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# The impact of bank FinTech on liquidity creation: Evidence from China

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ABSTRACT

This paper examines whether and how bank FinTech affects liquidity creation. Using panel data from Chinese commercial banks over the period 2008–2019 and bank-level FinTech indices constructed by a textual analysis method, we find robust evidence that banks with greater FinTech development create more liquidity for the public. This effect operates through deposit inflow, risk management, and cost efficiency channels. Furthermore, we find that the positive effect of bank FinTech on liquidity creation is more pronounced for banks with non-state ownership, unlisted status, and less liquidity creation.

## 1. Introduction

In this paper, we examine the relationship between bank FinTech and liquidity creation in the Chinese banking industry. In contrast to the existing literature (Arner et al., 2015; Buchak et al., 2018; Fuster et al., 2019; Goldstein et al., 2019; Phan et al., 2020; Berg et al., 2020; Lee et al., 2021), we focus on the influence of bank FinTech rather than non-bank FinTech on commercial banks.[1]

With the advancement of digital technologies such as artificial intelligence, blockchain, cloud computing, and big data, FinTech has become a prominent trend in global financial markets. The early FinTech was accompanied by exploitation of the information technology. It was not until after the 2007–2009 global financial crisis that the FinTech innovations broke out to meet market demand as in mortgage lending, leading to the boom of P2P lending markets. Since then, FinTech start-ups have flooded into financial markets. These new entrants have the potential to erode incumbent banks' customers, businesses, and profits (Buchak et al., 2018; Thakor, 2020), driving banks to adopt new technologies to reshape their business models, service methods, and organizational forms (Goldstein et al., 2019; Hornuf et al., 2021). Currently, more and more traditional banks are actively involved in the FinTech development wave and the COVID-19 pandemic further accelerates this trend (Berger and Demirgüç-Kunt, 2021; Dadoukis et al., 2021).

This rise of the FinTech phenomenon has attracted considerable academic and public attention. Fast-growing financial literature

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[1] According to the definition of the Financial Stability Board (FSB), FinTech denotes technology-enabled financial innovations which can generate new business models, applications, and products, and further exert notable effects on financial markets, institutions, and services (FSB, 2016). The development of FinTech is not only manifested by the rapid growth of FinTech companies but also by the tremendous acceleration of FinTech adoptions in banking sectors (International Monetary Fund, 2017; Huang and Huang, 2018; Ji et al., 2022). Thus, following Cheng and Qu (2020) and Murinde et al. (2022), we classify FinTech innovations in non-banking industries such as FinTech and Internet companies as "non-bank FinTech," while denoting FinTech innovations and applications in traditional banking sectors as "bank FinTech."

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documents that FinTech exerts significant effects on bank business performance, market share, risk taking, and operational efficiency (Hou et al., 2016; Buchak et al., 2018; Berg et al., 2020; Boot et al., 2021; Dadoukis et al., 2021; Lee et al., 2021; Wang et al., 2021). In addition, several papers also highlight the role of FinTech in micro enterprises and the real economy (Grossman and Tarazi, 2014; Kapoor, 2014; Cheng and Zhang, 2021; Ji et al., 2022; Lv and Xiong, 2022). However, almost all of these studies focus on the economic consequences of non-bank FinTech; to the best of our knowledge, research considering the implications of bank FinTech is scarce.

We aim to fill this academic gap by examining the impact of bank FinTech on liquidity creation. Liquidity creation is a major function performed by banks (Berger and Bouwman, 2009, 2017). The existing research investigates the determinants of bank liquidity creation from the perspective of bank characteristics, market competition, and the macro environment (Horváth et al., 2014; Berger et al., 2016; Díaz and Huang, 2017; Jiang et al., 2019; Duan et al., 2021; Berger et al., 2022a; Boubakri et al., 2023). Nonetheless, due to the limitations of bank FinTech data, few studies explore the link between bank FinTech and liquidity creation. This leaves considerable room for our work, in which we seek to address the following questions. First, is there evidence that banks with greater FinTech development create more liquidity for the public? Second, what are the mechanisms underlying this impact? Third, does this effect vary with bank heterogeneity?

The Chinese banking industry provides an appropriate and interesting setting for us to examine the relation between bank FinTech and liquidity creation. Although bank FinTech in China emerged later compared to developed countries, it has evolved dramatically over time (Guo et al., 2020; Wang et al., 2021). According to data of the China Banking and Insurance Regulatory Commission, the transaction volume of online banking in China increased from US $ 48.66 trillion in 2009 to US $ 253.01 trillion in 2017; the transaction proportion over bank counters dropped from 36.77% in 2013 to 9.12% in 2020; and the investment scale of bank FinTech rose from US $ 16.99 billion in 2018 to US $32.98 billion in 2020. Apart from the fast growth of FinTech-related applications and investments in commercial banks, the user penetration rate of bank FinTech also increased significantly. The “2021 China Electronic Banking Survey Report” shows that the proportion of mobile banking APP users grew from 42% in 2016 to 71% in 2020, with an annual growth rate of 13%.

The boom of the Chinese bank Fintech can be attributed to three key factors that are closely linked to China’s unique institutional background, infrastructure environment, and government policies. The first contributing factor is the financial repression in China’s banking system. Although China’s banking reform has made remarkable progress, it has been at a slower pace than other transition economies (Hou et al., 2018). The repressed financial system leads to a supply shortage in bank-based financial markets; thus, non-bank FinTech companies began to thrive to fill this gap. Competition from such FinTech start-ups pushed banks to redefine business models and develop FinTech solutions (Bellardini et al., 2022).

The second contributing factor is the flourishing development of digital infrastructure in China. The Chinese government has made considerable investment in the fields of digital infrastructure, including 5 G networks, the industrial internet, Internet of Things, computing centers, and data centers. These digital infrastructures enable businesses and individuals to connect to digital platforms (Hua and Huang, 2021), thus improving the FinTech adoption rate in China. In fact, China displayed the highest FinTech adoption rate in the world at 87% in 2019, well above the world average of 64% (Ernst and Young, 2019). The high FinTech adoption rate creates a crucial customer base for the rapid growth of bank FinTech.

The last contributing factor is the pro-FinTech policies implemented by the Chinese government. For example, in 2015, the People’s Bank of China (PBC) put forward a series of policies to support the development of Internet finance in the “Guidelines on Promoting the Healthy Development of Internet Finance.” In 2019, the PBC further emphasized the urgency of reshaping the financial infrastructure system and the significance of facilitating FinTech development in the “FinTech Development Plan (2019–2021).” These policies provide a relatively accommodative regulatory environment for bank FinTech, promoting FinTech innovations and applications in the banking sector (Zhao et al., 2022).

The described context shows that compared to developed countries, China provides an intriguing setting for our subject. Therefore, we use panel data from 97 Chinese commercial banks over the period 2008–2019 and bank-level FinTech indices constructed by a textual analysis approach to investigate the relation between bank FinTech and liquidity creation. We find the following results. First, bank FinTech significantly promotes liquidity creation, i.e., banks with greater FinTech development create more liquidity for the public. Second, bank FinTech enhances liquidity creation through deposit inflow, risk management, and cost efficiency channels. Third, the positive effect of bank FinTech on liquidity creation is more pronounced for banks with non-state ownership, unlisted status, and less liquidity creation. Our results hold after a series of endogeneity checks and robustness tests.

We contribute to the literature in several ways. First, we complement the literature on the economic consequences of FinTech on the banking sector. While there is fast-developing literature on the influences of non-bank FinTech (Hou et al., 2016; Buchak et al., 2018; Fuster et al., 2019; Berg et al., 2020; Lee et al., 2021; Wang et al., 2021), empirical evidence on the implications of bank FinTech is scarce. This is despite the significant growth of FinTech investments and adoptions in banking sectors. Therefore, as far as we know, this paper is among the first to shed light on the impact of bank FinTech on liquidity creation.

Second, our paper enriches the work on the determinants of bank liquidity creation. A growing body of empirical research explores how liquidity creation is affected by bank attributes, market competition, regulatory interventions, and the macro environment (Berger and Bouwman, 2009; Horváth et al., 2014; Berger et al., 2016, 2020; Díaz and Huang, 2017; Jiang et al., 2019; Duan et al., 2021). Our study differs remarkably in terms of the factors examined. We not only identify the positive effect of bank FinTech on liquidity creation, but we also reveal the underlying economic channels from deposit inflow, risk management, and operational efficiency perspectives.

Third, we provide extension studies for this issue. Specifically, we analyze whether the impact of bank FinTech changes with bank ownership structure and listed status. Moreover, we employ a panel quantile regression to investigate the nonlinear effect of FinTech on banks with different liquidity creation levels. While bank liquidity creation is a necessity for the smooth functioning of financial markets, excessive liquidity creation is likely to reduce the liquidity of banks and increase the fragility of banking sectors (Berger and Bouwman, 2017; Davydov et al., 2021). Thus, it is of certain research significance to check the possible nonlinear relation between bank FinTech and liquidity creation. Collectively, we find that banks with non-state ownership, unlisted status, and less liquidity creation benefit more from FinTech than banks that are state-owned, listed, and have greater liquidity creation.

Finally, we construct bank-level FinTech indices to reflect the development of bank FinTech in China. Although previous literature offers some methods to measure FinTech development (Guo and Shen, 2016; Xie et al., 2018; Phan et al., 2020; Lee et al., 2021; Zhao et al., 2022), it only depicts the picture from the macro-level or the non-bank aspects. Perhaps surprisingly, the measurement of bank FinTech receives little attention in the existing studies. In the case of China, banks seldom disclose FinTech expenses in financial statements, but many of them issue FinTech-related text information in their annual reports. Therefore, to capture the development of bank FinTech, this paper builds bank-level FinTech indices by conducting a textual analysis of banks' annual reports.

The remainder of this paper proceeds as follows. Section 2 offers the related literature and hypotheses development. Section 3 presents our sample, variables, and model. Section 4 discusses the empirical results. Section 5 concludes the paper.

## 2. Literature review and hypotheses development

### 2.1. Literature review

Our findings relate to two sets of literature, namely, FinTech development and bank liquidity creation. For the former, scholars prefer to explore the impacts of FinTech; for the latter, they pay more attention to the determinants of bank liquidity creation.

#### 2.1.1. The effects of FinTech development

Fast-growing financial literature explores the potential impacts of FinTech. One stream of this research analyzes the influences of FinTech on the financial industry. Most previous papers view FinTech as a positive development, positing that FinTech has substantively transformed the traditional financial sector by introducing new technologies and methods into the processes of providing services, assessing risks, and gathering information (Fuster et al., 2019; Goldstein et al., 2019; Berg et al., 2020). Paying close attention to the relationship between FinTech and commercial banks, Hou et al. (2016), Cheng and Qu (2020), Lee et al. (2021), and Wang et al. (2021b) document that FinTech benefits banks in strengthening deposit discipline, optimizing risk control, and enhancing cost efficiency. Nonetheless, Buchak et al. (2018) and Thakor (2020) maintain that the advent of FinTech can also intensify market competition and destabilize commercial banks. Guo and Shen (2016), Wang et al. (2021), and Zhao et al. (2022) further provide supportive evidence on the asset quality deterioration effect brought about by the development of FinTech.

Another vein of research investigates the impact of FinTech on the real economy and micro enterprises. The benefits of FinTech for the real economy are demonstrated by, for example, Grossman and Tarazi (2014), Kapoor (2014), Aisaiti et al. (2019), and Couture et al. (2021), who argue that FinTech development creates business opportunities, lessens income disparity, smooths household consumption, and promotes economic growth. The role of FinTech in micro enterprises is also highlighted by Xie et al. (2018), Hua and Huang (2021), Ji et al. (2022), and Lv and Xiong (2022), who find that FinTech boosts entrepreneurship, reduces corporate bankruptcy risk, and improves corporate investment efficiency.

A few papers, closely related to our topic, aim to figure out the strategies and impacts of banks' FinTech development. Cheng and Qu (2020) and Guo et al. (2022) examine whether the growing adoption of FinTech in the Chinese banking sector can help reduce banks' risk. Hornuf et al. (2021) and Bellardini et al. (2022) explore how banks in advanced economies react to and interact with FinTech startups by analyzing banks' FinTech-related investments and strategies. While our major concern is different, the conclusions from these studies strongly support the development of our hypotheses and empirical models.

#### 2.1.2. The determinants of bank liquidity creation

The process of liquidity creation by transforming liquid deposits into illiquid assets is a major function performed by banks (Berger and Bouwman, 2009, 2017). However, liquidity creation appeared mainly in the theoretical research until Berger and Bouwman (2009) proposed a comprehensive measure of bank liquidity creation. Following this invention, a growing body of empirical literature examines the determinants of bank liquidity creation.

Most related studies focus on the effects of bank-specific attributes on liquidity creation. The relationship between capital structure and bank liquidity creation is a key debate in this literature. Lei and Song (2013), Horváth et al. (2014), and Berger et al. (2020) find that banks with a fragile capital structure are more likely to expand loans and create liquidity, consistent with the "financial fragility-crowding out" hypothesis. On the contrary, Niu (2021) shows that the capital ratio is positively correlated with bank liquidity creation growth, supporting the "risk absorption" view. The influences of asset size, cost efficiency, income structure, and governance mechanism on bank liquidity creation are also evaluated. Díaz and Huang (2017) and Duan et al. (2021) claim that better governed and cost-efficient banks create more liquidity, while Hou et al. (2018) and Toh (2019) document that liquidity creation decreases as the amount of bank assets and non-traditional income increases.

Beside bank characteristics, several papers also examine the role of the macroeconomic environment. Horváth et al. (2016) and Jiang et al. (2019) observe a negative link between market competition and bank liquidity creation. Berger et al., (2016, 2020) find that regulatory interventions and government guarantees reduce bank liquidity creation. Davydov et al. (2018) and Niu (2021b) verify the procyclicality of liquidity creation by analyzing the nexus between business cycle fluctuations and bank liquidity creation.

Though significant research investigates the effects of FinTech and the determinants of bank liquidity creation, the association between bank FinTech and liquidity creation is not highly visible in prior literature. Therefore, we aim to complement and strengthen this body of research.

### 2.2. Hypotheses development

In this subsection, we develop three testable hypotheses by exploring the link between bank FinTech and liquidity creation. We first focus on whether and how bank FinTech affects liquidity creation. Then, we investigate the moderating role of bank attributes in the relation of bank FinTech-liquidity creation.

#### 2.2.1. The impact of bank FinTech on liquidity creation

Liquidity creation is a key function performed by banks (Bhattacharya and Thakor, 1993; Berger and Bouwman, 2009, 2017). In theory, banks should choose an appropriate level of liquidity creation to maximize profit and control risk under a series of constraints, such as regulatory policies, market competition, and bank characteristics (Horváth et al., 2014; Berger et al., 2016, 2020; Díaz and Huang, 2017; Jiang et al., 2019; Duan et al., 2021). Nowadays, digitalization and FinTech are significant trends in the banking sector, with more and more commercial banks employing FinTech in their operations (Cheng and Qu, 2020; Berger and Demirgüç-Kunt, 2021). FinTech has transformed traditional commercial banks by introducing new technologies and methods in service delivery, risk assessment, and information collection processes (Buchak et al., 2018; Goldstein et al., 2019). As a result, banks with fast-developed FinTech have advantages over their counterparts in terms of customer relationships, risk management, and operational efficiency (Boot et al., 2021; Dadoukis et al., 2021). Thus, we maintain that bank FinTech can facilitate liquidity creation through the following channels.

The first channel is deposit inflow. FinTech-intensive banks are better at broadening customer bases, maintaining customer relationships, and raising deposit funds (Boot et al., 2021). More specifically, investments in artificial intelligence, online channels, and big data make the transactions more customizable, more convenient, less expensive, and more secure (Lv and Xiong, 2022), thereby improving customer satisfaction and retention, and ultimately ensuring cheaper and larger deposit inflows (Dadoukis et al., 2021). Since deposit resources are the prerequisite for banks to create liquidity, easy and stable access to deposit funding will prompt banks to create liquidity. Therefore, from the customer relationship perspective, FinTech adoption enhances banks' liquidity creation by expanding their deposit inflow.

The second channel is risk management. FinTech can relieve information asymmetry and help banks to make appropriate lending decisions (Fuster et al., 2019). FinTech enables financial institutions to obtain firm information in a more timely and comprehensive manner, which reduces information asymmetries between banks and firms (Gomber et al., 2017). The improvement of information transparency allows banks to choose the best borrowers and mitigate credit risks (Berg et al., 2020; Dadoukis et al., 2021). Consequently, banks with greater FinTech development are more capable and motivated to make profits by providing credit and creating liquidity. Thus, from the risk management perspective, FinTech improves banks' liquidity creation through reducing their credit risks.

The third channel is cost efficiency. Banks with better FinTech development are superior in operational efficiency. In the management process, artificial intelligence and data visualization technologies can help banks improve internal governance and internal control, reduce unnecessary delays in the decision-making process, and thus cut down management costs (Buchak et al., 2018; Cheng and Qu, 2020). In the service process, digital platforms and online channels will capture more businesses and profits than brick-and-mortar outlets at the same cost (Guo et al., 2020; Wang et al., 2021b). When cost pressures lessen, banks will better perform their liquidity creation function (Baltas et al., 2017; Duan et al., 2021). Hence, from the operational efficiency perspective, FinTech applications benefit banks' liquidity creation by lowering their cost burden.

Based on the above-mentioned analyses, we argue that bank FinTech enhances liquidity creation through three possible channels in the context of China. Therefore, we propose hypotheses H1 and H2:

**Hypothesis 1**. **(H1):** Bank FinTech promotes liquidity creation. That is, there is a positive association between bank FinTech and liquidity creation.

**Hypothesis 2**. **(H2):** Bank FinTech enhances liquidity creation through deposit inflow, risk management, and cost efficiency channels.

#### 2.2.2. The moderating role of bank characteristics

The benefits of bank FinTech in enhancing liquidity creation depend on the extent to which banks need to adopt FinTech to broaden customer base, optimize risk management, and improve cost efficiency. Extant literature has well documented that banks with different ownership, listed status, and liquidity creation levels have heterogeneous market resources, management capacity, and regulatory environment (Lin and Zhang, 2009; Barry et al., 2011; Horváth et al., 2016). We therefore conjecture that the positive effect of bank FinTech on liquidity creation differs by bank ownership, listed status, and liquidity creation level.

First, state-owned banks have comparative advantages over non-state-owned banks in terms of customer base, deposit resources, risk management, and risk resistance (Lin and Zhang, 2009; Guo et al., 2020; Cheng and Qu, 2020). Therefore, the roles of Fintech in raising deposit funding, reducing credit risks, and enhancing liquidity creation will be less pronounced in state-owned banks than in non-state-owned banks.

Second, in contrast to unlisted banks, listed banks enjoy easier access to capital markets and also face stricter market discipline (Barry et al., 2011; Jiang et al., 2013). Consequently, listed banks usually have better governance mechanisms, stronger management abilities, and greater cost efficiency than unlisted banks (Cheng and Qu, 2020). These features will lead to a weaker impact of FinTech on liquidity creation in listed banks than in unlisted banks.

Third, excessive liquidity creation has the potential to reduce banks' liquidity level and increase banking sectors' fragility (Berger and Bouwman, 2017; Davydov et al., 2021). Thus, banks with excessive liquidity creation may have high levels of risk (Horváth et al., 2016). For security purposes, these banks tend to employ FinTech to select the best borrowers and optimize asset structure rather than to expand liquidity creation. In sharp contrast, for banks with low liquidity creation, utilizing FinTech will help banks capture deposits and save costs, thereby encouraging them to create more liquidity. As a result, the positive influence of bank FinTech will be more significant in banks with less liquidity creation.

Based on these considerations, we expect that the role of bank FinTech in enhancing liquidity creation differs by bank ownership, listed status, and liquidity creation level. Hence, we formulate hypothesis H3:

**Hypothesis 3. (H3):** The positive effect of bank FinTech on liquidity creation is more pronounced for banks with non-state ownership, unlisted status, and less liquidity creation.

## 3. Sample, variables, and model

### *3.1. Sample and data*

We compile data from three sources: 1) the financial data of Chinese commercial banks are obtained from the ORBIS Bank Focus database; 2) the macroeconomic data are collected from the CEIC database, and 3) the unstructured text data for building bank-level FinTech indices are gathered from banks' annual reports. These reports are downloaded from the official website of each bank.

We begin with all Chinese commercial banks in the ORBIS Bank Focus database and apply the following sample selection process. First, to construct a complete set of variables, we remove observations that have missing data on key variables. Second, to ensure the stability and reliability of data, a sample bank should have observations covering at least three years. Third, to relieve the influence of outliers, all continuous variables are winsorized at the 1- and 99-percentile levels. Our final sample includes 795 bank-year observations of 97 commercial banks from 2008 to 2019. These banks, including five state-owned banks, 12 joint-equity commercial banks, 69 city commercial banks, and 11 rural commercial banks, account for approximately 90% of the total assets of all Chinese commercial banks.

### *3.2. Variables*

#### *3.2.1. Bank liquidity creation*

To calculate bank liquidity creation, we employ the three-step approach proposed by Berger and Bouwman (2009) and revised by Berger et al. (2019). In step 1, all bank activities are classified as liquid, semiliquid, or illiquid based on the product category. In step 2, weights 1/2, 0, and − 1/2 are assigned to all classified activities. In step 3, a liquidity creation measure (*LC*) is built by combining the activities classified in step 1 and the weights assigned in step 2.[2] Similar to Berger and Bouwman (2009), Jiang et al. (2019), and Davydov et al. (2021), we standardize *LC* by total assets for a better comparison across banks. Appendix A provides more details on the calculation of the liquidity creation measure.

#### *3.2.2. Bank FinTech*

To measure bank FinTech, we construct bank-level FinTech indices by conducting a textual analysis of banks' annual reports. The reasons for our adoption of this approach are twofold. First, in the case of China, banks seldom disclose FinTech expenses in financial statements, but many of them issue FinTech-related text information in their annual reports.[3] Second, according to the text mining theory, large amounts of unstructured data contain a variety of valuable knowledge that researchers can use (Feldman and Dagan, 1995; Askitas and Zimmermann, 2009). Existing literature finds that the more information-related or digitalization-related keywords are included in a firm's annual report, the better the information practices or digital transformation of this firm (Saunders and Tambe, 2013; Zhang et al., 2021; Zhai et al., 2022). Following these works, we maintain that the number of occurrences of FinTech-related keywords in banks' annual reports can be an appropriate proxy to reflect the development of bank FinTech. Thus, we employ the textual analysis method based on word segmentation algorithms and word frequency statistics to build bank FinTech indices.

Moreover, the development of bank FinTech is inseparable from both the technology inputs like artificial intelligence and the innovation outputs like mobile payment (Zavolokina et al., 2016). Therefore, in addition to the bank FinTech index (*FTI*), we also construct a bank FinTech input index (*FTII*) and a bank FinTech output index (*FTOI*). Appendix B describes specific steps taken to develop bank FinTech indices.

#### *3.2.3. Control variables*

According to recent literature (Berger and Bouwman, 2013; Díaz and Huang, 2017; Duan et al., 2021; Berger et al., 2022b), we

[2] This liquidity creation measure is referred to as "cat fat" in the work of Berger and Bouwman (2009).

[3] In China, banks' annual reports not only need to be audited by the internal board of directors and external certified public accountants, but also must be submitted to the China Banking and Insurance Regulatory Commission. Therefore, the information in these reports presents a relative objective and reliable picture of bank operations.

**Table 1**
Variable definitions.

| Symbol | Definition |
|---|---|
| *LC* | Bank liquidity creation, measured by the ratio of total bank liquidity creation to total assets |
| *FTI* | Bank FinTech index, constructed by a textual analysis method |
| *FTII* | Bank FinTech input index, constructed by a textual analysis method |
| *FTOI* | Bank FinTech output index, constructed by a textual analysis method |
| *Size* | Bank size, expressed by the natural logarithm of total assets |
| *Equity* | Bank equity, expressed by the equity to assets ratio |
| *ROA* | Bank profitability, expressed by the return on assets ratio |
| *CR*4 | Market concentration, measured by the ratio of the four largest banks' assets to total banking assets |
| *NFT* | Non-bank FinTech development, measured by the natural logarithm of 1 plus the number of non-bank FinTech companies |
| *GDP* | Economic growth, represented by the GDP growth rate |
| *INF* | Inflation rate, represented by the percent change in the consumer price index |

Note: This table provides the definitions of the variables used in our regressions.

**Table 2**
Descriptive statistics.

| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| *LC* | 795 | 17.0573 | 8.6032 | -20.2583 | 53.8399 |
| *FTI* | 795 | 0.2663 | 0.2359 | 0.0000 | 1.0000 |
| *FTII* | 795 | 0.2675 | 0.2141 | 0.0000 | 1.0000 |
| *FTOI* | 795 | 0.2619 | 0.2671 | 0.0000 | 1.0000 |
| *Size* | 795 | 18.8102 | 1.6864 | 15.0363 | 24.0903 |
| *Equity* | 795 | 7.2789 | 2.0711 | 1.5524 | 12.7318 |
| *ROA* | 795 | 0.8132 | 0.4633 | -0.0203 | 2.5112 |
| *CR*4 | 795 | 39.1517 | 9.0032 | 36.0814 | 44.7766 |
| *NFT* | 795 | 8.6830 | 0.8388 | 5.3110 | 9.1195 |
| *GDP* | 795 | 7.8095 | 6.7013 | 6.0000 | 14.1600 |
| *INF* | 795 | 2.6701 | 1.6603 | -0.7000 | 5.9000 |

Note: This table shows summary statistics for variables included in our database. The sample consists of 795 bank-year observations over the 2008–2019 period. *LC* is the ratio of total bank liquidity creation to total assets. *FTI*, *FTII*, and *FTOI* are the bank FinTech index, bank FinTech input index, and bank FinTech output index, respectively. *Size* is the natural logarithm of total assets. *Equity* is the equity to assets ratio. *ROA* is the return on assets ratio. *CR*4 is the ratio of the four largest banks' assets to total banking assets. *NFT* is the natural logarithm of 1 plus the number of non-bank FinTech companies. *GDP* is the GDP growth rate. *INF* is the percent change in the consumer price index. All variables are shown in percentage terms, except for *FTI*, *FTII*, *FTOI*, *Size*, and *NFT*.

**Table 3**
Correlation matrix and variance inflation factor scores.

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | VIFs |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 *LC* | 1 | | | | | | | | | | | |
| 2 *FTI* | 0.34 * * | 1 | | | | | | | | | | 1.20 |
| 3 *FTII* | 0.30 * * | 0.55 * ** | 1 | | | | | | | | | 1.14 |
| 4 *FTOI* | 0.37 * * | 0.45 * ** | 0.41 * ** | 1 | | | | | | | | 1.10 |
| 5 *Size* | 0.12 * * | 0.18 * | 0.14 * | 0.19 * | 1 | | | | | | | 1.04 |
| 6 *Equity* | -0.09 | 0.16 | 0.13 | 0.17 | -0.08 * | 1 | | | | | | 1.11 |
| 7 *ROA* | -0.12 * * | -0.07 | -0.06 | -0.07 | -0.19 * | 0.22 * | 1 | | | | | 1.03 |
| 8 *CR*4 | 0.09 | -0.07 | -0.08 | -0.07 | 0.02 | 0.28 | 0.16 | 1 | | | | 1.13 |
| 9 *NFT* | -0.07 * | 0.05 * | 0.03 * | 0.06 * | 0.18 | 0.04 | -0.11 | 0.06 | 1 | | | 1.14 |
| 10 *GDP* | 0.22 * | 0.03 * | 0.02 * | 0.04 * | 0.38 | 0.03 | 0.19 * | -0.03 | 0.10 | 1 | | 1.24 |
| 11 *INF* | -0.14 | -0.11 | -0.11 | -0.10 | 0.03 | 0.02 | 0.03 | 0.37 * | 0.13 | | 1 | 1.19 |

Note: This table shows the Pearson pairwise correlation matrix and the variance inflation factor scores (VIFs) for the main explanatory variables. The sample consists of 795 bank-year observations over the 2008–2019 period. *LC* is the ratio of total bank liquidity creation to total assets. *FTI*, *FTII*, and *FTOI* are the bank FinTech index, bank FinTech input index, and bank FinTech output index, respectively. *Size* is the natural logarithm of total assets. *Equity* is the equity to assets ratio. *ROA* is the return on assets ratio. *CR*4 is the ratio of the four largest banks' assets to total banking assets. *NFT* is the natural logarithm of 1 plus the number of non-bank FinTech companies. *GDP* is the GDP growth rate. *INF* is the percent change in the consumer price index. * ** , * *, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

control for variables at both the bank and macro levels to eliminate the effects of potentially confounding factors. The bank-level control variables include bank size (*Size*, the natural logarithm of total assets), bank equity (*Equity*, the equity to assets ratio), and bank profitability (*ROA*, the return on assets ratio). The macro-level control variables include market concentration (*CR*4, the ratio of the four largest banks' assets to total banking assets), non-bank FinTech development (*NFT*, the natural logarithm of 1 plus the number of non-bank FinTech companies), economic growth (*GDP*, the GDP growth rate), and inflation rate (*INF*, the percent change in the

**Table 4**
Basic results: Effect of bank FinTech on liquidity creation.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | *LC* | *LC* | *LC* | *LC* | *LC* | *LC* |
| *FTI* | 3.3121 *** | | | 2.8938 *** | | |
| | (3.54) | | | (2.99) | | |
| *FTII* | | 3.1153 *** | | | 2.8276 *** | |
| | | (3.31) | | | (2.68) | |
| *FTOI* | | | 3.8918 *** | | | 3.2269 *** |
| | | | (3.76) | | | (3.32) |
| *Size* | | | | 4.1334 *** | 4.8076 *** | 3.4466 *** |
| | | | | (7.77) | (8.00) | (7.43) |
| *Equity* | | | | 0.1222 | 0.1262 | 0.1081 |
| | | | | (0.27) | (0.28) | (0.23) |
| *ROA* | | | | -3.7946 *** | -3.8280 *** | -3.7671 *** |
| | | | | (−2.93) | (−2.94) | (−2.90) |
| *CR4* | | | | -0.0774 ** | -0.0884 *** | -0.0639 ** |
| | | | | (−2.28) | (−2.64) | (−2.08) |
| *NFT* | | | | -0.0462 ** | -0.0477 ** | -0.0437 ** |
| | | | | (−2.04) | (−2.13) | (−1.97) |
| *GDP* | | | | 0.7774 ** | 0.8200 ** | 0.7586 ** |
| | | | | (2.27) | (2.41) | (2.16) |
| *INF* | | | | -0.8311 | -0.8210 | -0.8499 |
| | | | | (−0.29) | (−0.28) | (−0.31) |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 | 795 | 795 | 795 |
| R-Squared | 0.1563 | 0.1585 | 0.1563 | 0.2165 | 0.2290 | 0.2110 |

Notes: This table reports OLS regression estimates for analyzing the effects of bank FinTech on liquidity creation. The sample consists of 795 bank-year observations over the 2008–2019 period. The dependent variable is *LC* (bank liquidity creation), which is the ratio of total bank liquidity creation to total assets. The key explanatory variables are *FTI* (bank FinTech index), *FTII* (bank FinTech input index), and *FTOI* (bank FinTech output index), respectively, in columns (1) and (4), (2) and (5), and (3) and (6). We include a set of bank-level controls such as *Size* (the natural logarithm of total assets), *Equity* (the equity to assets ratio), and *ROA* (the return on assets ratio), and a set of macro-level controls such as *CR*4 (the ratio of the four largest banks' assets to total banking assets), *NFT* (the natural logarithm of 1 plus the number of non-bank FinTech companies), *GDP* (the GDP growth rate), and *INF* (the percent change in the consumer price index). All explanatory variables are lagged one year. Columns (1)–(3) include only bank FinTech measures with both bank and year fixed effects. Columns (4)–(6) add bank- and macro-level controls. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

consumer price index). Table 1 provides an overview of the definitions of the variables included in our empirical study.

### 3.2.4. *Descriptive statistics and correlations*

Table 2 reports the descriptive statistics for the main variables used in our regressions. *LC* has a mean of 17.0573% and ranges from − 20.2583–53.8399%, indicating that there is considerable dispersion across banks in the level of liquidity creation. *FTI* varies between 0.0000 and 1.0000 with a mean of 0.2663, meaning that the sample exhibits heterogeneity in terms of the development of FinTech. Table 2 also shows that the banks included in our sample differ in asset scale, capital ratio, and financial performance.

Table 3 reports the Pearson pairwise correlation matrix and the variance inflation factor scores (VIFs) for the main variables. We find that bank FinTech indices (*FTI*, *FTII*, and *FTOI*) are significantly and positively related to *LC*, providing preliminary support for our hypothesis H1. The results in the last column of Table 3 show that the VIFs range from 1.03 for *ROA* to 1.24 for *GDP*, below the conventional threshold of 10. Therefore, we conclude that high multicollinearity does not appear to be a problem in our estimates.

## 3.3. *Model*

To examine the impact of bank FinTech development on liquidity creation, we estimate the following basic regression Model (1):

$$LC_{it} = \beta_0 + \beta_1 FinTech_{i,t-1} + \beta_2 Control_{i,t-1} + Bank_i + Year_t + \varepsilon_{it} \tag{1}$$

where $i = 1, 2\ldots, N$ indicates banks and $t = 1, 2\ldots, T$ signifies year. $LC_{it}$ represents the liquidity creation of bank $i$ in year $t$. $FinTech_{i,t\text{-}1}$ denotes the development of FinTech of bank $i$ in year $t$-1, measured by $FTI_{i,t\text{-}1}$, $FTII_{i,t\text{-}1}$, and $FTOI_{i,t\text{-}1}$. $Control_{i,t\text{-}1}$ refers to a vector of control variables, including $Size_{i,t\text{-}1}$, $Equity_{i,t\text{-}1}$, $ROA_{i,t\text{-}1}$, $CR4_{t\text{-}1}$, $NFT_{t\text{-}1}$, $GDP_{t\text{-}1}$, and $CPI_{t\text{-}1}$. $Bank_i$ and $Year_t$ are bank and year fixed effects, respectively. $\varepsilon_{it}$ is the error term. The explanatory variables are lagged one year to eliminate the reverse causality concern. Bank and year fixed effects are included to control for time-invariant bank heterogeneity and time-variable macroeconomic shocks, respectively. Moreover, in all regressions, standard errors are clustered at the bank level to account for heteroscedasticity and autocorrelation. All variables are defined in Table 1.

**Table 5**
Channel analysis from the deposit inflow perspective.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | *DepositG* | *DepositG* | *DepositG* | *LC* | *LC* | *LC* |
| *FTI* | 2.5803 * ** | | | | | |
| | (6.42) | | | | | |
| *FTII* | | 2.0695 *** | | | | |
| | | (6.50) | | | | |
| *FTOI* | | | 2.8006 *** | | | |
| | | | (5.57) | | | |
| *DepositG_P_FTI* | | | | 1.1947 *** | | |
| | | | | (3.37) | | |
| *DepositG_P_FTII* | | | | | 0.9744 ** | |
| | | | | | (2.42) | |
| *DepositG_P_FTOI* | | | | | | 1.3104 *** |
| | | | | | | (3.72) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 | 795 | 795 | 795 |
| R-Squared | 0.2414 | 0.2418 | 0.2378 | 0.2293 | 0.2319 | 0.2236 |

Notes: This table reports OLS regression estimates for analyzing the deposit inflow channel. The sample consists of 795 bank-year observations over the 2008–2019 period. We use a two-step regression approach. Columns (1)–(3) give the first-step results. The dependent variable is *DepositG* (deposit growth), which is calculated as the total deposits of bank *i* in year *t* minus its total deposits in year *t*-1 and scaled by its total deposits in year *t*-1. The key explanatory variables are *FTI* (bank FinTech index), *FTII* (bank FinTech input index), and *FTOI* (bank FinTech output index), respectively, in columns (1), (2), and (3). Columns (4)–(6) give the second-step results. The dependent variable is *LC* (bank liquidity creation), which is the ratio of total bank liquidity creation to total assets. The key explanatory variables are the predicted deposit growth, i.e., *DepositG_P_FTI*, *DepositG_P_FTII*, and *DepositG_P_FTOI*, respectively, in columns (4), (5), and (6). All regressions control for bank- and macro-level characteristics as well as bank and year fixed effects. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

## 4. Empirical results

### 4.1. Basic results

In this subsection, we are interested in whether the development of bank FinTech is conducive to liquidity creation. Table 4 presents the ordinary least squares (OLS) regression results for model (1) with *FTI*, *FTII*, and *FTOI* as the independent variables. In columns (1)–(3), we include only bank FinTech measures with both bank and year fixed effects. In columns (4)–(6), we further add bank- and macro-level controls. Across all regressions, the coefficients on *FTI*, *FTII*, and *FTOI* are positive and significant, suggesting that banks with greater FinTech development create more liquidity for the public. These results are also economically significant. Based on the estimates from columns (4)–(6), a 1 standard deviation increase in *FTI*, *FTII*, and *FTOI* could lead to 4.00, 3.55, and 5.05% point increases in *LC*, respectively.[4] Overall, these outcomes confirm hypothesis H1 and show that banks better perform their liquidity creation function if they develop and apply more FinTech.

With respect to control variables, *Size* has a significant and positive impact on *LC*, indicating that larger banks create more liquidity for the public than smaller banks. This may be explained by observing that, in the context of China, large banks have advantages over small banks in terms of market power and customer base (Lin and Zhang, 2009; Guo et al., 2020), and thus they have more capacity to absorb deposits and supply loans. Consistent with Dan (2020), *ROA* is significantly and negatively related to *LC*, showing that less profitable banks have more incentives to create liquidity. The negative and significant signs for *CR*4 suggest that highly concentrated markets prevent commercial banks from creating more liquidity. The coefficients of *NFT* are negative and significant at the 5% level. These results are consistent with the findings of Thakor (2020) and Zhao et al. (2022), showing that the development of non-bank FinTech companies can erode incumbent banks' businesses, customers, and profits, thereby negatively influencing banks' financial intermediation and liquidity creation functions. The coefficients estimated for *GDP* are significantly positive in all columns, revealing the procyclicality of liquidity creation in the Chinese banking system (Davydov et al., 2018; Niu, 2021).

[4] The coefficients on *FTI*, *FTII*, and *FTOI* are about 2.8938, 2.8276, and 3.2269, respectively; the standard deviations of *FTI*, *FTII*, and *FTOI* are 0.2359, 0.2141, and 0.2671, respectively, and the mean of *LC* is 17.0573. Thus, if *FTI*, *FTII*, and *FTOI* increase by 1 standard deviation, *LC* will increase by 2.8938 * 0.2359/17.0573 = 4.00, 2.8276 * 0.2141/17.0573 = 3.55, and 3.2491 * 0.2671/17.0573 = 5.05% points, respectively.

**Table 6**
Channel analysis from the risk management perspective.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | *NPL* | *NPL* | *NPL* | *LC* | *LC* | *LC* |
| *FTI* | -0.1790 *** | | | | | |
| | (−3.47) | | | | | |
| *FTII* | | -0.1377 *** | | | | |
| | | (−3.36) | | | | |
| *FTOI* | | | -0.2096 *** | | | |
| | | | (−3.26) | | | |
| *NPL_P_FTI* | | | | -6.0048 *** | | |
| | | | | (−3.37) | | |
| *NPL_P_FTII* | | | | | -4.2479 ** | |
| | | | | | (−2.42) | |
| *NPL_P_FTOI* | | | | | | -6.2723 *** |
| | | | | | | (−3.72) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 | 795 | 795 | 795 |
| R-Squared | 0.1537 | 0.1528 | 0.1541 | 0.2293 | 0.2319 | 0.2236 |

Notes: This table reports OLS regression estimates for analyzing the risk management channel. The sample consists of 795 bank-year observations over the 2008–2019 period. We use a two-step regression approach. Columns (1)–(3) give the first-step results. The dependent variable is *NPL* (credit risk), which is measured by the ratio of nonperforming loans to total loans. The key explanatory variables are *FTI* (bank FinTech index), *FTII* (bank FinTech input index), and *FTOI* (bank FinTech output index), respectively, in columns (1), (2), and (3). Columns (4)–(6) give the second-step results. The dependent variable is *LC* (bank liquidity creation), which is the ratio of total bank liquidity creation to total assets. The key explanatory variables are the predicted *NPL*, i.e., *NPL_P_FTI*, *NPL_P_FTII*, and *NPL_P_FTOI*, respectively, in columns (4), (5), and (6). All regressions control for bank and macro-level characteristics as well as bank and year fixed effects. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

### 4.2. Channel analysis

In this subsection, we examine three possible channels through which bank FinTech enhances liquidity creation. As discussed in Section 2, the first channel is deposit inflow. FinTech-intensive banks have comparative advantages in expanding customer bases, maintaining customer relationships, and raising deposit funds (Boot et al., 2021), so they have more resources to create liquidity than their counterparts. The second channel is risk management. Investing in FinTech helps banks to strengthen monitoring and screening capabilities, optimize lending decisions, and reduce credit risks (Berg et al., 2020; Dadoukis et al., 2021). Accordingly, banks with greater FinTech development have more capabilities and incentives to seek profits by supplying credit and creating liquidity. The third channel is cost efficiency. Banks with fast-developed FinTech are superior in operational efficiency. As the costs of making decisions and providing services go down, banks can better perform their liquidity creation function (Baltas et al., 2017; Duan et al., 2021).

To conduct our channel analysis, we employ a two-step regression approach following Duan et al. (2021b) and Griffin et al. (2021). In the first step, we regress channel variables on bank FinTech indices and controls (see Model (2)). In the second step, we regress bank liquidity creation on the channel variables predicted from the first step (see Model (3)).

$$Z_{it} = \beta_0 + \beta_1 FinTech_{i,t-1} + \beta_2 Control_{i,t-1} + Bank_i + Year_t + \varepsilon_{it} \tag{2}$$

where $Z_{it}$ represents channel variables, including deposit growth ($DepositG_{it}$), credit risk ($NPL_{it}$), and cost inefficiency ($Inefficiency_{it}$). $DepositG_{it}$ is calculated as the total deposits of bank *i* in year *t* minus its total deposits in year *t*-1 and scaled by its total deposits in year *t*-1. $NPL_{it}$ is the nonperforming loan ratio of the bank, measured by the ratio of nonperforming loans to total loans for bank *i* in year *t*. $Inefficiency_{it}$ is the ratio of overhead expenses to total assets for bank *i* in year *t*, with a higher ratio meaning less bank efficiency. These data are obtained from the ORBIS Bank Focus database.

$$LC_{it} = \beta_0 + \beta_1 Z\_P_{it} + \beta_2 Control_{i,t-1} + Bank_i + Year_t + \varepsilon_{it} \tag{3}$$

where $Z\_P_{it}$ denotes the predicted channel variables from the first-step regression (Model (2)), including $DepositG\_P_{it}$, $NPL\_P_{it}$, and $Inefficiency\_P_{it}$; the remaining variables are consistent with the basic regression.

Table 5 tests the deposit inflow channel. Columns (1)–(3) provide the first-step results, with deposit growth (*DepositG*) as the dependent variable; columns (4)–(6) provide the corresponding second-step results, with liquidity creation (*LC*) as the dependent variable. In the first step, we find that the coefficients of *FTI*, *FTII*, and *FTOI* are positive and significant at the 1% level, implying an obvious and beneficial role of bank FinTech in capturing deposit funds. In the second step, the effects of the predicted values of deposit growth on liquidity creation are positive and significant. These results reveal that FinTech development in banks enhances their liquidity creation by improving deposit inflow.

Table 6 tests the risk management channel. Columns (1)–(3) give the first-step results, where the dependent variable is credit risk

**Table 7**
Channel analysis from the cost efficiency perspective.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | *Inefficiency* | *Inefficiency* | *Inefficiency* | *LC* | *LC* | *LC* |
| *FTI* | -0.2336 *** | | | | | |
| | (−3.72) | | | | | |
| *FTII* | | -0.1770 *** | | | | |
| | | (−3.55) | | | | |
| *FTOI* | | | -0.2805 *** | | | |
| | | | (−3.59) | | | |
| *Inefficiency_P_FTI* | | | | -4.1208 *** | | |
| | | | | (−3.37) | | |
| *Inefficiency_P_FTII* | | | | | -3.4610 ** | |
| | | | | | (−2.42) | |
| *Inefficiency_P_FTOI* | | | | | | -4.7558 *** |
| | | | | | | (−3.72) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 | 795 | 795 | 795 |
| R-Squared | 0.1629 | 0.1615 | 0.1638 | 0.2293 | 0.2319 | 0.2236 |

Notes: This table reports OLS regression estimates for analyzing the cost efficiency channel. The sample consists of 795 bank-year observations over the 2008–2019 period. We use a two-step regression approach. Columns (1)–(3) display the first-step results. The dependent variable is *Inefficiency* (cost inefficiency), which is measured by the ratio of overhead expenses to total assets. The key explanatory variables are *FTI* (bank FinTech index), *FTII* (bank FinTech input index), and *FTOI* (bank FinTech output index), respectively, in columns (1), (2), and (3). Columns (4)–(6) display the second-step results. The dependent variable is *LC* (bank liquidity creation), which is the ratio of total bank liquidity creation to total assets. The key explanatory variables are the predicted *Inefficiency*, i.e., *Inefficiency_P_FTI*, *Inefficiency_P_FTII*, and *Inefficiency_P_FTOI*, respectively, in columns (4), (5), and (6). All regressions control for bank- and macro-level characteristics as well as bank and year fixed effects. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

(*NPL*). *FTI*, *FTII*, and *FTOI* are negatively and significantly related to *NPL*, meaning that FinTech-intensive banks report less credit risk than their peers.[5] Columns (4)–(6) report the second-step results, where the dependent variable is bank liquidity creation (*LC*). The negative and significant signs on the predicted values of *NPL* show that better risk management leads to a larger liquidity creation. These results mean that FinTech development in banks will improve their liquidity creation by reducing credit risks. Our conjecture is therefore supported.

Table 7 tests the cost efficiency channel. Columns (1)–(3) describe the first-step results, with cost inefficiency (*Inefficiency*) as the dependent variable; columns (4)–(6) describe the corresponding second-step results, with liquidity creation (*LC*) as the dependent variable. In the first step, the negative and significant coefficients on *FTI*, *FTII*, and *FTOI* indicate that banks with better-developed FinTech are associated with less cost inefficiency. In the second step, the predicted values of cost inefficiency exhibit negative and significant coefficients. These findings confirm that FinTech development in banks benefits their liquidity creation by boosting cost efficiency.

Collectively, our results support the hypothesis H2, showing that bank FinTech enhances liquidity creation through deposit inflow, risk management, and cost efficiency channels.[6]

### *4.3. Heterogeneous and nonlinear analysis*

In this subsection, we shift our attention to the heterogeneous and nonlinear effects of bank FinTech on liquidity creation. Specifically, we consider how bank attributes, including ownership, listed status, and liquidity creation level, moderate the relation between bank FinTech and liquidity creation.

#### *4.3.1. Heterogeneous impact on banks with different ownership*

Our sample contains both state-owned banks and non-state-owned banks. State-owned banks have comparative advantages over non-state-owned banks in terms of customer base, deposit resources, risk management, and risk resistance (Lin and Zhang, 2009). To

[5] Considering that it takes some time to reveal the riskiness of loans issued in the current period, we further check the impact of bank FinTech on credit risks in future years to improve the robustness of our finding. Specifically, we estimate the impact of *FTI* (*FTII* or *FTOI*) in year $t$-1 on *NPL* in year $t + 1$, $t + 2$, and $t + 3$ in succession. The results in Table C1 in Appendix C show that the coefficients of *FTI* (*FTII* or *FTOI*) are significantly negative, which demonstrates the consistency of our results. We highly appreciate an anonymous referee for the suggestions regarding these robustness checks.

[6] To address the endogeneity concern, we further report the IV-2SLS regression estimates for analyzing the channels through which bank FinTech affects liquidity creation. The results in Tables C2–C4 in Appendix C suggest that our results hold in the IV-2SLS regressions. We highly appreciate an anonymous referee for the suggestions regarding these checks.

**Table 8**
Heterogeneous and nonlinear analysis.

| **Panel A: Heterogeneous results based on bank ownership.** | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Variables | *LC* | *LC* | *LC* |
| *FTI* | 4.9951 *** (3.00) | | |
| *FTII* | | 4.6378 *** (3.13) | |
| *FTOI* | | | 5.2897 *** (3.51) |
| *FTI* × *Ownership* | -2.5719 ** (−2.05) | | |
| *FTII..Ownership* | | -2.1529 * (−1.93) | |
| *FTOI* × *Ownership* | | | -2.4108 ** (−2.09) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 |
| R-Squared | 0.2465 | 0.2484 | 0.2426 |
| **Panel B: Heterogeneous results based on bank list status.** | | | |
| | (1) | (2) | (3) |
| Variables | *LC* | *LC* | *LC* |
| *FTI* | 3.9873 *** (4.22) | | |
| *FTII* | | 3.1761 *** (3.99) | |
| *FTOI* | | | 4.5280 *** (4.00) |
| *FTI..List* | -2.0500 *** (−2.63) | | |
| *FTII* × *List* | | -1.5561 ** (−2.14) | |
| *FTOI* × *List* | | | -2.5753 *** (−3.40) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 |
| R-Squared | 0.2493 | 0.2496 | 0.2484 |
| **Panel C: Nonlinear results based on bank liquidity creation level.** | | | |
| | (1) | (2) | (3) |
| Variables | *q*30 *LC* | *q*60 *LC* | *q*90 *LC* |
| *FTI* | 3.0525 *** (4.09) | 2.0509 *** (2.58) | 4.5160 (1.25) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| *Year* | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 |
| R-Squared | 0.2184 | 0.1755 | 0.1557 |

Notes: This table reports regression estimates for analyzing the heterogeneous and nonlinear effects of bank FinTech on liquidity creation. The sample consists of 795 bank-year observations from 2008 to 2019. Panel A presents the heterogeneous results based on bank ownership. Panel B presents the heterogeneous results based on bank list status. Panel C presents the nonlinear results based on bank liquidity creation level. We employ the panel quantile regression proposed by Konenker (2004) and select three quantiles (30%, 60%, and 90%) to display the nonlinear relationship between bank FinTech and liquidity creation. *LC* is the bank liquidity creation, which is measured by the ratio of total bank liquidity creation to total assets. *FTI*, *FTII*, and *FTOI* are the bank FinTech index, bank FinTech input index, and bank FinTech output index, respectively. *Ownership* is a dummy variable that equals 1 if bank *i* is a state-owned bank and 0 otherwise. *List* is a dummy variable that equals 1 if bank *i* goes public in year *t* and 0 otherwise. Regressions in panels A and B control for bank- and macro-level characteristics as well as bank and year fixed effects, while regressions in Panel C control for bank- and macro-level characteristics as well as year dummies. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

explore whether the effect of FinTech will differ between state-owned and non-state-owned banks, we create a new variable (*Ownership*$_i$) to measure bank ownership. *Ownership*$_i$ is a dummy variable that equals 1 if bank ***i*** is a state-owned bank and 0 otherwise. Then, we add the interaction variable (*Fintech* × *Ownership*) to Model (1) and set up Model (4).

$$LC_{it} = \beta_0 + \beta_1 FinTech_{i,t-1} + \beta_2 FinTech_{i,t-1} \times Ownership_i + \beta_3 Ownership_i \\ + \beta_4 Control_{i,t-1} + Bank_i + Year_t + \varepsilon_{it} \tag{4}$$

where *FinTech*$_{i,t\text{-}1}$ represents bank FinTech indices, *Ownership*$_i$ refers to bank ownership, and the remaining variables are consistent with the basic regression.

Panel A of Table 8 shows the results for Model (4). Using three proxies for FinTech, we find that the coefficients of the interaction variables are significant and negative, implying that the benefit of bank FinTech is more obvious in non-state-owned banks. The possible reasons for this finding are as follows. First, in the context of China, state-owned banks have more stable customers and deposit resources compared to non-state-owned banks (Lin and Zhang, 2009; Guo et al., 2020). Second, as systematically important banks, state-owned banks are stronger than joint-stock, city, and rural banks in terms of risk management and risk resistance (Cheng and Qu, 2020). These advantages result in a smaller improvement in liquidity creation in state-owned banks when employing FinTech.

Hence, the positive effect of bank FinTech on liquidity creation is more pronounced among non-state-owned banks.

#### 4.3.2. Heterogeneous impact on banks with different list status

After the reform in the Chinese banking industry, more and more commercial banks go public. Listed banks and unlisted banks are confronted with different market resources and market discipline (Barry et al., 2011; Jiang et al., 2013). Thus, the role of list status in the relationship between bank FinTech and liquidity creation is worth examining. We create a new variable ($List_{it}$) to measure bank list status. $List_{it}$ is a dummy variable, taking the value of 1 if bank *i* goes public in year *t* and 0 otherwise. Then, we bring the interaction term (*Fintech* × *List*) into Model (1) and generate the following Model (5).

$$\begin{aligned} LC_{it} = {} & \beta_0 + \beta_1 FinTech_{i,t-1} + \beta_2 FinTech_{i,t-1} \times List_{it} + \beta_3 List_{it} \\ & + \beta_4 Control_{i,t-1} + Bank_i + Year_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where $FinTech_{i,t\text{-}1}$ denotes bank FinTech indices, $List_{it}$ identifies bank list status, and the remaining variables are consistent with the basic regression.

Panel B of Table 8 displays the empirical results for Model (5). Across all regressions, the coefficients of the interaction variables are significantly negative, revealing that unlisted banks benefit more from FinTech than listed banks. The main reason may be that unlisted banks have less access to capital markets and are subject to less market discipline (Jiang et al., 2013; Cheng et al., 2021), so they usually have fewer market resources, weaker internal governance structures, less risk management abilities, and lower cost efficiency than listed banks. Therefore, the deposit funding and management methods brought about by FinTech will lead to a stronger improvement in liquidity creation in unlisted banks.

#### 4.3.3. Nonlinear impact on banks with different liquidity creation levels

While bank liquidity creation is a necessity for the smooth functioning of financial markets (Dell'Ariccia et al., 2008; Berger and Sedunov, 2017), excessive liquidity creation has the potential to reduce banks' liquidity level, increase banking sectors' fragility, and even trigger a financial crisis (Berger and Bouwman, 2017; Davydov et al., 2021). Therefore, it is of certain research significance to consider the nonlinear impact of FinTech on banks with different liquidity creation levels. The regression Model (1) used above is actually a mean regression, with which it is difficult to provide comprehensive information on the nonlinear association between bank FinTech and liquidity creation. Thus, we employ the panel quantile regression proposed by Konenker (2004) to investigate the nonlinear impact of bank FinTech on liquidity creation. The specific panel quantile regression model is as follows:

$$\min_{\beta_q} \sum_{i:LC_{it} \geq x'_{i,t-1}\beta_q}^{n} q\left|LC_{it} - x'_{i,t-1}\beta_q\right| + \sum_{i:LC_{it} < x'_{i,t-1}\beta_q}^{n} (1-q)\left|LC_{it} - x'_{i,t-1}\beta_q\right| \tag{6}$$

where the value of bank liquidity creation in the *qth* quantile, described by $LC_{it}(x_{it})$, is equal to $x'_{i,t-1}\beta_q$; $x'_{i,t-1}$ includes bank FinTech index and all control variables, and $\beta_q$ is the estimated coefficient vector of $x'_{i,t-1}$ in the *qth* quantile. We select three quantiles (30%, 60%, and 90%) to display the nonlinear nexus between bank FinTech and liquidity creation.

Panel C of Table 8 shows the quantile regression estimates for Model (6), with *FTI* as the independent variable.[7] The coefficient on *FTI* is statistically significant and positive in the 30th and 60th quantiles but becomes insignificant in the 90th quantile, indicating that the positive effect of bank FinTech is weaker when the level of liquidity creation is on the right side of its conditional distribution. These outcomes may be due to the following reason. Banks with excessive liquidity creation have high levels of risk (Horváth et al., 2016). For security purposes, these banks tend to employ FinTech to select the best borrowers and optimize asset structure rather than to increase liquidity creation. Thus, the positive impact of bank FinTech is more significant in banks with less liquidity creation.

Overall, these results support our hypothesis H3, suggesting that banks with non-state ownership, unlisted status, and less liquidity creation benefit more from FinTech than banks that are state-owned, listed, and have greater liquidity creation.

### 4.4. Endogeneity issue

Although we lagged all explanatory variables and included bank and time fixed effects in the regression equations, an endogeneity issue is still possible between bank FinTech and liquidity creation. In this subsection, we employ the instrument variable (IV), the propensity score matching (PSM), and the two-step system generalized method of moments (system GMM) approaches to alleviate endogeneity concerns.

#### 4.4.1. Instrument variable approach

We first conduct an instrumental variable analysis to address the possible endogeneity. Following recent studies by Arner et al. (2015), Cheng and Qu (2020), Ji et al. (2022), and Neef and Schandlbauer (2021, 2022), we employ the weighted average internet penetration rate (*W_Internet*) and the weighted average proportion of employees in the information industry (*W_Employee*) as two

[7] The nonlinear impact of bank FinTech on liquidity creation holds if we use *FTI*, *FTII*, and *FTOI* as the independent variable. For brevity, we report only the estimates on the coefficients of *FTI*.

instrumental variables (IVs).[8] These IVs are appropriate for the following reasons. First, the *W_Internet* and *W_Employee* measures quantify the Internet and information environment faced by each bank through its branches in each city around the country, which affects the advancement of bank FinTech (Cheng and Qu, 2020). Second, *W_Internet* and *W_Employee* do not directly influence bank liquidity creation.[9] Furthermore, the results of under-, weak-, and over-identification tests confirm the relevance and exogeneity of these IVs. More precisely, *W_Internet* and *W_Employee* are calculated with Eq. 7 and Eq. 8, respectively, as follow.

$$W\_Internet_{i,t-1} = \sum_{c=1}^{C} Branch\_Bank_{i,c,t-1} \times Internet_{c,t-1} \tag{7}$$

$$W\_Employee_{i,t-1} = \sum_{c=1}^{C} Branch\_Bank_{i,c,t-1} \times Employee_{c,t-1} \tag{8}$$

where $i = 1, 2\ldots, N$ indicates banks, $c = 1, 2\ldots, C$ denotes cities, and $t = 1, 2\ldots, T$ signifies year. $Branch\_Bank_{i,c,t\text{-}1}$ is the proportion of bank $i$'s branches in city $c$ in year $t$-1. $Internet_{,t\text{-}1}$ is the number of Internet broadband users per 10,000 people in city $c$ in year $t$-1. $Employee_{c,t\text{-}1}$ is the ratio of the number of employees in information transmission, computer services, and software industries to the number of total employees in city $c$ in year $t$-1.[10]

Panel A of Table 9 presents the two-stage least squares (2SLS) regression results. In the first-stage regression, we use *FTI*, *FTII*, and *FTOI* as the dependent variables, respectively, in columns (1)–(3). We find that the two IVs are significantly and positively related to the development of bank FinTech. Meanwhile, the p-values of the Kleibergen-Paap rk LM statistics are 0.00, suggesting that the model is identified; the Kleibergen-Paap rk Wald F statistics are larger than the Stock-Yogo critical value, rejecting the null hypothesis that these IVs are weak, and the p-values of the Hansen J statistics are larger than 0.10, indicating that we cannot reject the null hypothesis that these IVs are uncorrelated with the error term. Thus, these IVs satisfy the relevance and exogeneity restrictions. In the second-stage regression, we employ *LC* as the dependent variable in all columns. The predicted bank FinTech indices (*FTI_P*, *FTII_P*, and *FTOI_P*) have strongly positive signs in all three versions, suggesting that banks with greater FinTech development create more liquidity than their peers. Thus, our conclusions are robust after controlling for the endogenous bias.

#### 4.4.2. Propensity score matching approach

We use a propensity score matching approach proposed by Rosenbaum and Rubin (1983) to reduce the possible endogeneity. The PSM approach works as follows. First, we randomize the panel data based on the study by Dehejia and Wahba (2002). Then, we employ a logistic function to estimate the conditional probability of receiving treatment and calculate the propensity score. Further, we match each treated bank (a bank whose FinTech indices are larger than the average FinTech level) with two control banks (banks whose FinTech indices are smaller than the average FinTech level) that have the closest total size, equity, and profitability. Finally, we re-estimate Model (1) using the matched sample.

Panel B of Table 9 reports the PSM regression results, with *FTI*, *FTII*, and *FTOI* as the independent variables. The coefficients on variables *FTI*, *FTII*, and *FTOI* reveal a significant and positive relationship between bank FinTech and liquidity creation, meaning that sample selection bias does not drive our findings.

#### 4.4.3. System GMM approach

To further mitigate the endogeneity issue, we apply a two-step system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). The two-step system GMM estimator is appropriate for the following reasons. First, this estimator can control for time persistence in the series of liquidity creation, given that bank liquidity creation may persist over time owing to the relationship with customers and regulators. Second, this estimator can eliminate unobserved bank-specific effects and remove the strict exogenous assumption for variables. Third, this estimator brings efficiency gains in the presence of heteroscedasticity and cross-sectional dependence. Overall, the two-step system GMM provides another method for checking the robustness of our conclusions. However, as shown in Bond's (2002) study, the two-step system GMM estimator is likely to improve the significance of the coefficients by underestimating their standard errors. Therefore, we employ the methodology developed by Windmeijer (2005) to correct standard errors.

Panel C of Table 9 presents the system GMM results. We find that the coefficients on bank FinTech indices remain positive and significant across all regressions, confirming our hypothesis that the development of bank FinTech is conducive to liquidity creation. In addition, our regressions cannot reject the null hypotheses of the Arellano-Bond test or the Sargan test, which validates the two-step GMM estimator.

[8] We appreciate an anonymous referee for pointing out that employing information about one city to build IVs may not be representative enough, especially for some banks that establish branches nationwide. Therefore, we adopt a weighted average method to construct IVs.

[9] There might be concerns that *W_Internet* and *W_Employee* may affect bank liquidity creation through their relations with non-bank FinTech (*NFT*). To address this concern, we control the impact of *NFT* in all regressions. Also, we caculate these two IVs at the bank-level, so they are less likely relevant to the overall development of non-bank FinTech.

[10] The number of bank branches is manually collected from the Financial License Inquiry System of the China Banking and Insurance Regulatory Commission. The number of Internet broadband users and the number of information practitioners are retrieved from the China Urban Statistical Yearbook.

**Table 9**
Endogeneity tests.

| **Panel A: IV-2SLS regression results.** | | | |
|---|---|---|---|
| **Second stage** | | | |
| | (1) | (2) | (3) |
| Variables | *LC* | *LC* | *LC* |
| *FTI_P* | 3.1809 *** (3.31) | | |
| *FTII_P* | | 2.6454 *** (3.39) | |
| *FTOI_P* | | | 4.0517 *** (3.15) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 |
| R-Squared | 0.2429 | 0.2438 | 0.2406 |
| **First stage** | | | |
| | (1) | (2) | (3) |
| Variables | *FTI* | *FTII* | *FTOI* |
| *W_Internet* | 0.7449 *** (19.55) | 0.5104 *** (15.52) | 0.9042 *** (17.34) |
| *W_Employee* | 0.7852 *** (8.36) | 0.6463 *** (9.07) | 0.8389 *** (6.81) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Kleibergen-Paap rk LM test | 0.00 | 0.00 | 0.00 |
| Kleibergen-Paap rk Wald F test | 233.56 | 243.09 | 200.88 |
| Hansen J test | 0.33 | 0.36 | 0.31 |
| Observations | 795 | 795 | 795 |
| R-Squared | 0.1919 | 0.1937 | 0.1966 |
| **Panel B: PSM regression results.** | | | |
| | (1) | (2) | (3) |
| Variables | *LC* | *LC* | *LC* |
| *FTI* | 3.7321 *** (2.85) | | |
| *FTII* | | 2.8186 *** (2.92) | |
| *FTOI* | | | 6.2415 *** (2.80) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 303 | 291 | 316 |
| R-Squared | 0.2928 | 0.2933 | 0.2923 |
| **Panel C: System GMM regression results.** | | | |
| | (1) | (2) | (3) |
| Variables | *LC* | *LC* | *LC* |
| *FTI* | 2.7075 *** (5.60) | | |
| *FTII* | | 2.4361 *** (4.18) | |
| *FTOI* | | | 2.8903 *** (7.09) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| *Year* | Yes | Yes | Yes |
| AR (2) test | 0.4733 | 0.4702 | 0.4417 |
| Sargan Test | 0.7203 | 0.7217 | 0.7206 |
| Observations | 698 | 698 | 698 |
| R-Squared | 0.2463 | 0.2484 | 0.2421 |

Notes: This table reports results on endogeneity tests. Panel A presents the IV-2SLS regression results. The sample consists of 795 bank-year observations over the 2008–2019 period. We employ *W_Internet* (the weighted average internet penetration rate) and *W_Employee* (the weighted average proportion of employees in the information industry) as two instruments. The Kleibergen-Paap rk LM test reports the p-value of the null hypothesis that the equation is under-identified. The Kleibergen- Paap rk Wald F test reports the statistical value of the null hypothesis that the instruments are weak. The Hasan J test reports the p-value of the null hypothesis that the instruments are not correlated with the error term. Panel B presents the PSM regression results. We use PSM to match banks, so the sample consists of 303, 291, and 316 bank-year observations over the 2008–2019 period in columns (1), (2), and (3), respectively. Panel C presents the two-step system GMM regression results. The sample consists of 698 bank-year observations over the 2008–2019 period. We treat all bank-level variables as endogenous and all macro-level variables as pre-determined. We employ the first lag of pre-determined variables and the second lag of endogenous variable as instruments. The AR(2) test reports the p-value of the null hypothesis that the residuals exhibit no second-order autocorrelation. The Sargan test reports the p-value of the null hypothesis that the instruments are not correlated with the residuals. *LC* is the bank liquidity creation, which is measured by the ratio of total bank liquidity creation to total assets. *FTI*, *FTII*, and *FTOI* are the bank FinTech index, bank FinTech input index, and bank FinTech output index, respectively. Regressions in panels A and B control for bank- and macro-level characteristics as well as bank and year fixed effects, while regressions in Panel C control for bank- and macro-level characteristics as well as year dummies. Standard errors in panels A and B are clustered at the bank level, while standard errors in Panel C are corrected for heteroscedasticity following Windmeijer (2005) methodology. T-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**Table 10**
Robustness results.

| Panel A: Alternative measure of bank liquidity creation. | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Variables | *LTgap* | *LTgap* | *LTgap* |
| *FTI* | 1.7149 *** (3.36) | | |
| *FTII* | | 1.3971 *** (2.90) | |
| *FTOI* | | | 1.8252 *** (3.42) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 |
| R-Squared | 0.1857 | 0.1873 | 0.1824 |
| **Panel B: Addressing the influence of global financial crisis.** | | | |
| | (1) | (2) | (3) |
| Variables | *LC* | *LC* | *LC* |
| *FTI* | 2.7432 *** (2.85) | | |
| *FTII* | | 2.6288 *** (2.63) | |
| *FTOI* | | | 3.0524 *** (3.12) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 733 | 733 | 733 |
| R-Squared | 0.2464 | 0.2485 | 0.2422 |
| **Panel C: Addressing the influence of non-bank FinTech.** | | | |
| | (1) | (2) | (3) |
| Variables | *LC* | *LC* | *LC* |
| *FTI* | 3.3048 *** (2.72) | | |
| *FTII* | | 3.1385 *** (2.60) | |
| *FTOI* | | | 3.5401 *** (2.98) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 140 | 140 | 140 |
| R-Squared | 0.1670 | 0.1782 | 0.1566 |
| **Panel D: Addressing the influence of outliers.** | | | |
| | (1) | (2) | (3) |
| Variables | *LC* | *LC* | *LC* |
| *FTI* | 3.0479 *** (3.08) | | |
| *FTII* | | 2.7602 *** (2.97) | |
| *FTOI* | | | 3.1991 *** (3.18) |
| Bank controls | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 715 | 715 | 715 |
| R-Squared | 0.2341 | 0.2435 | 0.2280 |

Notes: This table reports results on robustness tests. Panel A uses an alternative measure of bank liquidity creation. The sample consists of 795 bank-year observations from 2008 to 2019. Panel B considers the influence of the global financial crisis. We exclude observations in years 2008 and 2009, so the sample consists of 733 bank-year observations from 2010 to 2019. Panel C considers the influence of non-bank FinTech. We utilize observations in periods before 2013, so the sample consists of only 140 bank-year observations from 2008 to 2012. Panel D considers the influence of outliers. We exclude banks with the highest or lowest liquidity creation, so the sample consists of 715 bank-year observations from 2008 to 2019. *LTgap* is the difference between liquid liabilities and liquid assets divided by total assets. *LC* is the bank liquidity creation, which is measured by the ratio of total bank liquidity creation to total assets. *FTI*, *FTII*, and *FTOI* are the bank FinTech index, bank FinTech input index, and bank FinTech output index, respectively. All regressions control for bank- and macro-level characteristics as well as bank and year fixed effects. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

### *4.5. Robustness tests*

#### *4.5.1. Alternative measure for bank liquidity creation*

In this subsection, we consider how an alternative measure of liquidity creation ($LTgap_{it}$) affects the relationship between bank FinTech and liquidity creation. Referring to Deep and Schaefer (2004), $LTgap_{it}$ is the difference between liquid liabilities and liquid assets divided by total assets for bank *i* in year *t*. The results in Panel A of Table 10 show that *FTI*, *FTII*, and *FTOI* are positively and significantly correlated with *LTgap*, indicating that our main conclusions are not likely driven by the measurement error.

**Table A1**
Classification of all bank activities.

| **Assets** | | |
|---|---|---|
| Liquid assets (weight=−1/2) | Semiliquid assets (weight=0) | Illiquid assets (weight=1/2) |
| Cash and due from institutions<br>Total securities<br>Trading assets | Residential mortgage loans<br>Other consumer/retail loans<br>Loans and advances to banks | Corporate and commercial loans<br>Other loans<br>Intangible assets<br>Fixed assets<br>Other assets |
| **Liabilities and equity** | | |
| Liquid liabilities(weight=1/2)<br>Customer deposits-current<br>Trading liabilities | Semiliquid liabilities(weight=0)<br>Customer deposits-term<br>Deposits from banks | Illiquid liabilities(weight=−1/2)<br>Subordinated borrowing<br>Credit impairment reserves |
| | Other deposits and short-term borrowing | Other liabilitiesEquity |
| **Off-balance sheet** | | |
| Liquid guarantees(weight=−1/2)<br>All derivatives | Semiliquid guarantees(weight=0)<br>Other off-balance sheet<br>exposure to securitizations<br>Guarantees | Illiquid guarantees(weight=1/2)<br>Acceptances and documentary credits reported off-balance sheet<br>Committed credit lines<br>Other contingent liabilities |

Note: This table reports the classification of all bank activities following Berger and Bouwman (2009) and Berger et al. (2019). We also made some adjustments depending on the availability of the items in the financial statements of the Chinese banking sector.

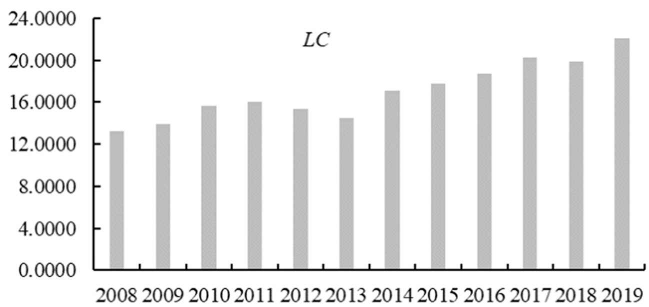


**Fig. A1.** The time trend of bank liquidity creation for 2008–2019.

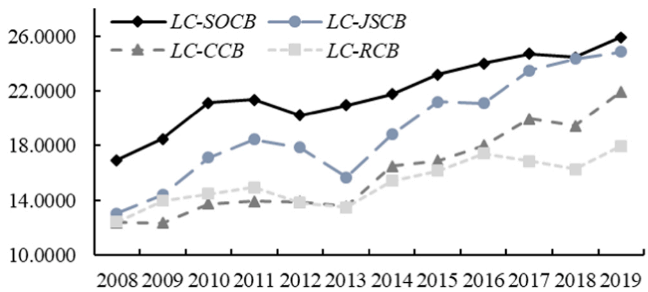


**Fig. A2.** The sample distribution of bank liquidity creation across different banks.

### *4.5.2. Addressing the influence of global financial crisis*

According to the studies by Berger and Bouwman (2013), Berger and Demirgüç-Kunt (2021), and Hasan et al. (2022), the 2007–2009 global financial crisis (GFC) lasted about 10 quarters from 2007:Q3–2009:Q4. Since we extract bank data from 2008 to 2019, our sample period includes the global financial crisis years (i.e., 2008 and 2009). To address the concern that commercial banks may adjust their behavior of adopting FinTech or supplying lending during crisis times, we remove the observations for 2008 and 2009 and re-estimate Model (1). The results in Panel B of Table 10 show a significant and positive role of bank FinTech in promoting liquidity creation. Therefore, our findings are robust after controlling for the influence of financial crisis.

### *4.5.3. Addressing the influence of non-bank FinTech*

It is worthwhile noting that non-bank FinTech is developing quickly during our sample period, especially after 2013 (Buchak et al.,

**Table B1**
Fintech-related keywords.

| **Technology input dimension** | | | |
|---|---|---|---|
| Artificial intelligencetechnology | Blockchaintechnology | Cloud computingtechnology | Big datatechnology |
| Artificial intelligence | Blockchain | Cloud computing | Big data |
| Face recognition | Alliance chain | Cloud service | Data flow |
| Voice recognition | Distributed ledger | Cloud platform | Data mining |
| Fingerprint recognition | Asymmetric encryption | Cloud architecture | Data visualization |
| **Innovation output dimension** | | | |
| Payment and settlementinnovation | Resource allocationinnovation | Risk managementinnovation | Channel constructioninnovation |
| Online payment | Online loan | Customer portrait | Online banking |
| Mobile payment | Online finance | Predictive model | Mobile banking |
| QR code payment | Lending platform | Credit evaluation | Internet banking |
| Digital wallet | Inclusive credit | Anti-fraud | Bank App |

Note: This table reports 32 Fintech-related keywords.

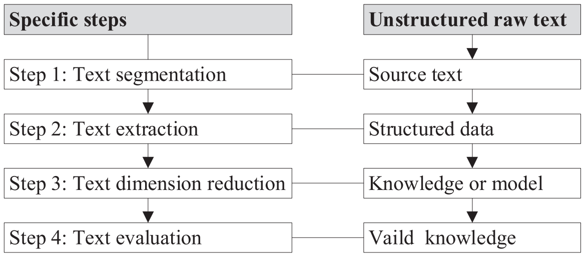


**Fig. B1.** Steps of the textual analysis method.

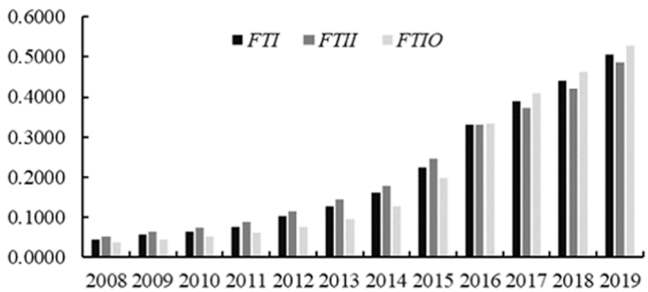


**Fig. B2.** The time trend of bank FinTech for 2008–2019.

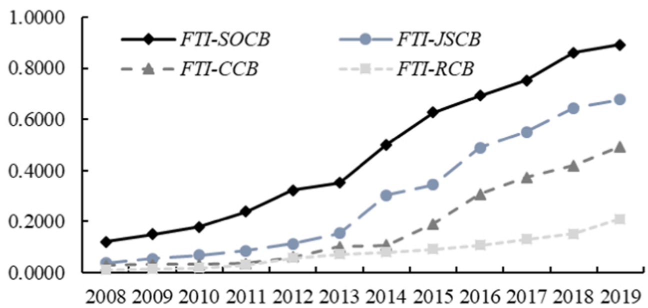


**Fig. B3.** The sample distribution of bank FinTech across different banks.

2021). To minimize the concern that our findings are driven by the confounding impact of non-bank FinTech, we check whether the main results hold for periods before 2013. The results in Panel C of Table 10 display positive and highly significant coefficients on *FTI*, *FTII*, and *FTOI*, confirming the robustness of our findings.

**Table C1**
Dynamic results: The risk management channel.

| Panel A: Considering *NPL* in year $t+1$. | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variables | *F.NPL* | *F.NPL* | *F.NPL* | *LC* | *LC* | *LC* |
| *FTI* | -0.1810 * ** | | | | | |
| | (−3.50) | | | | | |
| *FTII* | | -0.1393 * ** | | | | |
| | | (−3.39) | | | | |
| *FTOI* | | | -0.2122 * ** | | | |
| | | | (−3.30) | | | |
| *F.NPL_P_FTI* | | | | -6.1358 * ** | | |
| | | | | (−3.42) | | |
| *F.NPL_P_FTII* | | | | | -4.3356 * * | |
| | | | | | (−2.45) | |
| *F.NPL_P_FTOI* | | | | | | -6.3397 * ** |
| | | | | | | (−3.74) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 766 | 766 | 766 | 766 | 766 | 766 |
| R-Squared | 0.1649 | 0.1641 | 0.1623 | 0.2395 | 0.2420 | 0.2338 |
| Panel B: Considering *NPL* in year $t+2$. | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variables | *F2. NPL* | *F2. NPL* | *F2. NPL* | *LC* | *LC* | *LC* |
| *FTI* | -0.1712 * ** | | | | | |
| | (−3.33) | | | | | |
| *FTII* | | -0.1319 * ** | | | | |
| | | (−3.23) | | | | |
| *FTOI* | | | -0.1989 * ** | | | |
| | | | (−3.10) | | | |
| *F2. NPL_P_FTI* | | | | -5.7731 * ** | | |
| | | | | (−3.24) | | |
| *F2. NPL_P_FTII* | | | | | -4.0102 * * | |
| | | | | | (−2.29) | |
| *F2. NPL_P_FTOI* | | | | | | -6.0531 * ** |
| | | | | | | (−3.59) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 733 | 733 | 733 | 733 | 733 | 733 |
| R-Squared | 0.1743 | 0.1735 | 0.1716 | 0.2475 | 0.2496 | 0.2434 |
| Panel C: Considering *NPL* in year $t+3$. | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variables | *F3. NPL* | *F3. NPL* | *F3. NPL* | *LC* | *LC* | *LC* |
| *FTI* | -0.1584 * ** | | | | | |
| | (−3.05) | | | | | |
| *FTII* | | -0.1217 * ** | | | | |
| | | (−2.95) | | | | |
| *FTOI* | | | -0.1829 * ** | | | |
| | | | (−2.83) | | | |
| *F3. NPL_P_FTI* | | | | -5.3099 * ** | | |
| | | | | (−2.95) | | |
| *F3. NPL_P_FTII* | | | | | -3.5985 * * | |
| | | | | | (−2.03) | |
| *F3. NPL_P_FTOI* | | | | | | -5.6147 * ** |
| | | | | | | (−3.31) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 696 | 696 | 696 | 696 | 696 | 696 |
| R-Squared | 0.1631 | 0.1623 | 0.1605 | 0.2349 | 0.2374 | 0.2312 |

Notes: This table reports the dynamic results on the risk management channel. Panel A considers *NPL* in year $t+1$, so the sample consists of 766 bank-year observations from 2009 to 2019. Panel B considers *NPL* in year $t+2$, so the sample consists of 733 bank-year observations from 2010 to 2019. Panel C considers *NPL* in year $t+3$, so the sample consists of 696 bank-year observations from 2011 to 2019. *LC* is the bank liquidity creation, which is measured by the ratio of total liquidity creation to total assets. *FTI*, *FTII*, and *FTOI* are the bank FinTech index, bank FinTech input index, and bank FinTech output index, respectively. *F.NPL*, *F2. NPL*, and *F3. NPL* are *NPL* considered in years $t+1$, $t+2$, and $t+3$, respectively. *F.NPL_P*, *F2. NPL_P*, and *F3. NPL_P* are the predicted *F.NPL*, *F2. NPL*, and *F3. NPL*, respectively. All regressions control for bank- and macro-level characteristics as well as bank and year fixed effects. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

**Table C2**
IV-2SLS results: The deposit inflow channel.

| Second stage | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variables | *DepositG* | *DepositG* | *DepositG* | *LC* | *LC* | *LC* |
| *FTI_P* | 2.8255 * ** | | | | | |
| | (7.05) | | | | | |
| *FTII_P* | | 2.2637 * ** | | | | |
| | | (7.13) | | | | |
| *FTOI_P* | | | 3.0679 * ** | | | |
| | | | (6.13) | | | |
| *DepositG_P_FTI* | | | | 1.3507 * ** | | |
| | | | | (3.83) | | |
| *DepositG_P_FTII* | | | | | 1.1515 * ** | |
| | | | | | (2.88) | |
| *DepositG_P_FTOI* | | | | | | 1.4653 * ** |
| | | | | | | (4.18) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 | 795 | 795 | 795 |
| R-Squared | 0.2622 | 0.2626 | 0.2586 | 0.2511 | 0.2536 | 0.2454 |
| First stage | | | | | | |
| | (1) | | (2) | | (3) | |
| Variables | *FTI* | | *FTII* | | *FTOI* | |
| *W_Internet* | 0.7449 * ** | | 0.5104 * ** | | 0.9042 * ** | |
| | (19.55) | | (15.52) | | (17.34) | |
| *W_Employee* | 0.7852 * ** | | 0.6463 * ** | | 0.8389 * ** | |
| | (8.36) | | (9.07) | | (6.81) | |
| Bank controls | Yes | | Yes | | Yes | |
| Macro controls | Yes | | Yes | | Yes | |
| Bank FE | Yes | | Yes | | Yes | |
| Year FE | Yes | | Yes | | Yes | |
| Kleibergen-Paap rk LM test | 0.00 | | 0.00 | | 0.00 | |
| Kleibergen-Paap rk Wald F test | 233.56 | | 243.09 | | 200.88 | |
| Hansen J test | 0.33 | | 0.36 | | 0.31 | |
| Observations | 795 | | 795 | | 795 | |
| R-Squared | 0.1919 | | 0.1937 | | 0.1966 | |

Notes: This table reports IV-2SLS results on the deposit inflow channel, with *W_Internet* (the weighted average internet penetration rate) and *W_Employee* (the weighted average proportion of employees in the information industry) as two IVs. The sample consists of 795 bank-year observations from 2008 to 2019. *LC* is the bank liquidity creation, which is measured by the ratio of total liquidity creation to total assets. *FTI*, *FTII*, and *FTOI* are the bank FinTech index, bank FinTech input index, and bank FinTech output index, respectively. *FTI_P*, *FTII_P*, and *FTOI_P* are the predicted *FTI*, *FTII*, and *FTOI*, respectively. *DepositG* is the deposit growth, which is calculated as the total deposits of bank $i$ in year $t$ minus its total deposits in year $t$-1 and scaled by its total deposits in year $t$-1. *DepositG_P* is the predicted *DepositG*. All regressions control for bank-level and macro-level characteristics as well as bank and year fixed effects. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

### *4.5.4. Addressing the influence of outliers*

The level of liquidity creation varies considerably between banks. To ensure that our results are not driven by the effect of outliers, we use a subsample in which the liquidity creation is in the 5th–95th quantiles to rerun the empirical study. The results in Panel D of Table 10 show that the coefficients of *FTI*, *FTII*, and *FTOI* keep their positive signs and significances in all regressions. Thus, our findings are not influenced by the extrema of liquidity creation.

## 5. Conclusion

In recent years, FinTech has dramatically transformed the traditional banking industry. Despite the tremendous acceleration of FinTech innovations and applications in banking, little is known about how it affects the banking sector and to what extent banks have captured its benefits. To fill this gap, we examine the effects of bank FinTech on liquidity creation using panel data from Chinese commercial banks.

We find that the development of bank FinTech is conducive to liquidity creation, i.e., banks with greater FinTech development are likely to create more liquidity for the public. Our results hold after a series of endogeneity checks and robustness tests. We further

**Table C3**
IV-2SLS results: The risk management channel.

| Second stage | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variables | *NPL* | *NPL* | *NPL* | *LC* | *LC* | *LC* |
| *FTI_P* | -0.1991 * ** | | | | | |
| | (−3.89) | | | | | |
| *FTII_P* | | -0.1533 * ** | | | | |
| | | (−3.77) | | | | |
| *FTOI_P* | | | -0.2346 * ** | | | |
| | | | (−3.68) | | | |
| *NPL_P_FTI* | | | | -6.3077 * ** | | |
| | | | | (−3.58) | | |
| *NPL_P_FTII* | | | | | -4.5638 * ** | |
| | | | | | (−2.64) | |
| *NPL_P_FTOI* | | | | | | -6.5589 * ** |
| | | | | | | (−3.93) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 | 795 | 795 | 795 |
| R-Squared | 0.1700 | 0.1686 | 0.1711 | 0.2414 | 0.2467 | 0.2377 |
| First stage | | | | | | |
| | (1) | | (2) | | (3) | |
| Variables | *FTI* | | *FTII* | | *FTOI* | |
| *W_Internet* | 0.7449 * ** | | 0.5104 * ** | | 0.9042 * ** | |
| | (19.55) | | (15.52) | | (17.34) | |
| *W_Employee* | 0.7852 * ** | | 0.6463 * ** | | 0.8389 * ** | |
| | (8.36) | | (9.07) | | (6.81) | |
| Bank controls | Yes | | Yes | | Yes | |
| Macro controls | Yes | | Yes | | Yes | |
| Bank FE | Yes | | Yes | | Yes | |
| Year FE | Yes | | Yes | | Yes | |
| Kleibergen-Paap rk LM test | 0.00 | | 0.00 | | 0.00 | |
| Kleibergen-Paap rk Wald F test | 233.56 | | 243.09 | | 200.88 | |
| Hansen J test | 0.33 | | 0.36 | | 0.31 | |
| Observations | 795 | | 795 | | 795 | |
| R-Squared | 0.1919 | | 0.1937 | | 0.1966 | |

Notes: This table reports IV-2SLS results on the risk management channel, with *W_Internet* (the weighted average internet penetration rate) and *W_Employee* (the weighted average proportion of employees in the information industry) as two IVs. The sample consists of 795 bank-year observations from 2008 to 2019. *LC* is the bank liquidity creation, which is measured by the ratio of total liquidity creation to total assets. *FTI*, *FTII*, and *FTOI* are the bank FinTech index, bank FinTech input index, and bank FinTech output index, respectively. *FTI_P*, *FTII_P*, and *FTOI_P* are the predicted *FTI*, *FTII*, and *FTOI*, respectively. *NPL* is the credit risk, which is measured by the ratio of nonperforming loans to total loans. *NPL_P* is the predicted *NPL*. All regressions control for bank- and macro-level characteristics as well as bank and year fixed effects. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

analyze the underlying mechanisms and find that bank FinTech enhances liquidity creation through deposit inflow, risk management, and cost efficiency channels. Finally, focusing on the heterogeneous and nonlinear relationship between bank FinTech and liquidity creation, we observe that the positive effect of bank FinTech on liquidity creation is more pronounced for non-state-owned banks, unlisted banks, and banks with less liquidity creation.

Our results offer some important implications for banks and regulators. Applying FinTech enables banks to expand customer bases, reduce credit risks, and save operational costs. Therefore, banks should further increase investments in FinTech. While introducing the necessary hardware and software infrastructure, banks should also coordinate capabilities with digital technology and financial innovation. Regulators should devote more efforts to enhance digital infrastructure and promote the reasonable application of FinTech in banks, especially in non-state-owned and unlisted banks.

## CRediT authorship contribution statement

**Pin Guo**: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Funding acquisition, **Cheng Zhang**: Conceptualization, Methodology, Writing – review & editing.

## Declaration of competing interest

The authors declare no conflict of interest.

**Table C4**
IV-2SLS results: The cost efficiency channel.

| Second stage | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variables | *Inefficiency* | *Inefficiency* | *Inefficiency* | *LC* | *LC* | *LC* |
| *FTI_P* | -0.2493 * ** | | | | | |
| | (−4.00) | | | | | |
| *FTII_P* | | -0.1880 * ** | | | | |
| | | (−3.79) | | | | |
| *FTOI_P* | | | -0.2999 * ** | | | |
| | | | (−3.87) | | | |
| *Inefficiency_P_FTI* | | | | -4.5732 * ** | | |
| | | | | (−3.74) | | |
| *Inefficiency_P_FTII* | | | | | -3.9094 * ** | |
| | | | | | (−2.79) | |
| *Inefficiency_P_FTOI* | | | | | | -5.1009 * ** |
| | | | | | | (−3.99) |
| Bank controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Macro controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 795 | 795 | 795 | 795 | 795 | 795 |
| R-Squared | 0.1713 | 0.1694 | 0.1733 | 0.2477 | 0.2496 | 0.2423 |
| First stage | | | | | | |
| | (1) | | (2) | | (3) | |
| Variables | *FTI* | | *FTII* | | *FTOI* | |
| *W_Internet* | 0.7449 * ** | | 0.5104 * ** | | 0.9042 * ** | |
| | (19.55) | | (15.52) | | (17.34) | |
| *W_Employee* | 0.7852 * ** | | 0.6463 * ** | | 0.8389 * ** | |
| | (8.36) | | (9.07) | | (6.81) | |
| Bank controls | Yes | | Yes | | Yes | |
| Macro controls | Yes | | Yes | | Yes | |
| Bank FE | Yes | | Yes | | Yes | |
| Year FE | Yes | | Yes | | Yes | |
| Kleibergen-Paap rk LM test | 0.00 | | 0.00 | | 0.00 | |
| Kleibergen-Paap rk Wald F test | 233.56 | | 243.09 | | 200.88 | |
| Hansen J test | 0.33 | | 0.36 | | 0.31 | |
| Observations | 795 | | 795 | | 795 | |
| R-Squared | 0.1919 | | 0.1937 | | 0.1966 | |

Notes: This table reports IV-2SLS results on the cost efficiency channel, with *W_Internet* (the weighted average internet penetration rate) and *W_Employee* (the weighted average proportion of employees in the information industry) as two IVs. The sample consists of 795 bank-year observations from 2008 to 2019. *LC* is the bank liquidity creation, which is measured by the ratio of total liquidity creation to total assets. *FTI*, *FTII*, and *FTOI* are the bank FinTech index, bank FinTech input index, and bank FinTech output index, respectively. *FTI_P*, *FTII_P*, and *FTOI_P* are the predicted *FTI*, *FTII*, and *FTOI*, respectively. *Inefficiency* is the cost inefficiency, which is measured by the ratio of overhead expenses to total assets for bank *i* in year *t*. *Inefficiency_P* is the predicted *Inefficiency*. All regressions control for bank-level and macro-level characteristics as well as bank and year fixed effects. Standard errors are clustered at the bank level and t-statistics are reported in brackets. * ** , * *, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

## Data Availability

I have stated the data sources in the manuscript.


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## Appendices

### *Appendix A*

See Table A1 and Fig. A1 and Fig. A2.

To calculate bank liquidity creation, we use the three-step approach proposed by Berger and Bouwman (2009) and revised by Berger et al. (2019). In step 1, all bank activities (e.g, assets, liabilities, equity, and off-balance sheet guarantees) are classified as liquid, semiliquid, or illiquid, based on the information in the product category. Table A1 provides a detailed description of the classification of bank activities.

In step 2, weights 1/2, 0, and − 1/2 are assigned to all activities classified in step 1. According to the liquidity creation theory, banks create one unit of liquidity when using a unit of liquid liabilities to finance a unit of illiquid assets (e.g., banks utilize current customer deposits to make business loans). Banks destroy one unit of liquidity when employing a unit of illiquid liabilities or equity to finance a unit of liquid assets (e.g., banks utilize equity to buy securities). We thus apply the positive weight of 1/2 to illiquid assets, liquid liabilities, and illiquid off-balance sheet guarantees, the negative weight of − 1/2 to liquid assets, illiquid liabilities, equity, and liquid off-balance sheet guarantees, and the intermediate weight of 0 to all semiliquid assets, liabilities, and off-balance sheet guarantees.

In step 3, a liquidity creation measure (*LC*), as shown in Eq. A1, is built by combining the activities classified in step 1 and the weights assigned in step 2. This liquidity creation measure is referred to as "cat fat" in the work of Berger and Bouwman (2009). Meanwhile, similar to Berger and Bouwman (2009), Jiang et al. (2019), and Davydov et al. (2021), we standardize *LC* by total assets for a better comparison across banks.

$$\begin{aligned} LC = {} & 1/2 \times (illiquidassets + liquidliabilities + illiquidguarantees) \\ & +0 \times (semiliquidassets + semiliquidliabilities + semiliquidguarantees) \\ & -1/2 \times (liquidassets + illiquidliabilities + equity + liquidguarantees) \end{aligned} \tag{A1}$$

Fig. A1 provides the time trend of the *LC* measure from 2008 to 2019. As shown, the liquidity creation of the Chinese banking industry displays a fluctuating upward trend over the sample period. Specifically, the average *LC* of the entire banking sector increased from 13.3018% in 2008 to 22.1149% in 2019.

Note: This figure shows the time trend of the bank liquidity creation (*LC*) for the entire banking sector over the 2008–2019 sample period.

Fig. A2 shows the sample distribution of the *LC* measure across different banks. It is clear that the level of liquidity creation varies between banks. More precisely, state-owned banks and joint-stock banks have high liquidity creation ratios, with an average *LC* of 21.9326% and 19.2020%, respectively, while city banks and rural banks exhibit relatively low liquidity creation ratios, with an average *LC* of 16.0477% and 15.2693%, respectively.

Note: This figure plots the sample distribution of the bank liquidity creation (*LC*) across different banks. *LC-SOCB*, *LC-JSCB*, *LC-CCB*, and *LC-RCB* denote the liquidity creation of state-owned banks, joint-stock banks, city banks, and rural banks, respectively.

## *Appendix B*

See Table B1 and Figs. B1-B3.

To measure the development of FinTech in Chinese banks, we construct bank-level FinTech indices by performing a textual analysis of banks' annual reports. Building on the work of Saunders and Tambe (2013), Zhang et al. (2021), and Zhai et al. (2022), we believe that the greater the frequency of FinTech-related words in a bank's annual report, the better the bank FinTech development is. Therefore, we adopt a textual analysis method to construct bank FinTech indices. As shown in Fig. B1, the textual analysis method based on word segmentation algorithms and word frequency statistics includes four steps: text segmentation, text extraction, text dimension reduction, and text evaluation. After these steps, we can turn the unstructured raw text into valid and usable knowledge. We build bank-level FinTech indices following these four steps.

Note: This figure presents the specific steps of the textual analysis method based on word segmentation algorithms and word frequency statistics.

In step 1, we manually collect each bank's annual reports for 2008–2019 and perform word segmentation on these reports using Python software. Given the lack of Fintech-related keywords in the initial dictionary of "*Jieba Chinese Word Segmentation Module*" in Python, we establish an additional dictionary related to Fintech keywords. Moreover, advancements of FinTech are inseparable from both technology inputs and innovation outputs (FSB, 2016; Zavolokina et al., 2016). Therefore, we classify bank FinTech into two dimensions: (1) technology input dimensions, including inputs in artificial intelligence, blockchain, cloud computing, and big data, and (2) innovation output dimensions, including innovations of payment and settlement, resource allocation, risk management, and channel construction. As shown in Table B1, we set up 32 keywords for these two dimensions following the studies by Guo and Shen (2016), Cheng and Qu (2020), and Wang et al. (2021b).

In step 2, we calculate keyword frequencies at the bank-year level with the help of Python software. To relieve the concern that some of the keywords may be used in a broader context, for instance when describing industry dynamics, we use only the information in the "Management Discussion and Analysis" (MD&A) section of an annual report to compute the keyword frequencies.[11] Specifically, we first count the number of occurrences of each keyword in the MD&A section of a bank's annual report, and then divide that number by the total number of words in the report, to get the frequency of each keyword. Finally, we obtain the frequencies of the 32 keywords for 97 banks for 2008–2019.

[11] "Management Discussion and Analysis" (MD&A) is a section within a bank's annual report in which the executives present an analysis of the bank's financial fundamentals, management performance, and main events. The MD&A is an important source of information for analysts and investors to understand and review bank operations.

In step 3, we adopt the entropy weight method (EWM) to compute the weight of each keyword and then develop a bank FinTech input index (*FTII*), a bank FinTech output index (*FTOI*), and a bank FinTech index (*FTI*) in succession.[12] The EWM, based on the entropy coefficient proposed by Shannon (1948), is utilized to determine the weights of indicators. This method enables calculating the weights in an objective, simple, and uncomplicated way, so it has been extensively applied in various fields (Toumi et al., 2017; Cunha-Zeri et al., 2022). The methodological steps for constructing *FTII*, *FTOI*, and *FTI* employing the EWM are the following:

(1) Normalization of the keyword frequencies. Consistent with Cunha-Zeri et al. (2022), we use the zero-mean processing shown in Eq. B1 to normalize the keyword frequencies.

$$Y_{ijt} = \frac{X_{ijt} - \min(X_j)}{\max(X_j) - \min(X_j)} \tag{B1}$$

where $i = 1, 2\ldots, N$ indicates banks, $j = 1, 2\ldots, K$ denotes keywords, and $t = 1, 2\ldots, T$ signifies year. $X_{ijt}$ and $Y_{ijt}$ are the original and normalized frequencies of keyword $j$ of bank $i$ in year $t$, respectively.

(2) Definition of the entropy. The entropy of keyword $j$ is defined in Eq. B2.

$$E_j = -\frac{1}{\ln(NT)}\sum_{t=1}^{T}\sum_{i=1}^{N} P_{ijt}\ln P_{ijt}, P_{ijt} = \frac{Y_{ijt}}{\sum_{t=1}^{T}\sum_{i=1}^{N} Y_{ijt}} \tag{B2}$$

where $E_j$ is the entropy of keyword $j$.

(3) Calculation of the entropy weight. The EWM works on the principle that the lower the entropy is, the more information an indicator provides, and the higher the weight of that indicator. Consequently, with each entropy value, the entropy weight of keyword $j$ can be calculated with Eq. B3 as follow.

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{K}(1 - E_j)} \tag{B3}$$

where $W_j$ is the entropy weight of keyword $j$.

(4) Determination of the bank FinTech indices. With the normalized frequencies $Y_{ijt}$ and the entropy weight $W_j$, the bank FinTech indices can be developed with Eq. B4 below.

$$Fintech_{it} = \sum_{j=1}^{K} W_j Y_{ijt} \tag{B4}$$

where $Fintech_{it}$ is the FinTech indices of bank $i$ in year $t$, including $FTII_{it}$, $FTOI_{it}$, and $FTI_{it}$.[13]

In step 4, we assess the resulting bank FinTech indices based on the Chinese context. Fig. B2 displays the time trends of bank FinTech indices over the 2008–2019 period. The average *FTI* increased from 0.0048 in 2008–0.5048 in 2019, with an annual growth rate of 24.63%, indicating that the Chinese bank FinTech has experienced rapid development in recent years. From 2008–2015, banks actively increased their technology investments in FinTech, causing a higher *FTII* value. From 2016–2019, a large number of bank FinTech innovations emerged on the basis of earlier investments, resulting in a fast-growing *FTOI*.

Note: This figure presents the trends of bank FinTech indices for 2008–2019. *FTI*, *FTII*, and *FTOI* denote the bank FinTech index, the bank FinTech input index, and the bank FinTech output index, respectively.

Fig. B3 plots the bank FinTech index across different banks. State-owned banks (SOCB) show the highest development of FinTech, followed by joint-stock banks (JSCB), city banks (CCB), and rural banks (RCB). It is not surprising given that state-owned banks possess more technology infrastructures and human resources than other banks. Overall, these advancements are in line with the growth processes of Chinese bank FinTech.

Note: This figure provides the sample distribution of bank FinTech across different banks. *FTI-SOCB*, *FTI-JSCB*, *FTI-CCB*, and *FTI-RCB* denote the bank FinTech index of state-owned banks, joint-stock banks, city banks, and rural banks, respectively.

*Appendix C*

See Appendix Table C1, Table C2, Table C3, Table C4.

[12] Specifically, based on the keyword frequencies for each dimension, we first build the *FTII* and *FTOI* using EWM. Then, based on the values of *FTII* and *FTOI*, we develop the *FTI* using EWM.

[13] To ensure that these indices are positive, we use min-max processing to standardize the data between 0 and 1.

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