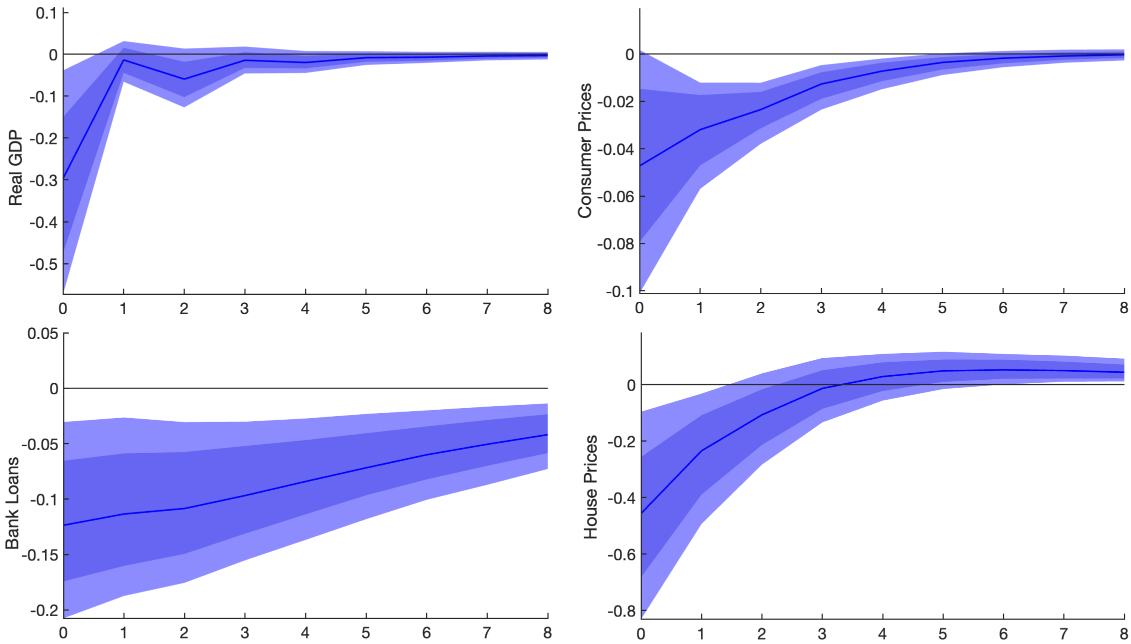
results, shown in the red (low) and blue (high) lines and areas, demonstrate the qualitative role of FinTech adoption in monetary policy transmission. Notably, we observe that the blue lines tend to lie below the red ones in all panels, indicating that the impulse responses to the same monetary policy shock with high FinTech adoption are smaller than those with low FinTech adoption.

Specifically, concerning real GDP growth, it increases contemporaneously by 0.45 percentage points in response to an easing monetary policy shock with low FinTech adoption. However, its response becomes smaller and statistically insignificant with high FinTech adoption, and the responses with high FinTech adoption remain below that with low FinTech adoption throughout the eight quarters. Regarding inflation, when FinTech adoption is low, it increases by 0.15 percentage points at impact, and the positive effect persists across the horizon. Meanwhile, when FinTech adoption is high, the response of inflation is 0.1 percentage points at impact, and it becomes statistically insignificant after three quarters. As for bank loan growth, the impact of an expansionary monetary policy is only significantly positive when FinTech adoption is low, showing an increase of 0.1 percentage points at the beginning and a persistent increase by 0.05 percentage points eight quarters after the shock. For housing price growth, the impact is more than doubled when FinTech adoption is low (an increase of 0.8 percentage points) compared to when FinTech adoption is high (an increase of 0.3 percentage points) in the two quarters following the monetary shock, and both impacts become statistically insignificant afterward.

To determine the statistical significance of the different effects, we calculate the differences between the responses with high and low FinTech adoption and test the significance of these differences using the same set of bootstrapped samples. Figure 4 illustrates the computed differences along with the 68% (in dark shades) and 90% (in light shades) confidence intervals. The detailed results visualized in this figure are also reported in Table

3, and we adhere to this practice to throughout the rest of the paper to present the IP-VAR results. Negative and significant values imply that higher FinTech adoption leads to a weaker response to an expansionary monetary policy shock. The results demonstrate that the transmission-mitigating role of FinTech is significant but temporary for real GDP growth and housing price growth, whereas it remains significant and persistent for inflation and bank loan growth. In particular, the weaker responses in bank loan growth due to high FinTech adoption are the most pronounced and persistent throughout the entire horizon.

Figure 4: Difference between Responses with Low and High FinTech Adoption



Notes: The subfigures present the differences in the responses of the growth of real GDP, consumer prices, bank loans, and house prices obtained from the baseline estimation. The blue solid lines denote the differences between impulse responses with high and low FinTech adoption. A value below zero indicates that higher FinTech adoption leads to a weakened response. The interior dark blue and exterior light blue areas correspond to the 68% and 90% confidence bands of the statistical test on the difference in impulse responses, respectively. The x-axis represents quarters after the shock, and the y-axis denotes the differences in the impulse responses in percentage points of the year-over-year growth rate.

Table 3: Significance of Difference of Impulse Responses with FinTech Adoption

Quarter	Real GDP	Consumer Prices	Bank Loans	House Prices
0	-0.307**	-0.051*	-0.119**	-0.464**
1	-0.014	-0.033**	-0.109**	-0.257**
2	-0.063*	-0.024**	-0.106**	-0.124*
3	-0.015	-0.013**	-0.094**	-0.022
4	-0.020*	-0.008**	-0.082**	0.023
5	-0.008	-0.004*	-0.071**	0.045*
6	-0.007	-0.002	-0.060**	0.051*
7	-0.004	-0.001	-0.050**	0.050**
8	-0.002	0.000	-0.042**	0.045**

Notes: The table presents a statistical test of the differences between impulse responses to an expansionary monetary policy shock with high and low FinTech adoption. We report the differences in the impulse responses of real GDP, consumer prices, bank loans and housing prices in the cells, up to eight quarters after the initial shock. A cell with * or ** denotes a statistically significant difference at the 68% or 90% confidence level, respectively.

To sum up, the baseline findings indicate that when facing the same monetary policy shock, FinTech adoption leads to significantly muted responses in the economy. Higher FinTech adoption is associated with weaker impacts on real output growth, inflation, bank loan growth, and housing price growth.

4.2 Robustness Checks

We conduct a battery of checks to further demonstrate the robustness of the baseline finding regarding the transmission-mitigating effect of FinTech adoption. First, we adopt alternative instrumental variables. To tackle the identification challenge arising from the endogeneity of FinTech adoption, we have implemented the instrumental variable approach in estimating IPVAR throughout the paper. In the main results, the instrumental variable used is the geographical distance to the hub city of FinTech development in China, i.e., Hangzhou, and we have controlled for demographics by including the ratio of the working-age population in both the first and second stage estimations. Now we show the results based on alternative combinations of instrumental variables and control variables.

Specifically, we consider two alternative instrumental variables: the travel hours by train to Hangzhou and the distance to technology-focused universities, along with an alternative control variable related to demographics: the ratio of the educated population. We have chosen these alternatives for the following reasons. First, using travel time instead of geographical distance allows us to account for the actual mobility to the hub city. Second, following Pierri and Timmer (2022), the distance to technology-focused universities can impact the diffusion of technical knowledge and promote more aggressive adoption of FinTech services among residents. Similar to the location of the technology hub city, the geographical locations of these technology-focused universities are plausibly exogenous with respect to most factors affecting monetary policy transmission efficiency in each region. To identify the relevant technology-focused universities, we select twelve universities rated as the top 10% (A grade) in the China Discipline Evaluation within the disciplines of electronic science and technology, information and communication engineering, control science and engineering, computer science and technology, and software engineering. These disciplines play a crucial role in the research and development of FinTech. We provide the list of the twelve technology-focused universities in Table A7 in the appendix, and show that their science-related enrollments dominate over those of humanities and arts. For each province, we retain the three nearest tech-focused universities and weigh their distance based on the annual enrollment size of each university. Consequently, this instrumental variable is time-varying. Third, similar to the rationale behind considering the working-age population, we acknowledge that higher levels of education in the population correlate with a higher probability of adopting FinTech services. However, these demographic variables may be less exogenous compared to geographical locations and could act as confounding factors. As a result, we include them as control variables in our analysis.

Table 4: Significance of Difference in Impulse Responses: Alternative Instrument Variables

Quarter	Real GDP	Consumer Prices	Bank Loans	House Prices
Panel A: Train Travel Hour to Hangzhou and Working-age Population				
0	-0.193*	-0.030	-0.110**	-0.488**
1	-0.011	-0.025*	-0.101**	-0.272**
2	-0.030	-0.021**	-0.095**	-0.139*
3	-0.008	-0.013**	-0.083**	-0.043
4	-0.011	-0.007**	-0.074**	0.010
5	-0.006	-0.004*	-0.064**	0.035
6	-0.005	-0.002	-0.055**	0.043*
7	-0.003	-0.001	-0.047**	0.043*
8	-0.002	-0.001	-0.040**	0.040**
Panel B: Physical Distance to Hangzhou and Educated Population				
0	-0.280*	-0.061**	-0.077*	-0.766**
1	-0.029	-0.045**	-0.071*	-0.452**
2	-0.055*	-0.031**	-0.076*	-0.262**
3	-0.017	-0.018**	-0.072**	-0.111*
4	-0.020*	-0.011**	-0.065**	-0.029
5	-0.010	-0.006**	-0.057**	0.012
6	-0.008	-0.003*	-0.049**	0.028
7	-0.005	-0.002	-0.041**	0.035*
8	-0.003	-0.001	-0.034**	0.034*
Panel C: Physical Distance to Hangzhou and Two Control Variables				
0	-0.273*	-0.060**	-0.113**	-0.577**
1	-0.019	-0.040**	-0.103**	-0.321**
2	-0.057*	-0.026**	-0.101**	-0.161*
3	-0.018	-0.015**	-0.091**	-0.039
4	-0.020*	-0.008**	-0.079**	0.012
5	-0.010	-0.004*	-0.067**	0.038
6	-0.008	-0.002	-0.056**	0.045*
7	-0.005	-0.001	-0.046**	0.043**
8	-0.003	0.000	-0.038**	0.040**
Panel D: Distance to Technical Universities and Working-age Population				
0	-0.114*	-0.023	-0.049*	-0.328
1	-0.011	-0.019**	-0.042*	-0.180
2	-0.024**	-0.013**	-0.038*	-0.083
3	-0.008	-0.008*	-0.036	-0.021
4	-0.009**	-0.004	-0.033	0.003
5	-0.005	-0.002	-0.029	0.015
6	-0.003	-0.001	-0.026	0.022
7	-0.002	-0.001	-0.022	0.020
8	-0.001	0.000	-0.019	0.018

Notes: This table reports the results of statistical tests on the significance of differences between impulse responses with high and low FinTech adoption, constructed using alternative instrumental variables and control variables. We report the differences in the impulse responses of real GDP, consumer prices, bank loans, and housing prices in the cells, up to eight quarters after the initial shock. A cell with * or ** denotes a statistically significant difference at the 68% or 90% confidence level, respectively.

Then we consider various sets of instrumental variables and control variables and repeat the IPVAR estimation. The first stage estimates are reported in Table A8 in the appendix, showing significant associations between these instrumental variables and FinTech adoption: proximity to the FinTech hub city in terms of travel time and proximity to technology-focused universities both positively correlate with FinTech adoption. Additionally, the F-statistics do not indicate weak instrument issues. Table 4 presents the differences in impulse responses between high and low FinTech based on the second stage of these IV-IPVAR estimates. The significant and negative estimates indicate that regions with higher FinTech adoption experience smaller responses in real GDP growth, inflation, bank loan growth, and housing price growth. Moreover, the magnitudes of these differences remain consistent with the baseline results. Thus, our baseline finding of a weaker monetary policy transmission with higher FinTech adoption persists when alternative instrumental variables are employed to measure FinTech adoption.

Second, we adopt the alternative method of local projections (LP) with an instrumental variable (IV-LP) to mitigate concerns about the estimating methodology of IPVAR. As discussed in Jordà (2005), Jordà et al. (2015), and Jordà et al. (2020), the LP framework offers the advantage of being less sensitive to model misspecification. However, the IPVAR approach is more general in that it allows us to specify not only the interaction between FinTech adoption and exogenous monetary policy shock but also the interaction between FinTech adoption and other endogenous variables contemporaneously. Furthermore, extending the general equivalence of impulse response estimated from LP and VAR approaches (Plagborg-Møller and Wolf 2021) to non-linear estimators, such as the specification with interaction terms in this study, is not evident. Therefore, we primarily rely on the IPVAR method for the main analysis, while also reporting the results from LP as robustness checks.

Specifically, we consider the following model specification for different horizons ($h =$

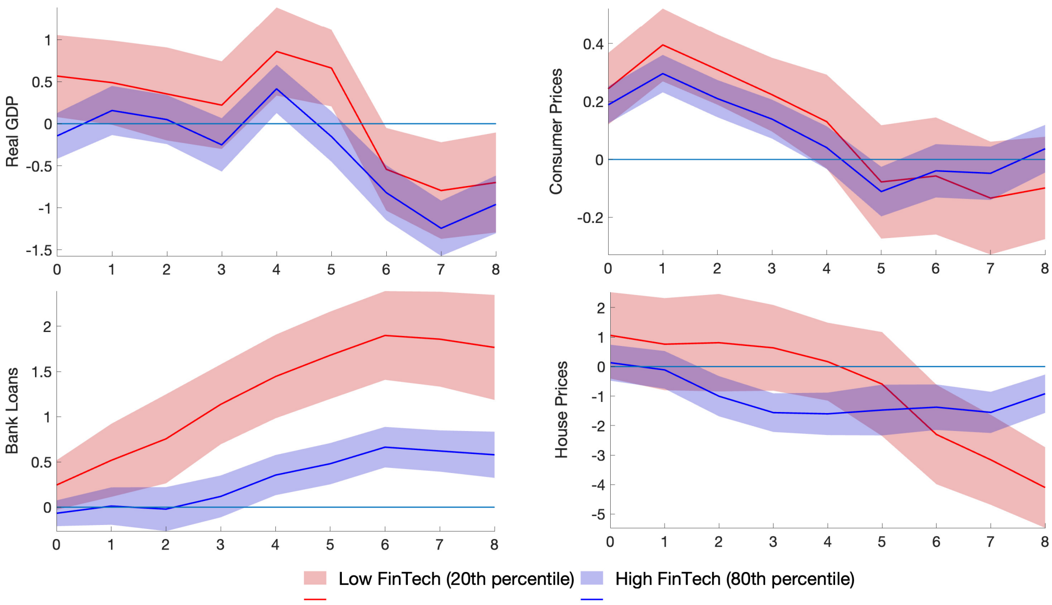
$0, 1, ..., 8)$:

$$\Delta Y_{it,h} = \gamma_{i,h} + \alpha_0(h)mp_t + \alpha_1(h)mp_t * \widehat{fintech}_{it} + \beta_1(h)X_{it} + U_{it,h} \tag{6}$$

where $\Delta Y_{it,h}$ presents the log first difference of economic variables, $Y_{i,t+h} - Y_{i,t+h-1}$, for each horizon h.[17] $\gamma_{i,h}$ denotes province fixed effects, and X_{it} represents a set of control variables including the lagged growths of macro-finance variables and the working-age population ratio, which is the same as in the baseline IPVAR specification. To make it more comparable to our baseline IPVAR, we consider two lags of macro-finance variables in the local projection analysis. $\widehat{fintech}_{it}$ is the fitted values obtained from the first stage regression that does not depend on the horizon h. More specifically, we regress $fintech_{it}$ on the distance to Hangzhou and a set of control variables in X_{it}. From the second stage regression, $\alpha_1(h)$ presents the response of the dependent variable to one unit increase in FinTech adoption given an expansionary monetary policy shock. We quantify the impact of the interaction term by multiplying low (20th percentile) and high (80th percentile) values of FinTech measure by $\alpha_1(h)$. For two-stage least square estimation using instrumental variable(s) in local projection, see Jordà et al. (2020) and Plagborg-Møller and Wolf (2021). Figure 5 plots the linear combination of estimated coefficients on monetary policy shock and its interaction term, $\alpha_0(h) + \kappa * \alpha_1(h)$, where κ denotes levels of low and high Fintech adoption. Additionally, Figure 6 illustrates the difference between impulse responses with high and low FinTech adoption. We observe substantial and statistically significant negative impulse responses of real GDP, inflation, bank loan, and house prices to changes in monetary policy when interacted with FinTech adoption. This finding aligns with our baseline result, indicating a weaker transmission from higher levels of FinTech adoption.

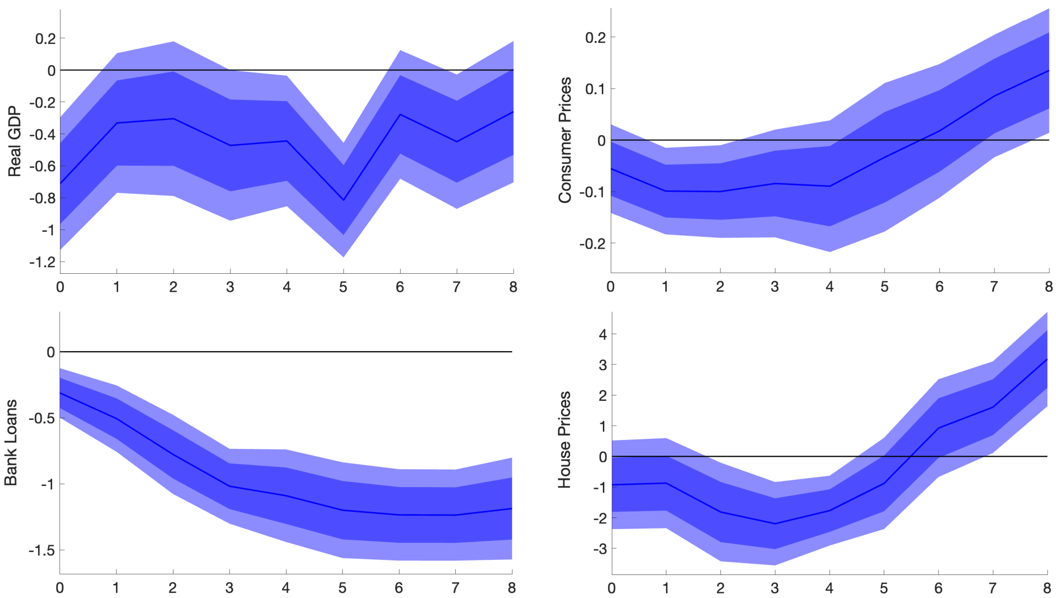
[17] For a clear comparison with impulse responses from IPVAR, we use usual impulse responses here instead of cumulative differences.

Figure 5: Local Projection: Responses with Low and High FinTech Adoption



Notes: The figure plots impulse responses with low and high FinTech adoption expressed as a linear combination of estimated coefficients on monetary policy shock and the interaction term for horizons $h = \{0, 1, 2, ..., 8\}$. The x-axis represents quarters after the shock, and the y-axis represents the impulse responses in percentage points of the year-over-year growth rate. The red (blue) solid lines and shading represent impulse responses and 90% confidence intervals at the 20th (80th) percentile of FinTech adoption, respectively.

Figure 6: Local Projection: Significance of Differences between Responses



Notes: The figure presents differences between impulse responses with high and low FinTech adoption obtained in the local projection framework for horizons $h = \{0, 1, 2, ..., 8\}$. A value below zero indicates that higher FinTech adoption leads to a weakened response. The interior dark blue and exterior light blue areas represent the 68% and 90% confidence bands of the significance of differences. The x-axis represents quarters after the shock, and the y-axis represents the impulse responses in percentage points of the year-over-year growth rate.

Lastly, we conduct a placebo test to address the concern that our results may be influenced by other province-level confounding factors and that FinTech adoption may be merely a function of previous economic conditions. To conduct this test, we retain the FinTech adoption measurements from the period 2011Q1-2018Q4 but utilize economic outcomes and monetary policy shocks from the pre-FinTech era, i.e., 2001Q1-2008Q4. As long as FinTech adoption is not solely derived from past economic conditions, it should not interact with falsified monetary policy shocks and economic outcomes. Table 5 shows the results. We observe no significant differences in the responses of pre-FinTech era outcomes between regions with high and low FinTech adoptions. This placebo test demonstrates that our baseline results are capturing the actual role of FinTech and helps to alleviate concerns about our measurement of regional FinTech adoption being endogenous to economic development.

Table 5: Placebo Test: Using Pre-FinTech Economic Variables

Quarter	Real GDP	Consumer Prices	Bank Loans	House Prices
0	-0.544	0.093	0.078	0.643
1	0.012	0.123	0.119	0.259
2	0.005	0.167*	0.071	0.106
3	0.016	0.134*	0.010	-0.044
4	0.005	0.064	-0.036	-0.192
5	-0.005	0.002	-0.051*	-0.242*
6	-0.015	-0.044	-0.044	-0.219*
7	-0.017*	-0.061*	-0.021	-0.129*
8	-0.013	-0.053*	0.007	-0.031

Notes: The table reports the results of statistical tests on the significance of differences between impulse responses with high and low FinTech adoption for placebo tests using FinTech adoption measures in the 2010s and macro variables and monetary policy shock in the 2000s. We report the differences in the impulse responses of real GDP, consumer prices, bank loans, and housing prices in the cells, up to eight quarters after the initial shock. A cell with * or ** denotes a statistically significant difference at the 68% or 90% confidence level.

5 Mechanisms

Now we examine three possible mechanisms linking FinTech adoption to the weakened monetary policy transmission.[18] First, increased FinTech adoption could relax credit

[18]Note that our focus here is on mechanisms related to FinTech credit. The FinTech adoption index captures not only the usage of credit but also encompasses various other aspects such as payments,

constraints and lead to a higher share of financially unconstrained firms in the economy. This, in turn, would dampen the financial acceleration and mitigate monetary policy transmission. Second, regulatory arbitrage is one of the drivers behind the rise of FinTech, particularly under the "wait-and-see" strategy employed by the Chinese government before recently reining it in. Thus, similar to other shadow banks, FinTech credit could offset the changes in bank credit and weaken transmission efficiency. Third, the competitive relationship between FinTech and existing financial intermediaries may impact the effectiveness of monetary policy transmission. If FinTech products are substitutes that compete for the same market segment, the transmission could be diluted due to reduced concentration and market power.

We label the three channels as the financial constraint, regulatory arbitrage, and competition mechanism. We use a province-level variable to proxy for each mechanism. We then divide the full sample into two subsamples based on the median value of the proxy variable and estimate the IPVAR for each subsample. Importantly, we evaluate the interaction effect in each subsample result using the same values of high and low FinTech adoption as those used in the baseline estimation. This ensures that any different findings in each subsample can be attributed to the mechanism variables rather than variations in FinTech adoption distributions.

5.1 Financial Constraint

Under the assumption that more financially-constrained agents are more responsive to monetary policy (Gertler and Gilchrist 1994, Kiyotaki and Moore 1997) - an assertion

insurance, money market funds, investment, and credit evaluation, as presented in Table A3. Several reasons underpin this specific focus. First, the most pronounced impact of mitigated transmission is observed with respect to bank loans. Second, credit carries the heaviest weight among the six dimensions of FinTech services within the overall adoption index (Guo et al. 2020). Third, other services are highly correlated with lending activities and may either facilitate or contribute to them. For example, the penetration of FinTech payments and credit evaluations plays an important role in risk assessment when issuing FinTech credit.

further supported by evidence from Chinese data in our sample, as presented in Figure A4 in the appendix - we first test the mechanism by which FinTech mitigates monetary policy transmission through alleviating financial constraints. This is achieved through factors such as data abundance, advanced credit assessment techniques, and improved value of firms operating in FinTech-equipped platforms (Berg et al. 2020, Gambacorta et al. 2023, De Fiore et al. 2023).[19] To investigate this mechanism, we construct a variable to measure the degree of financial constraints faced by firms in each province, and then create subsamples of regions with low and high financial constraints based on the median value of this variable. If this mechanism holds, we expect the effect of FinTech in reducing financial constraints to be stronger in the subsample where more firms are constrained. Furthermore, we anticipate that the weakened monetary policy transmission resulting from increased FinTech adoption will be more pronounced in this subsample.

Financial constraints are well-known to be difficult to measure as most financial variables are endogenous.[20] In this study, we follow Cloyne et al. (2023) and primarily rely on firm age and size to identify financial constraints. Specifically, we access the firm registration information of industrial and commercial enterprises from the State Administration of Market Regulation, which provides us with the establishment year of each firm in each province. We define financially constrained firms as those with an age of under five years or those categorized as self-employed enterprises (i.e., small businesses with a single or a

[19]The literature provides evidence emphasizing FinTech's reliance on cash flow-based rather than collateral-based lending (Gambacorta et al. 2023, Su 2021). Moreover, Lian and Ma (2021) demonstrate that with cash flow-based lending, the feedback from asset prices through firms' balance sheets may be dampened. Consequently, the transmission of shocks becomes less pronounced compared to collateral-based lending. Therefore, the reduced reliance on collateral associated with more FinTech adoption suggests a weaker impact of financial acceleration, which is typically tied to the value of physical assets. Such arguments would further support our finding of a mitigated monetary policy transmission. It is important to note, however, that the precise implications hinge on the relative responsiveness of business conditions to monetary policy compared to that of physical collateral, a discussion that lies outside the scope of this paper.

[20]For instance, the expected relationship between leverage and financing constraints is twofold: on the one hand, a highly-leveraged firm might feel unconstrained as it holds a lot of debt on its balance sheet, but on the other hand, this might make it difficult or costly for the firm to find new debt (Durante et al. 2022).

few employees). We then use the number of financially constrained firms per thousand population to measure the level of financial constraint in each province.[21] Alternatively, we also employ the share of short-term loans (with a maturity of less than one year) in total loans in each province as a proxy for the magnitude of financial constraint. The reason is that more constrained borrowers are more likely to obtain short-term loans rather than long-term loans. Finally, to create subsamples with low and high levels of financial constraint, we divide the full sample based on the median value of these variables.

Table 6 shows the results. We observe that the transmission-dampening effects of FinTech are more pronounced in subsamples with higher levels of financial constraints, as indicated by all three proxies. Specifically, with the exception of housing prices, there are significant negative differences in the impulse responses of real GDP growth, inflation, and bank loan growth to monetary policy shocks between the high and low FinTech groups on the right side across all panels. These results demonstrate the significant role of FinTech in regions facing greater financial constraints, suggesting that FinTech mitigates the transmission of monetary policy by alleviating financial constraints.

5.2 Regulatory Arbitrage

To discuss the regulatory arbitrage channel, it is necessary to elaborate on the regulatory regime applied to FinTech companies in China, such as Ant Financial. This issue is notably complicated due to the absence of unified regulations for different FinTech companies and the case-by-case and wait-and-see approach of regulatory policies. In our study, the FinTech credit we address is typically issued by a microcredit company founded by Ant Financial or nonbank financial institutions, such as trust companies, in collaboration with Ant Financial. In these cases, FinTech credit is not subject to the same regulations as traditional bank credit and is theoretically classified within the shadow

[21] Results are similar when we use alternative criteria, such as firms with an age of under ten or fifteen years, to define young firms.

Table 6: Significance of Difference of Impulse Responses: Financial Constraint Mechanism

Quarter	Real GDP	Inflation	Bank Loans	House Prices	Real GDP	Inflation	Bank Loans	House Prices
Panel A:	Low Density of Young Firms				High Density of Young Firms			
0	-0.061	-0.038	-0.034	-0.214	-0.696**	-0.053*	-0.128**	-0.192
1	-0.007	-0.025*	-0.020	-0.115	0.056	-0.024*	-0.130**	-0.033
2	-0.020	-0.013*	-0.026	-0.040	-0.109**	-0.021**	-0.123**	0.006
3	-0.013	-0.006	-0.028	0.007	-0.023*	-0.008	-0.100**	0.066
4	-0.009	-0.003	-0.027	0.022	-0.042**	-0.004	-0.081**	0.078*
5	-0.004	-0.001	-0.024	0.027	-0.022**	-0.002	-0.065**	0.083*
6	-0.003	-0.001	-0.020	0.027	-0.022**	-0.001	-0.050**	0.073**
7	-0.001	0.000	-0.017	0.022	-0.015**	0.000	-0.040**	0.061**
8	-0.001	0.000	-0.014	0.018	-0.013**	0.000	-0.032**	0.050**
Panel B:	Low Density of Self-Employed				High Density of Self-Employed			
0	0.049	-0.042	-0.058	-0.518*	-0.607**	-0.041	-0.197**	-0.370
1	-0.036	-0.032*	-0.033	-0.296**	-0.016	-0.030*	-0.205**	-0.144
2	-0.009	-0.016*	-0.033	-0.121*	-0.086*	-0.027**	-0.180**	-0.071
3	-0.017	-0.008*	-0.038	-0.037	-0.025	-0.018*	-0.149**	0.025
4	-0.006	-0.004	-0.035	0.003	-0.032*	-0.011*	-0.120**	0.062*
5	-0.004	-0.002	-0.031	0.021	-0.020	-0.006	-0.095**	0.076*
6	0.000	-0.001	-0.027	0.026	-0.017*	-0.004	-0.075**	0.070**
7	0.000	0.000	-0.024	0.025	-0.012	-0.002	-0.059**	0.065**
8	0.001	0.000	-0.020	0.022	-0.009	-0.001	-0.045**	0.052**
Panel C:	Low Share of Short-term Loan				High Share of Short-term Loan			
0	-0.300*	-0.036	-0.088	-0.609*	-0.403**	-0.064**	-0.130**	-0.423**
1	-0.019	-0.029*	-0.084	-0.251*	-0.020	-0.040**	-0.123**	-0.246**
2	-0.069*	-0.027**	-0.076	-0.144	-0.064*	-0.022**	-0.124**	-0.151**
3	-0.022	-0.017**	-0.062	-0.020	-0.014	-0.011**	-0.117**	-0.072*
4	-0.030*	-0.011*	-0.055	0.031	-0.009	-0.006*	-0.105**	-0.039*
5	-0.016*	-0.005	-0.047	0.062	0.002	-0.004*	-0.089**	-0.023
6	-0.014*	-0.003	-0.039	0.066	0.004	-0.003	-0.074**	-0.016
7	-0.008	-0.001	-0.033	0.061	0.005	-0.002	-0.062**	-0.013
8	-0.006	0.000	-0.027	0.057	0.005	-0.001	-0.051**	-0.011

Notes: The left and right panels present statistical tests for the differences in impulse responses between high and low FinTech adoption when the financial constraint is low and high, respectively. In panels A, B, and C, we define subsamples of low and high financial constraints using the median value of the number of firms under the age of five per thousand population, the number of self-employed firms per thousand population, and the share of short-term loans in total loans, respectively. We report the differences in the impulse responses of real GDP, consumer prices, bank loans, and housing prices in the cells for up to eight quarters after the initial shock. A cell with * or ** denotes a statistically significant difference at the 68% or 90% confidence level, respectively.

banking sector.[22] However, in recent years, Ant Financial has started to collaborate with city commercial banks and jointly issue credit with them, thus, it can be partially classified as bank loans, and the extent of regulatory arbitrage may have been reduced. We maintain the view that the FinTech credit in our sample period still reflects the context

[22] The shadow banking sector in China encompasses various components, including (i) non-loan assets in banks, such as entrusted loans, trusted loans, and bank acceptance, (ii) credits in nonbank financial institutions that are not regulated by loan-to-deposit ratios and safe-loan requirements, and (iii) local government debts channeled through wealth management products issued by banks.

of the early period and is subject to clear regulatory arbitrage.[23]

Regulatory arbitrage can be an important factor influencing monetary policy transmission. Evidence from the U.S. mortgage lending market, as highlighted by Buchak et al. (2018), suggests that regulation is a major driver of FinTech shadow banking growth. In the specific contexts of China and the U.S., respectively, Chen et al. (2018) and Elliott et al. (2020) find that the expansion of assets in the shadow banking system offsets the decline in bank loans, thereby mitigating the effectiveness of monetary policy tightening. Hachem and Song (2021) and Allen et al. (2019) demonstrate that regulatory tightening can lead to credit expansion through the growth of the shadow banking sector. Xiao (2020) focuses on the deposit side and finds that shadow banks are more likely to pass on rate hikes to depositors and attract more deposits during monetary policy tightening cycles, which dampens the impact of monetary policy. Hence, if the increased adoption of FinTech is primarily driven by the desire to avoid regulation, the regulatory arbitrage channel would predict a less effective transmission of monetary policy, particularly to bank loans.

To capture the presence of regulatory arbitrage, we employ three proxy measurements. First, we use the size of the shadow banking sector in each province. Specifically, we define shadow banking loans as the sum of entrusted loans, trusted loans, and bank acceptances, and we calculate the share of shadow banking loans in the total of traditional bank loans and shadow banking loans in each province.[24] We interpret a higher share of shadow banking loans as an indication of more stringent banking regulations and a greater presence of regulatory arbitrage in the province, and vice versa. Second, we use

[23]Table A9 in the appendix shows the results testing the significance of differences in impulse responses with high and low FinTech adoption using the sample up to 2016Q4, that is, earlier periods when the regulation for FinTech was clearly more relaxed than that for banks. The baseline findings that FinTech is associated with more muted responses continue to hold, if not more pronounced than the main results shown in Table 3.

[24]The data on entrusted loans, trusted loans, and bank acceptances are sourced from the total social financing statistics released by the PBC.

two indicators that serve as regulatory targets for banks in China: the loan-to-deposit ratio and the non-performing loan (NPL) ratio. As summarized in Chen et al. (2018), China's banking system is subject to two major regulations. The first is the loan-to-deposit ratio, with a regulatory ceiling of 75% imposed by the regulatory agency to manage the quantity of bank loans. The second is the safe-loan regulation, wherein the regulatory agency employs measures such as administrative notices or inspections to control the quality of bank lending. While there is no official indicator specifically monitoring the safe-loan regulation, we utilize the NPL ratio as a plausible proxy for bank loan quality. The loan-to-deposit ratio and NPL ratio are calculated based on aggregate loans, deposits, non-performing loans, and assets of the banking system within each province. Higher values of these indicators suggest greater pressure to meet regulatory ceilings and consequently, more regulatory arbitrage opportunities for FinTech lenders that are not subject to these regulations. We then use the median values of the three indicators to create subsamples representing high and low regulatory arbitrage. If the regulatory arbitrage channel holds true, we expect to observe a more prominent role of FinTech in mitigating monetary policy transmission in the high regulatory arbitrage subsample.

Table 7 presents the results. In the subsamples with low regulatory arbitrage, the gaps in impulse responses to real GDP growth, inflation, bank loan growth, and housing price growth between high and low FinTech adoption are similar or exhibit mixed signs. However, in the subsample with high regulatory arbitrage, the role of FinTech adoption in dampening the responses of bank loan growth is particularly pronounced across all three panels. Notably, the magnitude of the response gaps for bank loan growth is greater than the baseline estimates, indicating a stronger transmission-dampening effect of FinTech adoption when the regulatory arbitrage is high. As a robustness check, we also use the number of small credit institutions per million population to differentiate between low and high shadow banking subsamples, as we interpret provinces with a higher density of small credit institutions as having a larger shadow banking sector. The results, shown in Table A10 in the appendix, are consistent with the findings here, providing additional support for the hypothesis that regulatory arbitrage is a plausible mechanism through which FinTech adoption mitigates monetary policy transmission.

Table 7: Significance of Difference of Impulse Responses: Regulatory Arbitrage Mechanism

Quarter	Real GDP	Inflation	Bank Loans	House Prices	Real GDP	Inflation	Bank Loans	House Prices
Panel A:	Low Shadow Banking				High Shadow Banking			
0	-0.602*	-0.034	-0.115*	-0.455*	-0.246*	-0.040	-0.143*	-0.432*
1	-0.007	-0.021	-0.105*	-0.435*	-0.023	-0.029*	-0.126**	-0.168
2	-0.027	-0.019*	-0.086*	-0.334*	-0.062	-0.025**	-0.123**	-0.041
3	0.014	-0.012*	-0.069	-0.208*	-0.029*	-0.013*	-0.103**	0.041
4	0.007	-0.008*	-0.055	-0.126*	-0.033*	-0.006	-0.085**	0.074
5	0.009	-0.005	-0.047	-0.072	-0.021*	-0.002	-0.068**	0.074*
6	0.006	-0.003	-0.040	-0.043	-0.017**	-0.001	-0.053**	0.067*
7	0.007	-0.002	-0.034	-0.029	-0.012*	0.000	-0.042**	0.054*
8	0.006	-0.002	-0.028	-0.018	-0.009*	0.000	-0.032**	0.043*
Panel B:	Low Loan-to-Deposit Ratio				High Loan-to-Deposit Ratio			
0	-0.251*	-0.043*	-0.003	-0.024	-0.540**	-0.059*	-0.150*	-0.699*
1	-0.033	-0.014	0.008	-0.008	0.056	-0.055**	-0.151**	-0.395*
2	-0.052*	-0.012*	-0.001	0.008	-0.056	-0.035**	-0.144**	-0.257*
3	-0.012	-0.005	-0.002	0.016	0.021	-0.023**	-0.127**	-0.101
4	-0.011	-0.002	-0.002	0.014	-0.004	-0.014*	-0.109**	-0.022
5	-0.003	-0.001	-0.002	0.011	0.005	-0.009*	-0.092**	0.019
6	-0.002	0.000	-0.002	0.009	-0.002	-0.005*	-0.076**	0.037
7	-0.001	0.000	-0.002	0.007	0.000	-0.003	-0.062**	0.042
8	0.000	0.000	-0.001	0.005	-0.002	-0.002	-0.050**	0.042*
Panel C:	Low NPL Ratio				High NPL Ratio			
0	-0.598**	-0.043	-0.039	-0.657*	-0.543**	-0.048	-0.147*	-0.196
1	0.061	-0.034*	-0.027	-0.301*	-0.001	-0.027*	-0.148**	-0.114
2	-0.094*	-0.033**	-0.043	-0.212*	-0.078*	-0.023*	-0.137**	-0.022
3	-0.019	-0.015*	-0.030	-0.088	0.002	-0.017*	-0.116**	0.061
4	-0.035*	-0.008*	-0.030	-0.028	-0.010	-0.010*	-0.091**	0.088*
5	-0.010	-0.003	-0.026	0.001	-0.003	-0.005	-0.071**	0.096*
6	-0.009	-0.002	-0.022	0.011	-0.005	-0.002	-0.053**	0.084**
7	-0.003	-0.001	-0.018	0.013	-0.004	0.000	-0.040**	0.067**
8	-0.003	0.000	-0.015	0.013	-0.004	0.000	-0.030**	0.052**

Notes: The left and right panels present statistical tests for the differences in impulse responses between high and low FinTech adoption when regulatory arbitrage is low and high, respectively. In panels A, B, and C, we define subsamples of low and high regulatory arbitrage based on the size of the shadow banking sector, the loan-to-deposit ratio, and the NPL ratio, respectively. We report the differences in the impulse responses of real GDP, consumer prices, bank loans, and housing prices in the cells for up to eight quarters after the initial shock. A cell with * or ** denotes a statistically significant difference at the 68% or 90% confidence level, respectively.

The potential asymmetric effects between expansionary and contractionary monetary policy shocks merit a discussion as the literature suggests that the role of shadow banking is more pronounced when monetary policy tightens than when it eases (Chen et al. 2018, Xiao 2020). To save space, please see Section B in the appendix for more details.

5.3 Competition

The competitive relationship between FinTech and banks has gained increasing attention in recent literature and policy discussions, yet the findings are inconclusive. On one hand, Tang (2019) finds that peer-to-peer lending is more likely to substitute for bank lending, Fuster et al. (2019) document that FinTech lenders process mortgage applications faster and adjust supply more elastically than non-FinTech lenders, Bartlett et al. (2022) and Boot et al. (2021) show that FinTech would enhance competition in loan markets, and Buchak et al. (2022) suggest that FinTech lenders may replace banks in loans that are easily sold. On the other hand, Erel and Liebersohn (2022) and Cole et al. (2019) provide arguments for complementarity between FinTech and banks, based on evidence from the paycheck protection program and crowdfunding platform, respectively.

For our research question, the impact of FinTech on intensifying competition in the banking sector is crucial because market power plays a significant role in monetary policy transmission. Stronger market power implies a more pronounced response to monetary policy, and when FinTech increases competition, aggregate transmission could be weakened. This effect is demonstrated by Drechsler and Savov (2017) concerning the deposit channel of monetary policy: banks widen deposit spreads and experience deposit outflows when monetary policy tightens. In more concentrated markets, deposit spreads increase more, and more significant deposit outflows occur, affecting the overall transmission to the economy. Before examining the competition mechanism, we modify the conventional panel VAR setting by replacing loan growth with deposit growth and show the results in Figure A5 in the appendix, which demonstrates that the deposit channel also works in China. Furthermore, Figure A6 shows that the deposit channel is stronger in less competitive regions before accounting for FinTech adoption.

To capture the substitute-complement relationship, we employ two proxy variables. First, we use the bank branch density, measured as the number of bank branches per thousand population. The underlying assumption is that a higher density of bank branches indicates a deeper penetration of bank services, making FinTech more likely to be a competitor in these regions. Second, we utilize the share of deposits in non-state-owned banks in each province.[25] The rationale is that a larger market share held by non-state-owned banks suggests a more market-driven allocation of deposits in that region (La Porta et al. 2002, Ariff and Luc 2008, Carvalho 2014), and the unique political role of state-owned banks in China implies that they are less likely to face competition from FinTech. Consequently, in regions where non-state-owned banks hold a larger share of deposits, FinTech is more likely to intensify competition by offering money market fund products that feature security and liquidity, resembling bank deposits. Following the same approach as before, we divide the observations into two subsamples based on the median values of these proxy variables and perform the IPVAR analysis for each subsample.

Table 8 shows the results. We observe different patterns of impulse responses of real economic growth, bank loan growth, and housing price growth between the subsamples of low and high competition, as captured by both bank branch density and the share

[25]Note that data on bank deposits of state-owned banks in each province are very patchy. The state-owned banks, commonly referred to as the Big6, include the Bank of China, the Agricultural Bank of China, the Industrial and Commercial Bank of China, the China Construction Bank, the Bank of Communications, and the Postal Savings Bank of China. We obtain the total deposits in each province from the PBC and calculate the share of deposits in non-state-owned banks by subtracting the share of deposits in the Big6. The regional allocation of deposits for each of the Big6 is obtained from PBC and the annual reports of these banks. Data availability varies across years, however, necessitating the use of a patching method to impute missing data. Specifically, for each province, we use the data of the Postal Savings Bank of China as the base for the years 1990-2014 and the data of the Agricultural Bank of China as the base for the years 2015-2017. If data for another bank are missing, we use the average ratio of deposits in that bank to the deposits in the base bank to impute the missing values. Additionally, for the year 2018, we impute the data using the average growth rate observed from 2011 to 2017.

of non-state-owned banks. In the high competition subsamples on the right, there is a clear negative gap between high and low FinTech adoption in the response of bank loans after the shock, and this effect persists throughout the horizon. Moreover, the short-term responses in real GDP growth, inflation, and housing price growth are also significantly weaker with greater FinTech adoption. In contrast, these gaps in impulse responses are insignificant in the low competition subsamples on the left. To mitigate the concern that traditional banks may open or close branches in reaction to FinTech adoption, we use the bank branch density in the first quarter of the sample period, i.e., 2011Q1, to classify regions with low and high competition, and we report the results in Table A11 in the appendix. The findings are similar. These results support the notion that enhanced competition through FinTech adoption is a plausible mechanism to explain the muted transmission to the economy.

Table 8: Significance of Difference of Impulse Responses: Competitive Relationship with Banks

Quarter	Real GDP	Inflation	Bank Loans	House Prices	Real GDP	Inflation	Bank Loans	House Prices
Panel A:	Low Bank Branch Density				High Bank Branch Density			
0	-0.222	-0.035	0.060	-0.117	-0.682**	-0.035	-0.373**	-0.841**
1	0.000	-0.015	0.020	-0.150	0.087	-0.039*	-0.369**	-0.346*
2	-0.047	-0.013*	-0.005	-0.088	-0.071	-0.034**	-0.319**	-0.114
3	-0.004	-0.008	-0.012	-0.038	-0.003	-0.019**	-0.255**	0.080
4	-0.011	-0.006*	-0.015	-0.019	-0.041	-0.009	-0.206**	0.145*
5	-0.003	-0.003	-0.013	-0.003	-0.023	-0.003	-0.161**	0.163**
6	-0.003	-0.002	-0.010	0.003	-0.026	0.000	-0.124**	0.145**
7	-0.001	-0.001	-0.007	0.006	-0.018	0.001	-0.097**	0.121**
8	-0.001	0.000	-0.005	0.005	-0.015	0.001	-0.075**	0.095**
Panel B:	Low Share of Non-state-owned Banks				High Share of Non-state-owned Banks			
0	-0.354*	-0.009	-0.058	-0.308	-0.777**	-0.104**	-0.190**	-0.368*
1	-0.051	-0.017	-0.067	-0.199	0.078*	-0.021*	-0.145**	-0.205
2	-0.049	-0.017*	-0.069	-0.142	-0.172**	-0.029**	-0.156**	0.036
3	-0.020	-0.013*	-0.061	-0.056	-0.009	-0.005	-0.129**	0.126
4	-0.013	-0.008	-0.052	-0.011	-0.075**	-0.003	-0.113**	0.181**
5	-0.008	-0.004	-0.043	0.012	-0.031**	0.003	-0.092**	0.178**
6	-0.003	-0.002	-0.036	0.020	-0.043**	0.003	-0.078**	0.164**
7	-0.001	-0.001	-0.029	0.023	-0.028**	0.004*	-0.063**	0.141**
8	0.000	-0.001	-0.022	0.020	-0.026**	0.003*	-0.052**	0.121**

Notes: The left and right panels present statistical tests for the differences in impulse responses between high and low FinTech adoption when competition between FinTech and traditional banks is low and high, respectively. We report the differences in the impulse responses of real GDP, consumer prices, bank loans, and housing prices in the cells, up to eight quarters after the initial shock. A cell with * or ** denotes a statistically significant difference at the 68% or 90% confidence level, respectively.

6 Conclusion

This study employs an interacted panel VAR model to examine the effects of monetary policy transmission with different levels of FinTech adoption. By leveraging the heterogeneity in FinTech adoption across Chinese provinces and utilizing the geographic distance to the FinTech hub city as an instrumental variable, we estimate the impulse responses when FinTech adoption interacts with monetary policy shocks.

The main findings are twofold. First, FinTech adoption generally weakens monetary policy transmission. The impulse responses of real output, price level, bank loan, and house price are all muted with higher levels of FinTech adoption. This finding holds across various robustness checks, including different variable measurements, model specifications, and econometric methodologies. Second, we investigate potential mechanisms and find qualitative evidence supporting the financial constraint channel, regulatory arbitrage channel, and competition channel as explanations for the dampened monetary policy transmission due to FinTech adoption.

The findings presented in this study provide some of the first evidence regarding FinTech's role in monetary policy transmission and have significant implications for both monetary policy and financial regulation. Policymakers need to account for the rapid development of FinTech adoption when evaluating the impact of monetary policy. Moreover, the similarities and competition between FinTech and traditional bank services suggest that regulators should further expand their focus from financial entities to financial activities. Our study indicates that FinTech is likely to pose significant challenges to both monetary and regulatory policies, underscoring the need for further research in this area.

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