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Does bank FinTech reduce credit risk? Evidence from China

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ABSTRACT

Using data from Chinese commercial banks between 2008 and 2017, this paper explores the effects of bank FinTech on credit risk. We first construct and measure a bank FinTech index using web crawler technology and word frequency analysis. The results show that the development of bank FinTech is faster in state-owned banks than in other banks. Moreover, among the five subareas of bank FinTech, the development of internet technology is ahead of artificial intelligence technology, blockchain technology, cloud computing technology, and big data technology. Then, the impacts of bank FinTech on credit risk are examined. We find that bank FinTech significantly reduces credit risk in Chinese commercial banks, and further analyses show that the negative effects of bank FinTech on credit risk are relatively weak among large banks, state-owned banks, and listed banks.

1. Introduction

The objective of our study is to examine how bank FinTech affects credit risk. Using hand-collected data, we construct a bank FinTech index and examine the effects of bank FinTech on credit risk measured by the ratio of non-performance loans. In contrast to the existing literature (Nicoletti and Weis, 2017; Anagnostopoulos, 2018; Buchak et al., 2018; Goldstein et al., 2019), this paper not only focuses on the development of bank FinTech and its effects on credit risk but also questions whether bank heterogeneity moderates these effects.

Generally, FinTech refers to the combination of finance and technology, which is an emerging industry that uses technology to improve activities in the finance industry. In the past ten years, FinTech has become prominent in global financial markets, and FinTech enterprises have proliferated. The rapid development of FinTech is attracting much academic attention. Many studies have welcomed the rise of FinTech, claiming that newly emerging technologies have the potential to radically transform financial services by making transactions less expensive, more convenient, and more secure (Begenau et al., 2018; Fuster et al., 2019; Chen et al., 2019c; Zhu, 2019; Chiu and Koeppl, 2019).

With the rapid development of FinTech, the banking sector has also been affected by FinTech. Generally, the impacts of FinTech on the banking sector come from two aspects, i.e. outside FinTech and bank FinTech. Outside FinTech refers to FinTech outside the banking industry, such as FinTech companies. Outside FinTech affects commercial banks mainly through competition effects and technology spillover effects, among others. Some studies (Shen and Guo, 2015; Hou et al., 2016; Qiu et al., 2018; Guo and Shen, 2019) explore the effects of outside FinTech on the banking industry.

Bank FinTech refers to the application of emerging technologies in the banking industry, including artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and internet technology. In recent years, the development of bank FinTech has been the general trend in the FinTech industry. An increasing number of commercial banks employ

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bank FinTech in their operational processes. For example, the Industrial and Commercial Bank of China (ICBC) proposed a new development strategy named *E*-ICBC 2.0 based on big data technology and internet technology in 2015. With the help of artificial intelligence technology, the China Construction Bank (CCB) began to promote the application of robo-advisers in 2016. In addition, the Bank of China (BOC) and Tencent Technology Corporation established a joint FinTech laboratory based on artificial intelligence technology, blockchain technology, and big data technology in 2017 to promote its FinTech development. Against this background, how these applications affect bank credit risk becomes an interesting question that motivates us to explore this issue. In addition, policy considerations motivate this research. Although bank FinTech has become increasingly popular in China's banking industry, laws and regulations about bank FinTech remain scarce. The lack of bank FinTech regulations not only results in regulatory inefficiency but also creates many risks. Therefore, for FinTech regulators and policymakers, improving FinTech-related legislation is a top priority. In this paper, we explore the effects of bank FinTech on credit risk, which could provide empirical evidence for policymakers. Finally, existing studies further motivate this paper. Although some papers examine the effects of FinTech on the banking industry (Shen and Guo, 2015; Hou et al., 2016; Qiu et al., 2018; Guo and Shen, 2019), these studies focus mainly on the influence of outside FinTech. To the best of our knowledge, little research analyzes the impact of bank FinTech. Therefore, our research focuses on this academic gap and complements the existing literature.

We argue that bank FinTech affects credit risk based on the following two aspects. On the one hand, bank FinTech may reduce credit risk. First, bank employing emerging technologies contributes to improving bank risk management efficiency and thus reduces bank credit risk. Second, bank FinTech improves banks' internal governance and internal control and thus reduces bank credit risk. Finally, bank FinTech could increase bank diversification and produce diversification effect, which contributes to reducing bank credit risk. On the other hand, bank FinTech brings technical risk and regulatory risk, which could increase bank credit risk.

Using hand-collected data from China from 2008 to 2017, we construct a bank FinTech index and explore its effects on credit risk, and we find the following results. First, the development of bank FinTech and its subareas present an increasing trend from 2008 to 2017. Moreover, the development of bank FinTech is more rapid in state-owned banks than in other banks. Among the subareas of bank FinTech, internet technology is the fastest-growing, while artificial intelligence technology is the slowest growing. Second, our basic results show that bank FinTech and bank FinTech subareas are all negatively associated with bank credit risk, indicating that the development of bank FinTech reduces credit risk. Third, we also find that the negative effects of bank FinTech on credit risk are weaker in large banks, state-owned banks, and listed banks.

This paper makes two main contributions to the existing literature. First, it constructs a bank FinTech index that measures the development of FinTech in the banking industry. Although some papers have studied the development of FinTech, these studies explore this issue mostly from the macro-level perspective (Hou et al., 2016; Qiu et al., 2018). They examine mainly the development of FinTech in a country or region. To the best of our knowledge, little research measures the development of bank FinTech at the bank-year level. Therefore, this paper constructs bank FinTech indexes by using web crawler technology and word frequency analysis. Second, this paper explores the effects of bank FinTech on credit risk and examines whether these effects differ in different banks. Although some papers examine the effects of FinTech on the banking industry (Shen and Guo, 2015; Hou et al., 2016; Qiu et al., 2018; Guo and Shen, 2019), these studies focus mainly on the influence of outside FinTech. Little research examines the impact of bank FinTech.

We construct the remainder of this paper as follows. Section 2 provides the institutional context. Section 3 shows the related literature and hypothesis development. Section 4 presents our sample, variables, and methodology. Section 5 discusses the empirical results. Section 6 presents further analyses. Section 7 concludes.

2. Institutional context

2.1. Definitions of FinTech

In the past ten years, FinTech has received increasing worldwide attention and has become a global topic. However, there is no uniform definition of FinTech. For example, in 2016, the Financial Stability Board (FSB) defined FinTech as technology-driven financial innovation, while Navaretti et al. (2018) define FinTech as FinTech companies and classify FinTech according to the type of business, such as FinTech payment companies and FinTech lending companies. In China, Qiu et al. (2018) believe that FinTech refers to new FinTech products, such as Yu'e Bao, while Yang (2018) claims that FinTech is a new financial ecology formed outside the traditional financial system. In addition, the “FinTech Development Plan (2019-2021)” issued by the People's Bank of China (PBOC) in August 2019 defined FinTech as the application of emerging technologies.

For the bank FinTech definition, there is no clear statement among academic studies to date. In this paper, we follow the “FinTech Development Plan (2019-2021)” to define bank FinTech. Specifically, we define bank FinTech as the application of emerging technologies in the banking industry, including artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and internet technology.

2.2. Development process of FinTech

The core of FinTech is the integration of financial activity and advanced technology. Technological innovations are the driving force behind the development of FinTech. Therefore, according to technological development, we divide the development of FinTech in China into three stages as follows.

2.2.1. First stage: Internet finance (before 2010)

The first stage is the internet finance stage, represented by the initial combination of finance and internet. In this stage, the rapid development of internet technology led to the combination of the financial industry and internet technology. Specifically, some simple traditional financial businesses realized electronization through the application of internet technology. Meanwhile, traditional financial institutions also realized office automation. These combinations increased the efficiency of financial institutions.

Regarding bank FinTech in this stage, the most representative was online banking. Especially after the establishment of Alipay in 2004, the development of FinTech attracted more attention from commercial banks.[1] Many commercial banks began to accelerate the development of online banking. For example, ICBC's online banking business achieved remarkable development during this period. In 2009, the number of online banking customers exceeded 1.6 million, and the transaction volume accounted for 34.2% of the total online banking transactions.[2] In short, China's bank FinTech, especially online banking, obtained rapid development during this stage.

2.2.2. Second stage: mobile internet finance (2011–2015)

The second stage is the mobile internet finance stage. At this time, the emergence of smartphones greatly improved the efficiency of internet technology, improving the development of mobile internet technology. The penetration of mobile internet technology in the financial industry has gradually increased, and traditional financial institutions began to transform traditional financial channels and promote the development of mobile internet finance. In addition, some internet companies began to financialize. For example, the PBOC issued a third-party payment license to Alipay and Tenpay in June 2011.[3] Since then, the Alibaba Group and Tencent Technology Corporation have obtained licenses to begin legally operating mobile payment services.

In terms of bank FinTech, mobile banking became a popular FinTech product at this stage. Mobile banking was a new type of banking service channel that served as an extension of online banking. Mobile banking utilizes the ability of mobile internet technology to be available anytime and anywhere, which provides a more convenient and competitive service method for the banking industry. Taking the China Merchants Bank as an example, the total number of mobile banking customers in 2013 reached 12.434 million, and the accumulated mobile payment transactions reached 69.961 million, with a transaction amount of 12.719 billion yuan.[4] In this stage, the user and transaction volume of mobile banking developed rapidly.

2.2.3. Third stage: emerging technologies and finance (after 2015)

The third stage is the combination of finance and emerging technologies, such as artificial intelligence technology, blockchain technology, cloud computing technology, and big data technology. At this stage, by employing emerging technologies, the financial industry not only innovated traditional business models but also changed information collection, risk management, pricing strategy, and so on. These emerging technologies have not only greatly improved the efficiency of traditional finance but also helped traditional financial institutions better optimize their business models.

In this stage, Bank FinTech focused mainly on the application of artificial intelligence technology, blockchain technology, cloud computing technology, and big data technology in commercial banks. For instance, more than 100 commercial banks have optimized their business strategies and improved their efficiency through cloud computing technology through cooperation with the Alibaba Cloud.[5] In addition, the ICBC proposed a new development strategy named *E*-ICBC 2.0 based on big data technology and internet technology in 2015. With the help of artificial intelligence technology, the CCB began to promote the application of robo-advisers in 2016. The BOC and Tencent Technology Corporation established a FinTech joint laboratory based on artificial intelligence technology, blockchain technology, and big data technology in 2017 to promote its FinTech development. These FinTech applications have effectively helped these commercial banks improve their operational efficiency and risk management.

2.3. Regulations of FinTech

With the development of FinTech, Chinese government departments issued several FinTech laws and regulations. For example, the State Council of China has promulgated a series of policies about specific technologies to guide and regulate the development of FinTech since 2015. In January 2015, the “Opinions of the State Council on Promoting the Innovative Development of Cloud Computing and Cultivating New Formats of the Information Industry” stated that cloud computing is a new business ecology and that its development is conducive to information sharing and resource creation. In August 2015, the “Development Plan for Big Data” noted the promotion of big data technology in the financial industry. In July 2017, the “Development Plan of New Generation Artificial Intelligence” clarified the potential advantages of artificial intelligence technology for financial industry reform. Moreover, the PBOC and other relevant government departments directly promulgated the “Guiding Opinion on Promoting the Healthy Development of Internet Finance” in July 2015. This document aimed to guide the compliant and sustainable development of FinTech, regulate the market behaviors of industry institutions, and protect the legitimate rights and interests of the industry. The “FinTech Development Plan (2019-2021)” issued by the PBOC in August 2019 provided a comprehensive guide for the development

[1] Alipay is a third-party payment platform created by Alibaba Group in December 2004.

[2] News is from http://www.icbc.com.cn/icbc/

[3] Tenpay is an online payment platform launched by Tencent Technology Corporation in September 2005.

[4] News is from https://www.cmbchina.com/

[5] Alibaba Cloud is a cloud computing technology and service provider founded by Alibaba Group in 2009.

of FinTech. This plan stated the guiding ideology, the basic principles, and the development goals of China's FinTech development. In addition, it clarified the requirements for increasing risk prevention and strengthening supervision at the same time.

Overall, although there are some existing laws and regulations about FinTech, bank FinTech regulations are scarce. Only some of these laws and regulations propose measures for bank FinTech development. For example, the “Guiding Opinion on Promoting the Healthy Development of Internet Finance” and the “FinTech Development Plan (2019-2021)” all encourage banks to develop FinTech. The lack of bank FinTech regulations not only results in regulatory inefficiency but also creates many risks. Therefore, for bank FinTech regulators and policymakers, improving related legislation is a top priority.

3. Literature review and hypothesis development

3.1. Literature review

3.1.1. Literature on FinTech

We first distinguish between two related concepts: internet finance and FinTech. Internet finance refers to the combination of finance and internet technology. FinTech refers to the combination of finance and emerging technologies, including artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and internet technology. Internet finance is one type of FinTech. We first review internet finance studies and then discuss the FinTech literature.

The majority of the studies on internet finance consist of two parts. The first part focuses on the definition of internet finance and its characteristics. Some studies regard internet finance as a type of financial reform and believe that the traditional finance pattern will benefit from it (Shahrokhi, 2008; Berger and Gleisner, 2009; Xie and Zou, 2012). The second group of these studies focuses on the economic and financial results of internet finance. For example, Hou et al. (2016) show that internet finance development alters the sensitivity of deposit growth ratios to some bank risk measures, and the attenuation impact of internet finance development on market discipline for bank capitalization, instead, relatively increases in non-state-owned banks. Stoica et al. (2015) find that internet finance does not improve management efficiency. In addition, some studies also show that internet finance destabilizes financial markets (Gottschalk and Dean, 2009; Krueger, 2012; Syed and Nida, 2013).

Existing FinTech studies explore mainly the compositions and characteristics of FinTech. Bettinger et al. (1972) first introduced the word FinTech, and since then, many studies have extended FinTech-related study. For example, Christensen et al. (2003) state that FinTech includes two main categories: sustainable FinTech and disruptive FinTech. Gomber et al. (2017) believe that there will be new business models with the development of FinTech. Chen (2016) emphasizes that the technology of FinTech refers mainly to communication technology, such as internet technology. In addition, some studies explore the economic and financial consequences of FinTech. However, most of these are only qualitative analyses. For example, Anagnostopoulos (2018) reviews the effect of FinTech development on the broader FinTech environment. Buchak et al. (2018) discover that to other shadow banks, FinTech lenders serve more creditworthy borrowers with better financial services and are more active in the refinancing market. Qiu et al. (2018) argue that the development of FinTech promotes interest rate liberalization at the depository side, changes the bank's debt structure, reduces the proportion of banks' retail deposits, and increases the proportion of wholesale financings, such as interbank liabilities. Fuster et al. (2019) provide evidence that FinTech lenders process mortgage applications nearly 20% faster than other lenders in lending markets. Tang (2019) and Vallee and Zeng (2019) also analyze the effects of emerging technologies on the lending market. Foley et al. (2019) suggest that cryptocurrencies are transforming black markets by enabling “black e-commerce”. Chen et al. (2019c) find that most FinTech innovations yield substantial value to innovators, with blockchain being particularly valuable. Zhu (2019) shows that the introduction of big data increases price informativeness through decreased information acquisition costs, particularly in firms in which sophisticated investors have higher incentives to uncover information. Chiu and Koeppl (2019) argue that the U.S. corporate debt market yields net gains from a blockchain in the range of 1–4 bps.

In summary, although there have been many studies on FinTech and internet finance in recent years, they are still limited to discussions on the essence, characteristics, and categories of FinTech and internet finance. At this stage, few studies examine the impact of FinTech development from the micro perspective, such as bank FinTech. Therefore, this paper examines this issue.

3.1.2. Literature on bank credit risk

There are numerous studies on bank credit risk, and we focus on the literature regarding the determinants of bank credit risk. This section discusses the existing studies on the macro environment, market characteristics, and bank characteristics.

First, some researchers argue that the macroeconomic environment significantly affects bank risk. For example, Rajan (1994) present a low-frequency business cycle theory to explain the changes in credit risk. Borio and Zhu (2012) argue that the long-term loose monetary policy situation increases bank credit risks. Additionally, Louzis et al. (2012) find that the same macroeconomic environment has different effects on credit risks for different types of loans. Angeloni and Faia (2013) shows that monetary expansion and positive productivity shock increase bank leverage and credit risk. Finally, Antzoulatos and Chris (2014) find that a country's credit rating and management quality also significantly affect bank credit risk.

Second, some papers explore the influence of market characteristics on bank credit risk. Boyd and De Nicolo (2005) show that banks may enhance their risk-taking behaviors in less competitive markets. However, Wagner (2010) finds that this impact of market competition on banks is reversed if banks can adjust their loan portfolios. Furthermore, Martinez-Miera and Repullo (2010) argue that there exists a U-shaped relationship between competition and bank risk, and Jiménez et al. (2013) find that this U-shaped relationship exists only in the loan market. In addition, Hellmann et al. (2000) state that banks will have fewer incentives to take risks in a more collusive market, and Cheng et al. (2016) find that the market's attitude is a major factor influencing risk during the financial reform period.

Finally, some studies investigate the effects of bank characteristics on bank credit risk. For example, Saunders et al. (1990) investigate the relationship between bank ownership structure and risk-taking and suggest that stockholder-controlled banks have incentives to take a higher credit risk than managerially controlled banks. Kwan and Eisenbeis (1997) find that inefficiency has a positive effect on credit risk, while Jeitschko and Jeung (2005) find that credit risk increases first and then decreases as bank capitalization increases. Podpiera and Weill (2008) prove that there is a significant time correlation between bank cost efficiency and credit risk. Delis and Kouretas (2011) suggest that capital adequacy significantly affects bank credit risk. Fiordelisi et al. (2011) find that changes in the capital structure affect credit risk. Khan et al. (2017) examine the relationship between funding liquidity and bank risk-taking and show that bank sizes and capital buffers usually limit banks from taking more credit risk. Chen et al. (2019a) explore the impact of the capital adequacy requirement on financial institutions' risk-taking behavior from a novel perspective and conclude that risk-based capital plays an important role in this impact.

Overall, the existing studies focus mainly on the determinants of bank credit risk, including the macro environment, market characteristics, and bank characteristics. In recent years, the application of bank FinTech has become increasingly popular in China's banking industry. However, we find that existing studies have paid less attention to the impact of bank FinTech on credit risk. Therefore, this paper focuses on this issue.

3.2. Hypothesis development

This section proposes the research hypothesis regarding the effect of bank FinTech on credit risk based on the following two aspects.

On the one hand, we argue that bank FinTech may reduce credit risk. First, bank FinTech reduces credit risk based on spillover effects. Some studies show that commercial banks could obtain technology spillover effects when they employ emerging technology (Blalock and Gertler, 2008; Newman et al., 2015), which contributes to improving bank risk management efficiency and thus reduces bank credit risk. For example, the ICBC intercepted approximately 900,000 risky transactions by employing emerging technology in April 2018, significantly reducing the ICBC's credit risk.[6] With the help of emerging technologies such as blockchain technology and cloud computing technology, bank FinTech achieves the real-time and systematic management of data isolation and resource dispersion, which improves bank risk management efficiency and thus reduces credit risk. Second, bank FinTech improves banks' internal governance and internal control and thus reduces bank credit risk. The China Banking and Insurance Regulatory Commission has also emphasized that banking financial institutions should embed big data applications into the process of business operations, risk management, and internal control to effectively capture risks. Finally, bank FinTech could improve banks' business models and increase bank diversification, thus reducing bank credit risk (Demirgüç-Kunt and Huizinga, 2010). On the other hand, bank FinTech may increase credit risk. First, bank FinTech brings technical risk, such as data security risk, privacy protection risk, transaction security risk, identity authentication risk, and so on, which could all increase bank credit risk. In addition, bank FinTech increases regulatory risk. Although bank FinTech has achieved rapid development in China's banking sector, the related supervision of bank FinTech has developed slowly, as mentioned in Subsection 2.3. This situation could result in banks engaging in illegal activities by using bank FinTech, such as regulatory arbitrage, which may increase bank credit risk.

In addition, we also analyze the effect of FinTech on credit risk through an improved DLM model (details of the model are shown in Appendix A).[7] The DLM model also provides two opposite predictions about the relationship between bank FinTech and credit risk. Based on the above discussions, we propose hypothesis 1 (H1). If we reject H1, this paper argues the development of bank FinTech increases credit risk in China's economic environment.

H1. : The development of bank FinTech reduces credit risk.

4. Sample, variables, and methodology

4.1. Sample and data

Our sample consists of data from 60 commercial banks from 2008 to 2017. We start our sample period in 2008 because bank FinTech applications, such as big data, artificial intelligence, cloud computing, and blockchain, entered the marketplace after 2008. These banks, including 6 state-owned commercial banks, 12 joint-stock commercial banks, 33 city commercial banks, and 9 rural commercial banks,[8] account for more than 90% of the total assets of all Chinese commercial banks. For financial data, we use the income statement and balance sheet data for these banks from the ORBIS Bank Focus database from 2008 to 2017. Some missing financial data are obtained from the Financial Yearbook of China and the CSMAR database. We manually collect the data for constructing the FinTech index from the Baidu search engine (www.baidu.com), which is China's most popular search engine.

[6] News is from http://www.icbc.com.cn/icbc/

[7] DLM model refers to the bank risk taking model developed by Dell' Ariccia et al. (2010).

[8] This classification is based on the “List of banking institutions (2018)” issued by the PBOC in December 2018.

4.2. Variables

4.2.1. Credit risk

Our credit risk refers to the default risk of bank loans. Following existing studies by Festi'c et al. (2011) and Papadopoulos (2019), we employ the nonperforming loan ratio (NPL_{it}) measure of credit risk in China's banks in our empirical models. NPL_{it} is measured by the ratio of nonperforming loans to total loans for bank i in year t. The larger the NPL_{it} value is, the higher the credit risk.

4.2.2. Bank FinTech

Measuring the application status of bank FinTech is the premise of our study. However, the quantitative measurement of bank FinTech is seldom discussed in existing studies. In this paper, we construct a bank FinTech index to measure the application status of bank FinTech. More specifically, we build a bank FinTech index following the general idea of text mining. Based on intelligent algorithms, text mining extracts effective information from a large number of unstructured and heterogeneous texts by applying data mining methods and technologies. Common text mining techniques include word frequency statistics, text clustering, text classification, etc. This paper employs the word frequency statistics of text mining. The specific implementation steps of the bank FinTech index (FT_{it}) are described in Appendix B. In addition, we also measure the subareas' bank FinTech indexes, including the artificial intelligence technology index (FTA_{it}), blockchain technology index (FTB_{it}), cloud computing technology index (FTC_{it}), big data technology index (FTD_{it}), and internet technology index (FTI_{it}) for bank i in year t in Appendix B.

4.2.3. Control variables

Based on the existing studies by Gambacorta and Mistrulli (2004), Laeven and Levine (2009), Dell' Ariccia et al. (2010) and Barrell et al. (2010), we choose $Size_{it}$, $Liquidity_{it}$, $Overhead_{it}$, CIR_{it}, NIM_{it}, Ownership, and List to control for the effects of bank characteristics. $Size_{it}$ is the logarithm of total size for bank i in year t. $Liquidity_{it}$ is the ratio of total bank loans to total deposits for bank i in year t. $Overhead_{it}$ is the logarithm of overheads for bank i in year t. CIR_{it} is the ratio of total bank cost to total income for bank i in year t. NIM_{it} is the ratio of net interest income to the average size of interest-earning assets for bank i in year t. Ownership is a dummy variable that is equal to 1 if a bank is a state-owned bank, and 0 otherwise. List is a dummy variable that is equal to 1 if a bank has gone public and 0 otherwise. Table 1 provides the definitions of the variables included in our empirical study.

4.3. Methodology

To analyze the impacts of bank FinTech on credit risk, we estimate the following basic regression model.

$$NPL_{it} = Constant + a * FinTech_{it} + b * Control_{it} + Bank_i + Year_t + \varepsilon. \text{ Model} \quad (1)$$

where i indexes banks and t indexes time. NPL_{it} indicates the bank credit risk for bank i in year t. $FinTech_{it}$ reflects the development of the bank's internal FinTech for bank i in year t, measured by the FT_{it}, FTA_{it}, FTB_{it}, FTC_{it}, FTD_{it}, and FTI_{it}. $Control_{it}$ is a matrix of additional bank controls, containing the bank size ($Size_{it}$), liquidity ratio ($Liquidity_{it}$), bank overhead ($Overhead_{it}$), cost-to-income ratio (CIR_{it}), net interest margin (NIM_{it}), bank ownership structure (Ownership) and listed status (List). $Bank_i$ and $Year_t$ are bank and year fixed effects, respectively, and ε refers to the error term. All variables can be seen in Table 1.

Table 1
Variable definitions.

Variable	Variable design
NPL_{it}	The ratio of nonperforming loans to total loans for bank i in year t
LLR_{it}	The ratio of loan loss reserves to total loans for bank i in year t
FT_{it}	The development of bank FinTech for bank i in year t
FTA_{it}	The development of artificial intelligence technology for bank i in year t
FTB_{it}	The development of blockchain technology for bank i in year t
FTC_{it}	The development of cloud computing technology for bank i in year t
FTD_{it}	The development of big data technology for bank i in year t
FTI_{it}	The development of internet technology for bank i in year t
$Size_{it}$	The logarithm of total size for bank i in year t
$Liquidity_{it}$	The ratio of total bank loans to total deposits for bank i in year t
$Overhead_{it}$	The logarithm of overheads for bank i in year t
CIR_{it}	The ratio of total bank cost to total income for bank i in year t
NIM_{it}	The ratio of net interest income to the average size of interest-earning assets for bank i in year t
Ownership	Dummy variable, equal to 1 if a bank is a state-owned bank, and 0 otherwise
List	Dummy variable, equal to 1 if a bank has gone public, and 0 otherwise
$Income_{it}$	The average income level of the city in which the R&D department of bank i is located in year t
$Post_{it}$	Dummy variable, equal to 1 for bank observation is after the promulgation of related policy and 0 otherwise
$Treat_{it}$	Dummy variable, equal to 1 for High FT-bank and 0 for Low FT-bank
Year	Dummy variables, each year dummy variable equals 1 if an observation is for the corresponding year and 0 otherwise

Table 2
Descriptive statistics.

Variable	Observation	Mean	Std. Dev.	Minimum	Maximum
NPL_{it}	600	0.0115	0.7258	0.0001	0.1018
LLR_{it}	600	0.0275	1.0394	0.0054	0.0957
FT_{it}	600	0.2646	0.3438	0.0000	1.0000
FTA_{it}	600	0.2209	0.3183	0.0000	1.0000
FTB_{it}	600	0.2386	0.3174	0.0000	1.0000
FTC_{it}	600	0.2593	0.3214	0.0000	1.0000
FTD_{it}	600	0.2476	0.3212	0.0000	1.0000
FTI_{it}	600	0.3559	0.3565	0.0000	1.0000
$Size_{it}$	600	18.1768	1.4652	14.8106	22.0254
$Liquidity_{it}$	600	0.2174	10.7972	0.0245	0.6591
$Overhead_{it}$	600	13.5187	1.5541	9.0402	17.4464
CIR_{it}	600	0.3187	0.0894	0.0025	0.7388
NIM_{it}	600	0.0252	13.7098	0.0100	0.0495

Note: See Table 1 for variable measurements.

5. Empirical results

5.1. Descriptive statistics

Table 2 reports the descriptive statistics of the variables used in the regression analyses. The average NPL_{it} is 1.1474%, with a standard deviation of 0.7258%. The average FT_{it} is 0.2646, and the volatility of FinTech (0.3438) varies greatly during the sample period. Please see Table 2 for additional statistics. In addition, Figs. 1 and 2 show the development tendency of bank FinTech in the 2008–2017 period. FT-State refers to bank FinTech in state-owned banks. FT-Joint refers to bank FinTech in joint-stock banks, while FT-Other refers to bank FinTech in city and rural banks. From Fig. 1, the results show that bank FinTech experienced rapid development during the 2008–2017 period. In addition, the development of internet technology is ahead of artificial intelligence technology, blockchain technology, cloud computing technology, and big data technology. Based on Fig. 2, we find that state-owned banks have the earliest and highest development of bank FinTech, whether at the overall level of bank FinTech or the subareas level of bank FinTech, followed by joint-stock banks and other commercial banks.

5.2. Effects of Bank FinTech on credit risk

Before performing the regression analysis, we first test the multicollinearity of our explanatory variables. The variance inflation factors (VIFs) all suggest that high multicollinearity does not exist. Second, we first employ a CD test and Fisher tests to determine whether our data require the utilization of panel estimation or pooled estimation techniques. The results (not tabulated for brevity)

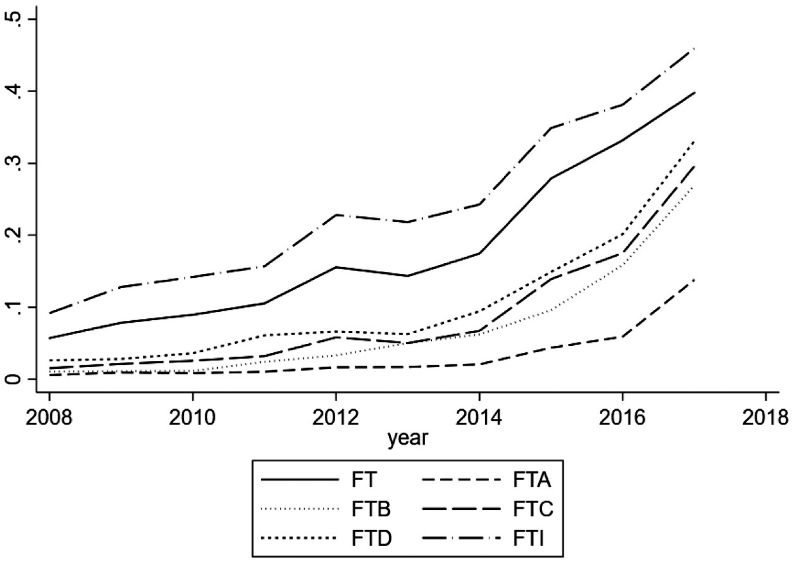

Fig. 1. The development of bank FinTech.

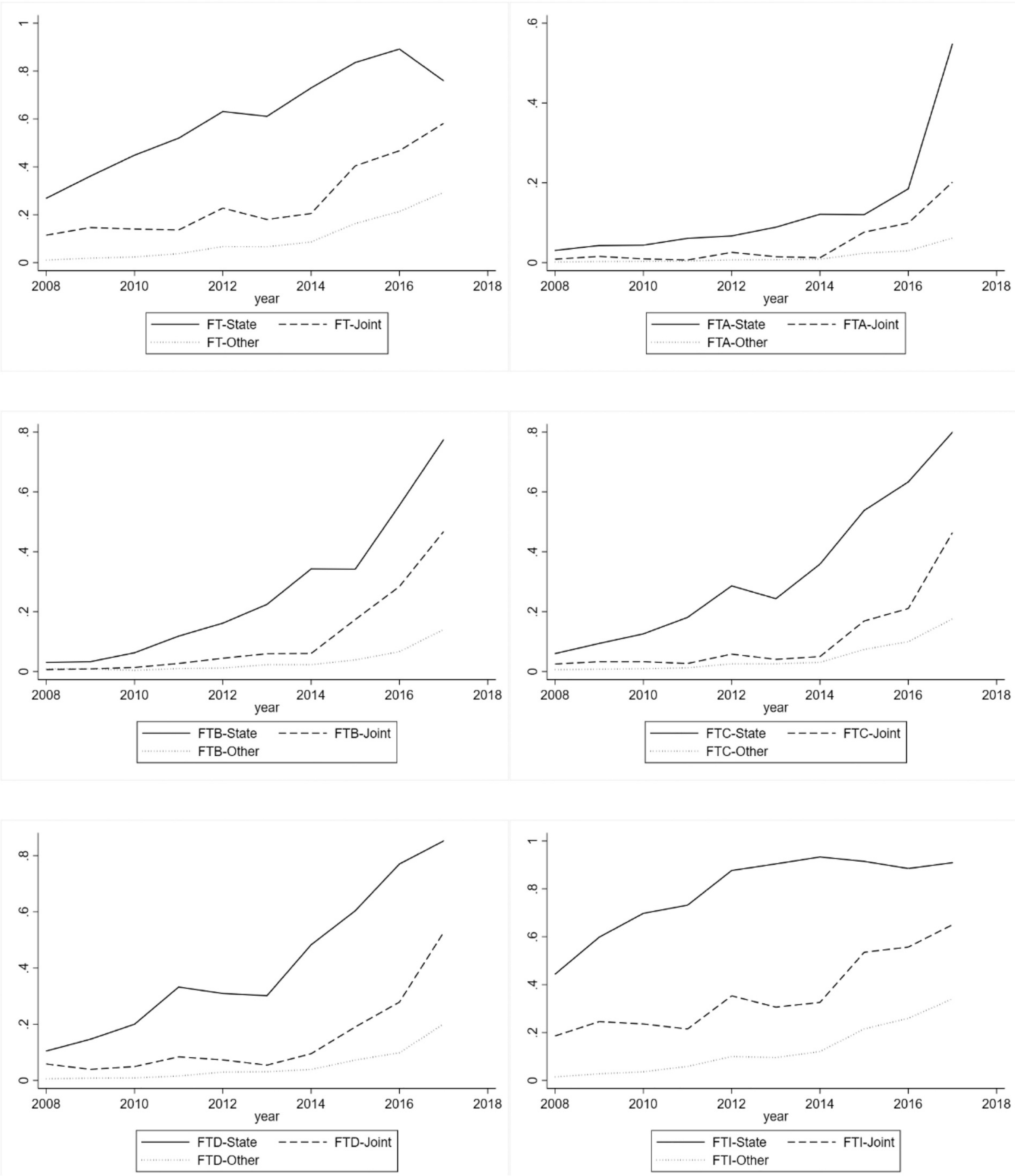

Fig. 2. The development of bank FinTech in different banks.

lead us to use panel data estimations.[9] In addition, most panel data models are estimated under either fixed effects or random effects assumptions. We perform a Hausman test (Hausman, 1978) to choose between these two basic models. The Hausman tests (not tabulated for brevity) indicate that the fixed effects model is more efficient than the random effects model.

Table 3 reports the results, which are obtained with two-way fixed effect panel data estimations (bank and year fixed effects). Meanwhile, we handle the possible heteroscedasticity by using the White (1980) methodology when estimating the equations.

[9] The authors can provide the results if needed.

Table 3
Effects of bank FinTech on credit risk (Fixed effects model).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}
FT_{it}	−1.0458** (0.3966)					
FTA_{it}		−1.1773** (0.5074)				
FTB_{it}			−0.8973** (0.4187)			
FTC_{it}				−1.0894** (0.4412)		
FTD_{it}					−1.0141** (0.3914)	
FTI_{it}						−0.7267** (0.3276)
$Size_{it}$	−0.4542*** (0.1705)	−0.4634* (0.1722)	−0.4623*** (0.1736)	−0.4617** (0.1752)	−0.4664** (0.1773)	−0.4560*** (0.1662)
$Liquidity_{it}$	−0.0177** (0.0083)	−0.0179** (0.0087)	−0.0176** (0.0084)	−0.0171** (0.0083)	−0.0171** (0.0083)	−0.0185** (0.0087)
$Overhead_{it}$	0.3058** (0.1329)	0.3461** (0.1316)	0.3287** (0.1350)	0.3108** (0.1372)	0.3197** (0.1380)	0.3290** (0.1273)
CIR_{it}	−0.4678 (0.3716)	−0.5697 (0.3772)	−0.5535 (0.3744)	−0.5100 (0.3785)	−0.5556 (0.3762)	−0.5155 (0.3702)
NIM_{it}	0.0006 (0.0005)	0.0005 (0.0005)	0.0006 (0.0005)	0.0006 (0.0005)	0.0006 (0.0005)	0.0005 (0.0004)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	5.7603* (2.9507)	5.4088* (3.0285)	5.5778* (3.0206)	5.7877* (3.0689)	5.7817* (3.0245)	5.5539* (2.9357)
N	600	600	600	600	600	600
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
Adjusted-R^2	0.3555	0.3397	0.3463	0.3522	0.3547	0.3461
F	10.0800***	11.9900***	10.5500***	10.8300***	10.1200***	11.1000***

Note: We estimate all regressions using fixed effects models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We also winsorize all continuous variables at the 1- and 99-percentile levels to mitigate the impact of outliers. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

Table 3 shows that the coefficients of the FinTech variables are all significantly negative, suggesting that banks will have significantly lower credit risk if they apply more bank FinTech. This result is consistent with our H1, indicating that the beneficial effects of bank FinTech overcome its negative effects in China's commercial banks.

5.3. Endogenous issue

5.3.1. Instrumental variable approach

Although the fixed effects models can solve the problem of missing variables to a certain extent, endogeneity is still possible between FinTech and bank credit risk. For example, if the influences of FinTech on bank credit risk were able to cause banks to adjust their development of FinTech, endogeneity may bias our results. In this section, we estimate an instrumental variable approach to reduce possible endogeneity (Roberts and Whited, 2013). Arner et al. (2015) believe that the development of FinTech is related to labor transfers. They argue that skilled financial practitioners in the labor market and fresh graduates facing employment jointly created a new era of FinTech. Therefore, we consider that if a city becomes more attractive to technical employees related to bank FinTech, it will accumulate many potential FinTech workers and thus promote the development of bank FinTech. We adopt the average income level of the city in which the bank's R&D department is located as a city attractiveness variable ($Income_{it}$), which serves as our instrumental variable. $Income_{it}$ is measured by the average wage for the city in which the R&D department of bank i is located in year t. The logic is that this variable contributes to attracting technical employees that are related to bank FinTech and thus affects the development of bank FinTech but is not directly related to bank credit risk.

Table 4 presents the results of the first-stage regression estimates. The results show that the instrumental variable is significantly positively related to the development of bank FinTech in every column. The related tests at the bottom of Table 4 also reject the null hypothesis that this variable is a weak instrumental variable. Table 5 presents the results for the second-stage regression estimates. We replace bank FinTech variables by their predicated values, i.e., $P\text{-}FT_{it}$, $P\text{-}FTA_{it}$, $P\text{-}FTB_{it}$, $P\text{-}FTC_{it}$, $P\text{-}FTD_{it}$, and $P\text{-}FTI_{it}$, from the first-stage regression. The results reported in Table 5 suggest that the relationships between bank FinTech and bank credit risk continue to hold after correcting for potential endogeneity bias, indicating that our results are not driven by the potential endogeneity bias.

5.3.2. System GMM approach

To further reduce the potential endogeneity issue, we also estimate our empirical results using a two-step system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998). System GMM is appropriate for the following reasons. First, the system GMM estimator

Table 4
Effects of bank FinTech on credit risk (First stage of the instrumental variable approach).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	FT_{it}	FTA_{it}	FTB_{it}	FTC_{it}	FTD_{it}	FTI_{it}
$Income_{it}$	0.0005***	0.0001***	0.0004***	0.0004***	0.0004***	0.0005***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Size_{it}$	0.0374	0.0134*	0.0288*	0.0312*	0.0324	0.0339
	(0.0245)	(0.0076)	(0.0174)	(0.0274)	(0.0213)	(0.0312)
$Liquidity_{it}$	0.0013**	0.0004*	0.0006	0.0010**	0.0009*	0.0015*
	(0.0006)	(0.0002)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
$Overhead_{it}$	−0.0932***	−0.0206***	−0.0543***	−0.0692***	−0.0691***	−0.0919***
	(0.0234)	(0.0072)	(0.0166)	(0.0166)	(0.0203)	(0.0298)
CIR_{it}	0.2513***	0.0843***	0.1571***	0.1640***	0.1806***	0.2413***
	(0.0689)	(0.0214)	(0.0490)	(0.0491)	(0.0600)	(0.0879)
NIM_{it}	0.0001***	0.0001	0.0001***	0.0001***	0.0001**	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	507	507	507	507	507	507
SW Meijer mult-F	33.0600***	24.9600***	47.5900***	41.8000***	32.5300***	16.6300**
Anderson LM	31.7800***	24.4100***	44.3700***	39.4400***	31.3000***	16.5700***
CD Wald F	33.0600***	24.9600***	47.5900***	41.8000***	32.5300***	16.6300**
Stock Wright LM S	3.4100*	3.4100*	3.4100*	3.4100*	3.4100*	3.4100*

Note: We estimate all regressions using the panel instrumental variable approach. We adopt the number of graduates in the city where the R&D department of each bank is located per year. All test statistics are reported at the bottom of each regression table. They include the under-identification test, weak instruments test, and so on. Because we use only one instrumental variable, the results do not include the Sargan test results. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

Table 5
Effects of bank FinTech on credit risk (Second stage of the instrumental variable approach).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}
$P\text{-}FT_{it}$	−1.4828* (0.7790)					
$P\text{-}FTA_{it}$		−5.5113* (3.0528)				
$P\text{-}FTB_{it}$			−1.7398* (0.9387)			
$P\text{-}FTC_{it}$				−1.8524* (0.9835)		
$P\text{-}FTD_{it}$					−1.7176* (0.9169)	
$P\text{-}FTI_{it}$						−1.6410* (0.8925)
$Size_{it}$	−0.3685***	−0.3502***	−0.3738***	−0.3661***	−0.3682***	−0.3682***
	(0.1112)	(0.1194)	(0.1137)	(0.1126)	(0.1130)	(0.1151)
$Liquidity_{it}$	−0.0055*	−0.0055*	−0.0065**	−0.0056*	−0.0059**	−0.0050
	(0.0029)	(0.0031)	(0.0028)	(0.0029)	(0.0029)	(0.0031)
$Overhead_{it}$	0.2587**	0.2837**	0.3025***	0.2688**	0.2782**	0.2461*
	(0.1190)	(0.1193)	(0.1125)	(0.1177)	(0.1162)	(0.1267)
CIR_{it}	−0.2686	−0.1768	−0.3679	−0.3375	−0.3311	−0.2453
	(0.3708)	(0.4212)	(0.3540)	(0.3558)	(0.3594)	(0.3910)
NIM_{it}	0.0006**	0.0005*	0.0005**	0.0006**	0.0005**	0.0005**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	507	507	507	507	507	507
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
Adjusted-R^2	0.3971	0.3297	0.3461	0.3841	0.3776	0.3539
F	17.4200***	15.6700***	16.5200***	17.0600***	16.8800***	16.2600***

Note: We estimate all regressions using the panel instrumental variable approach. The FinTech indexes with estimated symbols represent the fitted value of explanatory variables from Step I of panel instrumental regression. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

enables us to remove the strict exogenous assumption for the regressions and eliminate the unobserved bank-specific effects. Second, the estimation of the dynamic panel model can be applied to control for path dependence in the series of the dependent variable. Third, system GMM allows bank lending to be modeled dynamically, given that bank lending may persist over time owing to intertemporal risk smoothing, competition, banking regulations, or a banking relationship with risky customers.

Table 6
Effects of bank FinTech on credit risk (System GMM approach).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}
$NPL_{i,t-1}$	0.8974***	0.8736***	0.9012***	0.8930***	0.8945***	0.8956***
	(0.0174)	(0.0214)	(0.0200)	(0.0180)	(0.0190)	(0.0192)
$NPL_{i,t-2}$	−0.0888***	−0.0806***	0.9012***	−0.1085***	−0.1037***	−0.0807***
	(0.0098)	(0.0098)	(0.0310)	(0.0103)	(0.0109)	(0.0102)
FT_{it}	−0.1523**					
	(0.0666)					
FTA_{it}		−0.8453***				
		(0.0575)				
FTB_{it}			−0.6203***			
			(0.0838)			
FTC_{it}				−0.4974***		
				(0.0934)		
FTD_{it}					−0.3713***	
					(0.0678)	
FTI_{it}						−0.1861*** (0.0502)
$Size_{it}$	−0.0088	−0.0199	−0.0884*	−0.0571	−0.0026	−0.0101
	(0.0435)	(0.0446)	(0.0479)	(0.0420)	(0.0488)	(0.0420)
$Liquidity_{it}$	−0.0025***	−0.0020***	−0.0010	−0.0019***	−0.0015**	−0.0028***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0008)
$Overhead_{it}$	0.0318	0.0343	0.0677*	0.0654*	0.0269	0.0348
	(0.0395)	(0.0402)	(0.0397)	(0.0394)	(0.0428)	(0.0389)
CIR_{it}	−0.1676**	−0.1059	−0.1350	−0.0997	−0.1634**	−0.1791**
	(0.0816)	(0.0860)	(0.0899)	(0.0808)	(0.0821)	(0.0819)
NIM_{it}	0.0001	0.0001**	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
List	0.8265***	0.7358***	0.7703***	0.8124***	0.7601***	0.8747***
	(0.1850)	(0.2092)	(0.2343)	(0.1866)	(0.1899)	(0.1733)
Ownership	0.9207***	1.0752***	1.1212***	1.0197***	0.9336***	0.9769***
	(0.2861)	(0.2272)	(0.2543)	(0.2315)	(0.2394)	(0.2719)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	−0.6198	−0.0336	0.7521	0.2139	−0.2477	−0.7140
	(0.5681)	(0.5376)	(0.5752)	(0.5462)	(0.5590)	(0.5517)
N	480	480	480	480	480	480
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
AR(1) (p-value)	0.0369	0.0314	0.0295	0.0368	0.0373	0.0354
AR(2) (p-value)	0.2051	0.3933	0.4528	0.3263	0.3121	0.1908
Sargan test (*p* value)	0.2852	0.2118	0.2236	0.2685	0.2933	0.2539

Note: We estimate all regressions using the two-step system GMM, as proposed by Arellano and Bover (1995) and Blundell and Bond (1998). All bank variables are treated as endogenous. We use the first leg of the predetermined variables and the second leg of the endogenous variable as instruments. We combine the columns of the optimal instrument matrix by addition and, hence, use only one instrument for each variable rather than one for each period. The validity of the instruments is tested using the Sargan test statistic. Furthermore, we test for first- and second-order autocorrelation in the residuals. All test statistics are reported at the bottom of each regression table. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

The system GMM results in Table 6 show that the FinTech variables are significantly negative in every column, indicating that the development of bank FinTech still reduces credit risk. These findings are similar to our main finding, which indicates that our results are not driven by a potential endogeneity bias. We also find that the coefficients of $NPL_{i,t-1}$ and $NPL_{i,t-2}$ are statistically significant, although they are different. This finding indicates that bank credit risk has regularity and continuity. Note that we include a second lag in the regression for NPL_{it} since the Arellano-Bond test indicates a second-order serial correlation in the residuals if only the first leg of the dependent variable is included. Table 6 reports the test results. We also test the validity of our instruments by using the Sargan test of overidentifying restrictions. In all models, the test statistic accepts the null hypothesis that the instruments are exogenous.

5.3.3. Difference in differences approach

This section also employs policy shocks concerning the development of bank FinTech to identify the causal effects between bank FinTech and credit risk. The PBOC, the Ministry of Finance and other government departments jointly published the “Guiding Opinion on Promoting the Healthy Development of Internet Finance” in July 2015. Although this guiding opinion seems to focus on internet finance only, i.e., a specific form of FinTech, it proposes a series of policy measures to encourage innovation and support the stable development of FinTech and bank FinTech. This guidance undoubtedly promotes the development of bank FinTech. We treat this guidance as policy shocks concerning the development of bank FinTech and employ the difference in differences method (DID) to

Table 7
Effects of bank FinTech on credit risk (DID approach).

Variables	NPL_{it}	NPL_{it}
$Treat_{it}$*$Post_{it}$	−0.4581**	−0.3573***
	(0.2027)	(0.1624)
$Size_{it}$		−0.4516*** (0.1690)
$Liquidity_{it}$		−0.0171** (0.0084)
$Overhead_{it}$		0.3179** (0.1292)
CIR_{it}		−0.6464 (0.4084)
NIM_{it}		0.0006 (0.0005)
Bank fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Cons.	1.2264***	5.5606*
	(0.0878)	(3.0485)
N	540	540
Clustering level	Bank	Bank
Adjusted-R^2	0.2846	0.3412
F	11.7500***	10.8100***

Note: We estimate all regressions using fixed effects models. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We also winsorize all continuous variables at the 1- and 99-percentile levels to mitigate the impact of outliers. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

reduce the potential endogeneity bias in our regression model. We argue that our main result is not driven by potential endogeneity bias if the treatment effects of this guiding opinion on bank credit risk are negative.

Then, we distinguish the treatment group and the control group based on the statistical eigenvalue of the related variables, following existing studies (Irani and Oesch, 2013; Doidge and Dyck, 2015; Ioannidou et al., 2015; Lepori, 2016; De Angelis et al., 2017; Koirala et al., 2018; Chen et al., 2019b; Deng et al., 2019). Specifically, with the help of original data obtained from the crawler program, we divide our sample into banks with the high development of bank FinTech (i.e., the treatment group) and banks with the low development of bank FinTech (i.e., the control group) based our bank FinTech-related news disclosure before this quasi-natural experiment year, i.e., 2015. News disclosure about bank FinTech in the treatment group is above the median value, and news disclosure about bank FinTech in the control group is below the median value. Finally, we estimate the following DID model, in which the coefficient of $Treat_{it}$*$Post_{it}$ reflects the treatment effects of this regulatory guidance on bank credit risk.

$$NPL_{it} = Constant + a * Treat_{it} * Post_{it} + r * Control_{it} + Bank_i + Year_t + \varepsilon.\ Model \tag{2}$$

where i indexes for banks, t indexes for time and NPL_{it} is the measurement of credit risk. $Treat_{it}$ is a dummy variable equal to one for banks with a high development of bank FinTech and zero for banks with the low development of bank FinTech. $Post_{it}$ equals one if the bank observation is after the promulgation of the related policy and zero otherwise. $Control_{it}$ is a matrix of additional bank controls, including the bank size ($Size_{it}$), liquidity ratio ($Liquidity_{it}$), bank overhead ($Overhead_{it}$), cost-to-income ratio (CIR_{it}), net interest margin (NIM_{it}), bank ownership structure (Ownership) and listed status (List). $Bank_i$ and $Year_t$ are bank and year fixed effects, respectively, and ε refers to the error term.

Before running this DID model, we test whether our data satisfy the parallel trends assumption. The results (not tabulated for brevity) show that the parallel trends assumption is supported and the DID approach is reasonable. Table 7 shows the results of the DID model. In all two columns, coefficients of $Treat_{it}$*$Post_{it}$ are significantly negative, indicating that the treatment effects of bank FinTech on bank credit risk are negative. These results also show that our main results are not driven by potential endogeneity bias.

5.4. Robust tests

In this section, we perform several tests to check whether our results are robust. Due to the advantages mentioned in Subsection 5.3.2, the subsequent sections employ the system GMM approach to perform the following checks.

5.4.1. Alternative measures of credit risk

In this subsection, we consider how FinTech affects an alternative measure of bank credit risk. We employ LLR_{it} to measure credit risk. LLR_{it} is measured by the ratio of loan loss reserves to total loans.

Then, we examine the effects of bank FinTech on the alternative measure of credit risk. The results in Table 8 show that all the FinTech variables are significantly negative in every column, indicating that the development of FinTech decreases an alternative measure of bank credit risk. These results confirm our main findings, indicating that our results are not driven by the measurement of credit risk.

5.4.2. Removing the observations before 2010

Our sample period is from 2008 to 2017. However, the development of FinTech was extremely low in 2008 and 2009. To prevent our results from being driven by the observations from 2008 and 2009, we exclude all samples for these years and then reanalyze the

Table 8
Effects of bank FinTech on credit risk (Alternative measures of credit risk).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	LLR_{it}	LLR_{it}	LLR_{it}	LLR_{it}	LLR_{it}	LLR_{it}
$LLR_{i,t-1}$	1.1426***	1.1586***	1.1588***	1.1567***	1.1586***	1.1465***
	(0.0147)	(0.0132)	(0.0132)	(0.0141)	(0.0172)	(0.0133)
$LLR_{i,t-2}$	−0.1468***	−0.1541***	−0.1565***	−0.1600***	−0.1609***	−0.1466***
	(0.0078)	(0.0083)	(0.0085)	(0.0081)	(0.0106)	(0.0082)
FT_{it}	−0.3714***					
	(0.0603)					
FTA_{it}		−0.0747 (0.0841)				
FTB_{it}			−0.0755 (0.0485)			
FTC_{it}				−0.2695***		
				(0.0635)		
FTD_{it}					−0.3196***	
					(0.0907)	
FTI_{it}						−0.2397*** (0.0377)
$Size_{it}$	−0.0987	−0.1373	−0.1437	−0.1262	−0.1561*	−0.1103
	(0.0892)	(0.0901)	(0.0908)	(0.0926)	(0.0897)	(0.0870)
$Liquidity_{it}$	0.0026*	0.0021	0.0019	0.0026*	0.0028**	0.0025*
	(0.0014)	(0.0016)	(0.0015)	(0.0014)	(0.0012)	(0.0015)
$Overhead_{it}$	−0.1485**	−0.1310*	−0.1225	−0.1131	−0.1037	−0.1381*
	(0.0749)	(0.0749)	(0.0755)	(0.1775)	(0.0773)	(0.0717)
CIR_{it}	−0.3358***	−0.3962***	−0.4161***	−0.2939**	−0.3530***	−0.3438***
	(0.1163)	(0.1124)	(0.1110)	(0.1205)	(0.1096)	(0.1180)
NIM_{it}	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
List	0.0674	0.1498	0.1470	0.0380	0.0532	0.0865
	(0.1484)	(0.1510)	(0.1469)	(0.1501)	(0.1579)	(0.1503)
Ownership	0.9577***	1.0457***	0.9982***	0.8944***	0.8993***	1.0195***
	(0.2397)	(0.2195)	(0.2141)	(0.2079)	(0.2024)	(0.2441)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	3.9022***	4.1934***	4.2391***	3.8752***	4.3340***	3.9180***
	(0.9116)	(0.9108)	(0.9102)	(0.9066)	(0.8755)	(0.9075)
N	480	480	480	480	480	480
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
AR(1) (*p*-value)	0.0012	0.0014	0.0014	0.0013	0.0011	0.0014
AR(2) (p-value)	0.5431	0.5630	0.5718	0.5309	0.5113	0.5607
Sargan test (*p* value)	0.2560	0.1197	0.1497	0.3008	0.2856	0.2202

Note: We estimate all regressions using the two-step system GMM, as proposed by Arellano and Bover (1995) and Blundell and Bond (1998). All bank variables are treated as endogenous. We use the first leg of the predetermined variables and the second leg of the endogenous variable as instruments. We combine the columns of the optimal instrument matrix by addition and, hence, use only one instrument for each variable rather than one for each period. The validity of the instruments is tested using the Sargan test statistic. Furthermore, we test for first- and second-order autocorrelation in the residuals. All test statistics are reported at the bottom of each regression table. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

remaining samples. The results in Table 9 show that all the FinTech variables are significantly negative in every column, which indicates that our views on bank credit risk and FinTech remain unchanged. These results confirm our main findings, indicating that our results are not driven by the extrema in 2008 and 2009.

5.4.3. Removing the extreme observations of FinTech

In our sample, the minimum FinTech is 0.0000, whereas the maximum FinTech is 1.0000. The span of FinTech is obviously wide. To prevent our results from being driven by the extrema of FinTech, we only use a sample of 40 banks ranked in the average FinTech rankings to examine the effects of FinTech on bank credit risk after dropping the samples with high and low FinTech levels. The results in Table 10 show that the main variables remain unchanged, indicating that our results are not driven by the extrema of bank FinTech.

6. Further analyses

Considering that bank heterogeneity may affect the relation between bank FinTech and credit risk, it is necessary to conduct heterogeneity research to help us identify the role of bank FinTech on credit risk more accurately. Specifically, we consider how bank characteristics, including bank size, bank ownership structure, and bank listed status, moderate the effects of FinTech on bank credit risk in this section.

Table 9
Effects of bank FinTech on credit risk (Removing the observations for 2008 and 2009).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}
$NPL_{i,t-1}$	0.8817***	0.8787***	0.8934***	0.8874***	0.8911***	0.8698***
	(0.0628)	(0.0255)	(0.0223)	(0.0221)	(0.0254)	(0.0304)
$NPL_{i,t-2}$	−0.0826***	−0.0785***	−0.1098***	−0.1056***	−0.1005**	−0.0736***
	(0.0093)	(0.0092)	(0.0131)	(0.0100)	(0.0110)	(0.0097)
FT_{it}	−0.1708***					
	(0.0661)					
FTA_{it}		−0.8494***				
		(0.0581)				
FTB_{it}			−0.6140***			
			(0.0846)			
FTC_{it}				−0.4983***		
				(0.0917)		
FTD_{it}					−0.3780***	
					(0.0679)	
FTI_{it}						−0.2152*** (0.0523)
$Size_{it}$	−0.0082	−0.0246	−0.0854*	−0.0732*	−0.0004	0.0067
	(0.0429)	(0.0440)	(0.0439)	(0.0388)	(0.0447)	(0.0414)
$Liquidity_{it}$	−0.0027***	−0.0021***	−0.0853	−0.0022***	−0.0015**	−0.0031***
	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0006)	(0.0008)
$Overhead_{it}$	0.0161	0.0274	0.0600	0.0660*	0.0188	0.0201
	(0.0379)	(0.0398)	(0.0385)	(0.0386)	(0.0444)	(0.0369)
CIR_{it}	−0.1587**	−0.1116	−0.1453*	−0.0941	−0.1617**	−0.1750**
	(0.0787)	(0.0829)	(0.0854)	(0.0790)	(0.0792)	(0.0785)
Nim_{it}	0.0001	0.0001	0.0000	0.0000	0.0001	0.0000
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
List	0.8034***	0.7075***	0.7604***	0.8331***	0.7528***	0.8300***
	(0.1842)	(0.2116)	(0.2346)	(0.1851)	(0.1888)	(0.1748)
Ownership	0.8995***	1.0777***	1.0445***	1.0674***	0.9126***	0.9590***
	(0.2570)	(0.2169)	(0.2358)	(0.2132)	(0.2279)	(0.2591)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	−0.6874	−0.2725	0.3046	0.0337	−0.5718	−0.7246
	(0.5426)	(0.5237)	(0.5158)	(0.4839)	(0.5072)	(0.5231)
N	360	360	360	360	360	360
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
AR(1) (p-value)	0.0451	0.0320	0.0327	0.0421	0.0407	0.0453
AR(2) (*p*-value)	0.1755	0.3400	0.4204	0.2876	0.2974	0.1683
Sargan test (p value)	0.3181	0.2178	0.2563	0.2969	0.3016	0.3091

Note: We estimate all regressions using the two-step system GMM, as proposed by Arellano and Bover (1995) and Blundell and Bond (1998). All bank variables are treated as endogenous. We use the first leg of the predetermined variables and the second leg of the endogenous variable as instruments. We combine the columns of the optimal instrument matrix by addition and, hence, use only one instrument for each variable rather than one for each period. The validity of the instruments is tested using the Sargan test statistic. Furthermore, we test for first- and second-order autocorrelation in the residuals. All test statistics are reported at the bottom of each regression table. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

6.1. The role of Bank size

In this subsection, we consider the role of bank size. Usually, compared to small banks, large banks have more perfect organizational structures and more adequate resources to develop FinTech. Additionally, large banks have better risk management and risk-taking capabilities. All these aspects may cause potential improvement in credit risk to be smaller in large banks. That is, the benefit effects of bank FinTech on credit risk may be weaker in large banks than in small banks. To explore this issue, we add the interaction between the FinTech variables and bank size (FT_{it}-$Size_{it}$, FTA_{it}-$Size_{it}$, FTB_{it}-$Size_{it}$, FTC_{it}-$Size_{it}$, FTD_{it}-$Size_{it}$, or FTI_{it}-$Size_{it}$) to Model (1).

Table 11 shows the empirical results. In every column, the coefficients of the interaction between the FinTech variables and bank size are significantly positive, showing that the negative impacts of FinTech and its subareas on credit risk are weaker for larger banks. These results are consistent with our expectations.

6.2. The role of bank ownership structure

In this subsection, we consider the role of bank ownership structure. Our sample contains state-owned banks and non-state-owned banks (joint-stock banks, city banks, and rural banks). Compared with non-state-owned banks, state-owned banks have different operational strategies, social attention, business orientations, corporate governance structures, risk management approaches, and so

Table 10
Effects of bank FinTech on credit risk (Removing extreme observations for FinTech).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}
$NPL_{i,t-1}$	0.8878*** (0.0571)	0.9355*** (0.0427)	0.9362*** (0.0341)	0.9192*** (0.0335)	0.9308*** (0.0510)	0.9063*** (0.0602)
$NPL_{i,t-2}$	−0.1615*** (0.0207)	−0.1801*** (0.0216)	−0.1610*** (0.0214)	−0.1817*** (0.0219)	−0.1846*** (0.0207)	−0.1669**** (0.0244)
FT_{it}	−0.6066*** (0.1716)					
FTA_{it}		−0.6539 (0.4677)				
FTB_{it}			−0.4622* (0.2630)			
FTC_{it}				−0.9446** (0.3856)		
FTD_{it}					−0.4699** (0.2190)	
FTI_{it}						−0.4087*** (0.1576)
$Size_{it}$	−0.3345*** (0.0671)	−0.2307*** (0.0651)	−0.1015 (0.0931)	−0.2953*** (0.0687)	−0.2598*** (0.0615)	−0.2530*** (0.0694)
$Liquidity_{it}$	−0.0021 (0.0015)	−0.0012 (0.0011)	−0.0017 (0.0013)	−0.0015 (0.0013)	−0.0019* (0.0011)	−0.0028* (0.0016)
$Overhead_{it}$	0.3255*** (0.0730)	0.2570*** (0.0041)	0.1401 (0.0870)	0.3086*** (0.0620)	0.2821*** (0.0630)	0.2729*** (0.0633)
CIR_{it}	−0.4555** (0.2023)	−0.3955** (0.1882)	−0.4975*** (0.1773)	−0.4265** (0.1921)	−0.4188** (0.1953)	−0.3456 (0.2157)
NIM_{it}	0.0001 (0.0001)	0.0002* (0.0000)	0.0001 (0.0001)	0.0002 (0.0001)	0.0002** (0.0001)	0.0001 (0.0001)
List	−0.2272*** (0.0746)	−0.3415*** (0.0531)	−0.4470*** (0.0641)	−0.3095*** (0.0566)	−0.3896*** (0.0491)	−0.3069*** (0.0834)
Ownership	−0.1083 (0.1747)	−0.1770 (0.1451)	0.0344 (0.1573)	−0.2036 (0.1544)	−0.1348 (0.1309)	−0.0839 (0.1574)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	2.2198*** (0.7921)	1.2222 (0.8263)	0.5601 (0.8989)	1.7299* (0.8854)	1.4685* (0.7803)	1.4897* (0.8946)
N	320	320	320	320	320	320
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
AR(1) (p-value)	0.0341	0.0291	0.0258	0.0253	0.0282	0.0321
AR(2) (p-value)	0.8583	0.7071	0.8319	0.6532	0.6556	0.8962
Sargan test (p value)	0.9491	0.9738	0.9934	0.9799	0.9637	0.9578

Note: We estimate all regressions using the two-step system GMM, as proposed by Arellano and Bover (1995) and Blundell and Bond (1998). All bank variables are treated as endogenous. We use the first leg of the predetermined variables and the second leg of the endogenous variable as instruments. We combine the columns of the optimal instrument matrix by addition and, hence, use only one instrument for each variable rather than one for each period. The validity of the instruments is tested using the Sargan test statistic. Furthermore, we test for first- and second-order autocorrelation in the residuals. All test statistics are reported at the bottom of each regression table. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

on. We argue that the effects of FinTech on bank credit risk will also differ between bank types. To explore this issue, we add the interaction between FinTech and the ownership structure variable (FT_{it}-Ownership, FTA_{it}-Ownership, FTB_{it}-Ownership, FTC_{it}-Ownership, FTD_{it}-Ownership, or FTI_{it}-Ownership) to Model (1).

Table 12 shows the empirical results. In every column, the coefficients of the interaction between FinTech and bank ownership structure are significantly positive, showing that the negative impacts of bank FinTech and its subareas on credit risk are weaker in state-owned banks. These effects may be due to the following reasons. State-owned banks, as the benchmark of China's commercial banks, may attract more news media and public attention. They usually have a perfect corporate governance structure and high risk management levels after bank privatization reforms. This may result in the potential improvement in credit risk being smaller in state-owned commercial banks and thus lead to the negative impacts of bank FinTech and its subareas on credit risk being weaker in state-owned banks.

6.3. The role of bank listed status

In this subsection, we consider the role of banks' listed status. Listed banks have greater access to capital markets and are subject to market discipline (Barry et al., 2011; Jiang et al., 2013). In the Basel II and III Capital Accords, market discipline is one of the three pillars, along with capital regulation and banking supervision, which are intended to regulate bank operations. The idea is to rely on market forces to enhance banking supervision. In addition, listed banks usually have perfect corporate governance structures, which

Table 11
Effects of bank FinTech on credit risk: The role of bank size.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}
$NPL_{i,t-1}$	0.8439***	0.8569***	0.8842***	0.8626***	0.8579***	0.8744***
	(0.0209)	(0.0204)	(0.0196)	(0.0172)	(0.0185)	(0.0199)
$NPL_{i,t-2}$	−0.0488***	−0.0763***	−0.1075***	−0.1001***	−0.0859***	−0.0582***
	(0.0123)	(0.0109)	(0.0129)	(0.0127)	(0.0139)	(0.0120)
FT_{it}	−0.4989***					
	(0.9072)					
FTA_{it}		−0.8578***				
		(0.2016)				
FTB_{it}			−0.5099***			
			(0.4589)			
FTC_{it}				−0.3956***		
				(0.1132)		
FTD_{it}					−0.4094***	
					(0.8619)	
FTI_{it}						−0.2849 (0.9956)
FT_{it}-$Size_{it}$	0.1835*** (0.0342)					
FTA_{it}-$Size_{it}$		0.2772*** (0.0778)				
FTB_{it}-$Size_{it}$			0.1640*** (0.0535)			
FTC_{it}-$Size_{it}$				0.1270*** (0.0403)		
FTD_{it}-$Size_{it}$					0.1376*** (0.0305)	
FTI_{it}-$Size_{it}$						0.1030*** (0.0382)
$Size_{it}$	−0.0197	−0.0519	−0.1107**	−0.0752*	−0.0237	−0.0184
	(0.0383)	(0.0499)	(0.0454)	(0.0457)	(0.0443)	(0.0414)
$Liquidity_{it}$	−0.0030***	−0.0023***	−0.0014*	−0.0025***	−0.0023***	−0.0030***
	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0008)
$Overhead_{it}$	0.0432	0.0752	0.0899**	0.0883*	0.0691	0.0378
	(0.0372)	(0.0474)	(0.0406)	(0.0456)	(0.0456)	(0.0387)
CIR_{it}	−0.1607*	−0.0623	−0.1368	−0.1232	−0.1643*	−0.1705**
	(0.0862)	(0.0909)	(0.0913)	(0.0883)	(0.0874)	(0.0792)
NIM_{it}	0.0001	0.0001**	0.0001**	0.0000	0.0001	0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
List	0.8731***	0.7839***	0.7055***	0.8505***	0.7988***	0.8689***
	(0.1564)	(0.2345)	(0.2545)	(0.1832)	(0.1754)	(0.1683)
Ownership	0.9896***	1.0871***	1.2201***	1.0163***	0.9046***	1.0074***
	(0.3063)	(0.2443)	(0.2487)	(0.2539)	(0.2531)	(0.2906)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	−0.9592*	0.0123	0.9346*	0.3074	−0.6796	−0.8907
	(0.5689)	(0.5524)	(0.5486)	(0.5524)	(0.5173)	(0.5652)
N	480	480	480	480	480	480
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
AR(1) (p-value)	0.0453	0.0313	0.0279	0.0405	0.0470	0.0388
AR(2) (*p*-value)	0.1539	0.3370	0.3850	0.3044	0.2975	0.1356
Sargan test (p value)	0.3008	0.2998	0.2826	0.3071	0.4068	0.2330

Note: We estimate all regressions using the two-step system GMM, as proposed by Arellano and Bover (1995) and Blundell and Bond (1998). All bank variables are treated as endogenous. We use the first leg of the predetermined variables and the second leg of the endogenous variable as instruments. We combine the columns of the optimal instrument matrix by addition and, hence, use only one instrument for each variable rather than one for each period. The validity of the instruments is tested using the Sargan test statistic. Furthermore, we test for first- and second-order autocorrelation in the residuals. All test statistics are reported at the bottom of each regression table. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

may result in the potential improvement in credit risk being smaller in listed commercial banks and thus lead to the negative impacts of bank FinTech and its subareas on credit risk being weaker in the listed banks. To explore this issue, we add the interaction between FinTech and listed status (FT_{it}-List, FTA_{it}-List, FTB_{it}- List, FTC_{it}- List, FTD_{it}- List, or FTI_{it}- List) to Model (1).

Table 13 shows the empirical results. The coefficients of the interaction variables between FinTech and bank listed status are significantly positive in every column, which suggests that the reduction effects of bank FinTech on credit risk are weaker in listed banks than in non-listed banks. These results are consistent with our expectations.

7. Conclusion

In recent years, FinTech applications have become prominent in global financial markets, especially in China, and have played an important role in the banking industry. This phenomenon is attracting a great deal of academic attention. However, existing studies

Table 12
Effects of bank FinTech on credit risk: The role of bank ownership structure.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}
$NPL_{i,t-1}$	0.8821***	0.8760***	0.9022***	0.8897***	0.8936***	0.8954***
	(0.0186)	(0.0205)	(0.0198)	(0.0177)	(0.0188)	(0.0184)
$NPL_{i,t-2}$	−0.0727***	−0.0788***	−0.1093***	−0.1067***	−0.1011***	−0.0797***
	(0.0116)	(0.0103)	(0.0128)	(0.0107)	(0.0106)	(0.0106)
FT_{it}	−0.2063***					
	(0.0694)					
FTA_{it}		−1.1952***				
		(0.1614)				
FTB_{it}			−0.6620***			
			(0.1000)			
FTC_{it}				−0.5070**		
				(0.1205)		
FTD_{it}					−0.4155***	
					(0.0793)	
FTI_{it}						−0.1905***
						(0.0522)
FT_{it}-Ownership	0.3781***					
	(0.1059)					
FTA_{it}-Ownership		0.4659***				
		(0.1591)				
FTB_{it}-Ownership			0.0774			
			(0.1142)			
FTC_{it}-Ownership				0.0425		
				(0.1428)		
FTD_{it}-Ownership					0.0415	
					(0.1016)	
FTI_{it}-Ownership						0.0494
						(0.0894)
$Size_{it}$	−0.0269	−0.0339	−0.0866*	−0.0589	−0.0215	−0.0107
	(0.0402)	(0.0466)	(0.0467)	(0.0463)	(0.0467)	(0.0419)
$Liquidity_{it}$	−0.0028***	−0.0022***	−0.0011	−0.0020***	−0.0016**	−0.0028***
	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)
$Overhead_{it}$	0.0344	0.0547	0.0707*	0.0661	0.0417	0.0355
	(0.0397)	(0.0427)	(0.0406)	(0.0470)	(0.0495)	(0.0387)
CIR_{it}	−0.1593*	−0.0874	−0.1103	−0.1253*	−0.1824**	−0.1785**
	(0.0817)	(0.0897)	(0.0872)	(0.0759)	(0.0742)	(0.0822)
NIM_{it}	0.0001	0.0001**	0.0001*	0.0001	0.0001	0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
List	0.8785***	0.7333***	0.7483***	0.8120***	0.7421***	0.8853***
	(0.1557)	(0.2208)	(0.2413)	(0.1883)	(0.1876)	(0.1777)
Ownership	0.9061***	1.0980***	1.1238***	1.0292***	1.0311***	0.9844***
	(0.2909)	(0.2323)	(0.2546)	(0.2536)	(0.2322)	(0.2745)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	−1.0048*	−0.0433	0.6867	0.2589	−0.0959	−0.7428
	(0.5391)	(0.5350)	(0.5792)	(0.5394)	(0.5038)	(0.5373)
N	480	480	480	480	480	480
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
AR(1) (p-value)	0.0390	0.0284	0.0291	0.0357	0.0346	0.0353
AR(2) (*p*-value)	0.1800	0.3532	0.4183	0.3202	0.3122	0.1854
Sargan test (p value)	0.3339	0.2489	0.2209	0.2582	0.2874	0.2558

Note: We estimate all regressions using the two-step system GMM, as proposed by Arellano and Bover (1995) and Blundell and Bond (1998). All bank variables are treated as endogenous. We use the first leg of the predetermined variables and the second leg of the endogenous variable as instruments. We combine the columns of the optimal instrument matrix by addition and, hence, use only one instrument for each variable rather than one for each period. The validity of the instruments is tested using the Sargan test statistic. Furthermore, we test for first- and second-order autocorrelation in the residuals. All test statistics are reported at the bottom of each regression table. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variables' measurements.

mostly focus on the effects of external FinTech on the banking industry, and few studies examine the influence of bank FinTech. Therefore, this paper explores this issue.

Using hand-collected data from China between 2008 and 2017, we construct and measure bank FinTech and examine the effects of bank FinTech on credit risk. The major findings are as follows. First, the development of bank FinTech and the subareas of bank FinTech show an increasing trend from 2008 to 2017. Moreover, the development of bank FinTech is more rapid in state-owned banks than in other banks. Among the subareas of bank FinTech, internet technology is the fastest-growing subarea, and artificial

Table 13
Effects of bank FinTech on credit risk: The role of banks' listed status.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}	NPL_{it}
$NPL_{i,t-1}$	0.8507***	0.8493***	0.8748***	0.8654***	0.8688***	0.8503***
	(0.0248)	(0.0207)	(0.0212)	(0.0176)	(0.0200)	(0.0259)
$NPL_{i,t-2}$	−0.0660***	−0.0759***	−0.1118***	−0.1069***	−0.0961***	−0.0575***
	(0.0119)	(0.0110)	(0.0131)	(0.0128)	(0.0144)	(0.0112)
FT_{it}	−0.5848***					
	(0.1346)					
FTA_{it}		−1.6545***				
		(0.3323)				
FTB_{it}			−1.1568***			
			(0.1895)			
FTC_{it}				−1.0327***		
				(0.1560)		
FTD_{it}					−0.6621***	
					(0.1196)	
FTI_{it}						−0.5152***
						(0.1157)
FT_{it}-List	0.5769***					
	(0.1359)					
FTA_{it}-List		0.8507***				
		(0.3598)				
FTB_{it}-List			0.5820***			
			(0.1931)			
FTC_{it}-List				0.5758***		
				(0.1614)		
FTD_{it}-List					0.3256***	
					(0.1052)	
FTI_{it}-List						0.4538***
						(0.1239)
$Size_{it}$	−0.0109	−0.0358	−0.1177***	−0.0806**	−0.0311	−0.0228
	(0.0431)	(0.0466)	(0.0446)	(0.0402)	(0.0447)	(0.0443)
$Liquidity_{it}$	−0.0022***	−0.0022***	−0.0013*	−0.0020***	−0.0018***	−0.0025***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0009)
$Overhead_{it}$	0.0191	0.0477	0.0781**	0.0697*	0.0523	0.0121
	(0.0373)	(0.0392)	(0.0372)	(0.0398)	(0.0410)	(0.0416)
CIR_{it}	−0.1470*	−0.0545	−0.1123	−0.1264	−0.1614**	−0.1307
	(0.0832)	(0.0929)	(0.0986)	(0.0939)	(0.0823)	(0.0815)
NIM_{it}	0.0001	0.0001**	0.0001*	0.0000	0.0001	0.0001
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
List	0.7173***	0.7136***	0.7461***	0.8206***	0.7258***	0.7539***
	(0.2181)	(0.2613)	(0.2626)	(0.2126)	(0.2042)	(0.2191)
Ownership	0.7664**	1.0400***	1.2210***	0.9934***	0.8885***	0.8230**
	(0.3388)	(0.2499)	(0.2399)	(0.2365)	(0.2705)	(0.3386)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Cons.	−0.3633	0.1290	1.2117**	0.6517	0.0035	−0.5200
	(0.6062)	(0.5729)	(0.5566)	(0.5448)	(0.6040)	(0.0.5877)
N	480	480	480	480	480	480
Clustering level	Bank	Bank	Bank	Bank	Bank	Bank
AR(1) (p-value)	0.0455	0.0347	0.0319	0.0423	0.0414	0.0455
AR(2) (p-value)	0.2340	0.3931	0.4261	0.3926	0.3303	0.1659
Sargan test (p value)	0.3407	0.2978	0.2794	0.2723	0.3899	0.2612

Note: We estimate all regressions using the two-step system GMM, as proposed by Arellano and Bover (1995) and Blundell and Bond (1998). All bank variables are treated as endogenous. We use the first leg of the predetermined variables and the second leg of the endogenous variable as instruments. We combine the columns of the optimal instrument matrix by addition and, hence, use only one instrument for each variable rather than one for each period. The validity of the instruments is tested using the Sargan test statistic. Furthermore, we test for first- and second-order autocorrelation in the residuals. All test statistics are reported at the bottom of each regression table. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. The standard error (in parentheses) is corrected for heteroscedasticity following White's (1980) methodology. See Table 1 for all variable measurements.

intelligence technology is the slowest growing. Second, our basic results show that bank FinTech and bank FinTech subareas are all negatively associated with bank credit risk, indicating that the development of bank FinTech reduces credit risk. Third, we also find that the negative effects of bank FinTech on credit risk are weaker in large banks, state-owned banks, and listed banks.

Although this paper shows that commercial banks benefit from bank FinTech, bank FinTech also has some negative effects on commercial banks, such as technical risk and regulatory risk. We also suggest some measures to guard against and control the potential risks of bank FinTech. On the one hand, the government should introduce full supervision laws, including entry and exit principles, information disclosure requirements, risk monitoring indicators, risk preparation requirements, and other measures, when supervising bank FinTech. On the other hand, commercial banks should effectively monitor and isolate new bank FinTech risks by strengthening employees' training, standardizing employees' behavior, checking the application defects of technologies, and making emergency plans.

Declaration of Competing Interest

None.

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Detailed analysis of the improved DLM model

In Appendix A, we employ an improved DLM model to analyze the effects of bank FinTech on credit risk. With the help of the basic work of Dell' Ariccia et al. (2017), we improve the DLM model to consider FinTech and make it more suitable for the Chinese context. We show a detailed analysis of the improved DLM model as follows.

To standardize our study, we propose the following eight assumptions.

Assumption 1. Balance sheet assumption.

We assume that the bank obtains deposits, pays the required reserves to the central bank, and does not possess additional excess reserves. We use equation $R + L = D + K$ to describe the bank's balance sheet, where the four variables represent the required reserves, loans, deposits, and equity capital. Then, we define the deposit reserve ratio $\rho = \frac{R}{D}$, almost capital adequacy ratio $k = \frac{K}{L}$ and loan-to-deposit ratio $\frac{D}{L} = \frac{1-k}{1-\rho}$. It is worth noting that these three ratios will not change when we solve the optimal problem below.

Assumption 2. Loan assumption.

Depending on basic economic theory, we regard a loan as a commodity offered by the bank and construct a supply function of the loan interest rate to the loan that can be expressed as $L = L(r_L)$, where r_L is the loan interest rate and L is the loan. This function satisfies the partial derivative relation $\frac{\partial L}{\partial r_L} < 0$, and the reason we use a partial derivative is that there may be other factors that influence the size of the loan besides the loan interest rate, which is ignored to simplify the calculation.

Assumption 3. Deposit assumption.

In the context of China's economy, given that the PBOC removed the upper limit of deposit interest rate fluctuations in October 2015, we assume that the deposit interest rate is equal to the market rate, which is nearly equal to the risk-free interest rate as well. That is, $r_D = r_M = \bar{r}_f$, where r_D, r_M, and $\bar{r}_f$ represent the deposit interest rate, market interest rate, and risk-free interest rate, respectively.

Assumption 4. Capital return assumption.

Bank shareholders holding equity capital will ask for an additional risk premium, and we can divide the capital return into the capital cost and the risk premium. We regard the cost here as the real deposit interest rate, i.e., $\frac{r_D}{1-\rho}$. Hence, we obtain the equation $r_K = r_P + \frac{r_D}{1-\rho} = r_P + \frac{\bar{r}_f}{1-\rho}$, where r_K is the capital return and r_P is the risk premium.

Assumption 5. Regulatory assumption.

Increased regulatory input leads to an increased recovery probability of loan default, which means less bank risk-taking. Therefore, we propose a significant substitution relation in our analysis as follows: we treat regulatory input as a negative level of bank credit risk. Here, we use ξ to symbolize the loan default recovery probability and $\xi \epsilon (0, 1]$.

Assumption 6. Interest margin profit assumption.

The interest margin profit can be explained as the unit loan profit minus the unit loan cost. With the help of Assumption 1, we know that $k = \frac{K}{L}$, i.e., $K = kL$. To a certain extent, this formula refers to a part of the loan equal to the capital. Further, in combination with Assumption 1, which tells us $L = K + (D - R)$, we obtain that when referring to the source of the loan, the k proportion of the loans is from the capital and the other $1 - k$ proportion of the loans is from deposit-deducted reserves. Namely, the unit loan cost is the $1 - k$ of the real deposit interest rate. Thus, we define that interest margin profit ε from equation $\varepsilon = r_L - \frac{1-k}{1-\rho} r_D = r_L - \frac{1-k}{1-\rho} \bar{r}_f$, and ε is greater than zero because of the rational man assumption. Additionally, banks do not have an incentive to put all deposits into loan origination, so $r_L < \frac{1}{1-\rho} r_D$.

Assumption 7. Bank management cost assumption.

There exist management costs for loans and deposits in the bank, and those costs are proportional to the loan and deposit amounts. Kopecky and VanHoose (2004) believe that management cost function has convexity and second-order derivability. Coupled with Assumption 5, the bank management cost function is written as $C = C_L(\xi)L + C_D(\xi)D$, where $C_L(\xi)$ is the unit loan management cost function and $C_D(\xi)$ is the unit deposit management cost function. Moreover, $\frac{\partial C_L}{\partial \xi} > 0$, $\frac{\partial C_D}{\partial \xi} > 0$, $\frac{\partial^2 C_L}{\partial \xi^2}$ and $\frac{\partial^2 C_D}{\partial \xi^2}$ all exist.

Assumption 8. FinTech assumption.

As previously discussed in Section 2, the development of bank FinTech changes the situation of the bank. To attract potential savers and lenders, the bank must adjust its loan and deposit strategies, r_L and r_D, respectively We believe that the relationship is as follows: $r_L = r_L(FT)$, and $r_D = r_D(FT)$, where FT is the development of FinTech. $\frac{\partial r_L}{\partial FT} < 0$ and $\frac{\partial r_D}{\partial FT} > 0$ are not predetermined but are post determined, which guarantees that we can decide on the timing of introducing FinTech into our analysis. For the risk premium in capital return, we believe that bank shareholders will ask for more risk compensation for the indeterminacy given by the progress of FinTech, so we obtain the following: $r_P = r_P(FT)$ and $\frac{\partial r_P}{\partial FT} > 0$. Finally, we need to decide how FinTech influences management costs. We believe that the management efficiency of the bank will increase with the development of FinTech because more scientific and efficient methods are used. Thus, we conclude these to be $\frac{\partial C_L}{\partial FT} < 0$ and $\frac{\partial C_D}{\partial FT} < 0$. As in Assumption 7, the requirements of convexity and second-order derivability, $\frac{\partial^2 C_L}{\partial FT^2}$ and $\frac{\partial^2 C_D}{\partial FT^2}$, all exist.

Now, we describe the bank's profit target as the profit function below:

$$\Pi = \left(r_L L - r_D \frac{D - R}{1 - \rho} \right) \xi - r_K K - C \tag{1}$$

Taking the conditions mentioned above, we obtain a more concrete form of the profit function as follows:

$$\Pi = \left[\left(r_L - \frac{1 - k}{1 - \rho} \bar{r}_f \right) \xi - \left(r_P + \frac{1}{1 - \rho} \bar{r}_f \right) k - \left(C_L(\xi) + \frac{1 - k}{1 - \rho} C_D(\xi) \right) \right] L(r_L) \tag{2}$$

According to the operational goal of the commercial bank, we can affirm that the bank's strategy is to maximize the profit function. The bank will flexibly adjust the inputs facing regulatory requirements and suitably price the service to obtain this goal. We summarize the bank's strategic behavior as follows:

$$G = G\{r_L; r_P; \xi\} = \underset{r_L, r_P, \xi}{arg\,max}\, \Pi \tag{3}$$

To solve the decision problem above more clearly, we rewrite the profit function Eq. (2) as follows:

$$\Pi = [(r_L - A_1)\xi - k r_P - C_L(\xi) - A_2 C_D(\xi) - A_3] L(r_L) \tag{4}$$

In Eq. (4), $A_1 = \frac{1-k}{1-\rho}\bar{r}_f$, $A_2 = \frac{1-k}{1-\rho}$, $A_3 = \frac{k}{1-\rho}\bar{r}_f$. It should be noted that these are the constants from the original optimization problem that we analyzed. We know that the answer to the foregoing function problem is as follows:

$$G = G\{r_L; r_P; \xi\} = arg \left\{ \frac{\partial \Pi}{\partial \xi} = 0; \frac{\partial \Pi}{\partial r_L} = 0; \frac{\partial \Pi}{\partial r_P} = 0 \right\} \tag{5}$$

We focus only on $\frac{\partial \Pi}{\partial \xi} = 0$ after taking the problem of credit risk ξ out of the simultaneous system of equations and using the derivative property of a partial derivative. The detailed analysis is as follows:

$$\left(r_L - A_1 - \frac{\partial C_L}{\partial \xi} - A_2 \frac{\partial C_D}{\partial \xi} \right) L(r_L) = 0 \tag{6}$$

Let F_1 equal $r_L - A_1 - \frac{\partial C_L}{\partial \xi} - A_2 \frac{\partial C_D}{\partial \xi}$, and it is known that $A_1 = A_2 \bar{r}_f$; rewriting Eq. (6), we obtain the optimal value ξ^* to satisfy the formula as follows:

$$F_1 = r_L - A_2 \bar{r}_f - \left(\frac{\partial C_L}{\partial \xi} + A_2 \frac{\partial C_D}{\partial \xi} \right) \Bigg|_{\xi = \xi^*} = 0 \tag{7}$$

Assumption 7 tells us that $C = C_L(\xi)L + C_D(\xi)D$, and we can use a similar concept of margin value to analyze.$F_1 = 0$. Let the marginal unit cost MC_ξ represent the unit cost change caused by the variational ξ, and its analytic expression is as follows:

$$MC_\xi = \frac{\partial C_L}{\partial \xi} + \frac{\partial C_D}{\partial \xi} \tag{8}$$

Naturally, we can redefine an adjustable margin unit cost function as follows:

$$MC_\xi^{AD} = \frac{\partial C_L}{\partial \xi} + \frac{1 - k}{1 - \rho} \frac{\partial C_D}{\partial \xi} \tag{9}$$

Combined with Assumption 5, we determine that the original solution value of ξ^* can be found using the following equation:

$$\varepsilon = MC_{\xi}^{AD}(\xi^*) \tag{10}$$

The equation becomes the following after bringing Assumption 8 into our analysis:

$$\varepsilon(FT) = MC_{\xi}^{AD}(\xi^*, FT) \tag{11}$$

Calculating the total differential of the two end regions of Eq. (11) and taking all factors influencing ε into account, we obtain the following:

$$\frac{\partial \varepsilon}{\partial FT}dFT + \sum \frac{\partial \varepsilon}{\partial x_{others}}dx_{others} = \frac{\partial MC_{\xi}^{AD}}{\partial \xi^*}d\xi^* + \frac{\partial MC_{\xi}^{AD}}{\partial FT}dFT \tag{12}$$

To simplify the equation, when ignoring all other factors influencing the interest margin profit ε except FinTech, we obtain the partial differential equation below:

$$\frac{\partial \varepsilon}{\partial FT}dFT = \frac{\partial MC_{\xi}^{AD}}{\partial \xi^*}d\xi^* + \frac{\partial MC_{\xi}^{AD}}{\partial FT}dFT \tag{13}$$

Furthermore, we obtain the direct differential of FinTech to ξ^* as follows:

$$\frac{d\xi^*}{dFT} = \frac{\frac{\partial \varepsilon}{\partial FT} - \frac{\partial MC_{\xi}^{AD}}{\partial FT}}{\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*}} \tag{14}$$

Combined with the significant substitution relation in Assumption 5, we find Eq. (14) as follows:

$$\frac{dCredit\ Risk}{dFT} = \frac{\frac{\partial MC_{\xi}^{AD}}{\partial FT} - \frac{\partial \varepsilon}{\partial FT}}{\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*}} \tag{15}$$

Eq. (15) is the quantitative expression of the effect of the development of FinTech on the credit risk of commercial banks under our assumptions. Now, simply analyze the value of Eq. (15).

Based on the results of the improved DLM model above, we find that the impact of FinTech on bank risk-taking depends on three main aspects. $\frac{\partial \varepsilon(FT)}{\partial FT}$ represents the impact on the interest margin profit from FinTech, which is also a quantitative measure of change; $\frac{\partial MC_{\xi}^{AD}(\xi^*, FT)}{\partial FT}$ and $\frac{\partial MC_{\xi}^{AD}(\xi^*, FT)}{\partial \xi^*}$ show the effects of FinTech and regulatory effort (reversed bank credit risk from Assumption 5) on the adjusted margin unit cost, respectively.

Then, with the help of the relationship between the above three parts, there are four possible situations of Eq. (15). In Situations 1a and 1b, $\frac{dCredit\ Risk}{dFT} < 0$, meaning that the development of FinTech in a commercial bank reduces credit risk; in Situations 2a and 2b, $\frac{dCredit\ Risk}{dFT} > 0$, meaning that the development of FinTech in a commercial bank increases credit risk.

Situation 1a. $\frac{\partial \varepsilon}{\partial FT} > \frac{\partial MC_{\xi}^{AD}}{\partial FT}$, $\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*} < 0$, which signifies that the impact on the interest margin profit from FinTech, $\frac{\partial \varepsilon}{\partial FT}$, is stronger than the effect of FinTech on the adjusted margin unit cost, $\frac{\partial MC_{\xi}^{AD}}{\partial FT}$; meanwhile, the effect of the regulatory effort on the adjusted margin unit cost, $\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*}$, stands at a negative value.

Situation 1b. $\frac{\partial \varepsilon}{\partial FT} < \frac{\partial MC_{\xi}^{AD}}{\partial FT}$, $\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*} > 0$, which signifies that the impact on the interest margin profit from FinTech, $\frac{\partial \varepsilon}{\partial FT}$, is weaker than the effect of FinTech on the adjusted margin unit cost, $\frac{\partial MC_{\xi}^{AD}}{\partial FT}$; meanwhile, the effect of the regulatory effort on the adjusted margin unit cost, $\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*}$, stands at a positive value.

Situation 2a. $\frac{\partial \varepsilon}{\partial FT} > \frac{\partial MC_{\xi}^{AD}}{\partial FT}$, $\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*} > 0$, which signifies that the impact on the interest margin profit from FinTech, $\frac{\partial \varepsilon}{\partial FT}$, is stronger than the effect of FinTech on the adjusted margin unit cost, $\frac{\partial MC_{\xi}^{AD}}{\partial FT}$; meanwhile, the effect of the regulatory effort on the adjusted margin unit cost, $\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*}$, stands at a positive value.

Situation 2b. $\frac{\partial \varepsilon}{\partial FT} < \frac{\partial MC_{\xi}^{AD}}{\partial FT}$, $\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*} < 0$, which signifies that the impact on the interest margin profit from FinTech, $\frac{\partial \varepsilon}{\partial FT}$, is weaker than the effect of FinTech on the adjusted margin unit cost, $\frac{\partial MC_{\xi}^{AD}}{\partial FT}$; meanwhile, the effect of the regulatory effort on the adjusted margin unit cost, $\frac{\partial MC_{\xi}^{AD}}{\partial \xi^*}$, stands at a negative value.

In addition, the above four situations are likely to exist in the corresponding empirical results of the FinTech development level, which is significantly positive or negative for bank risk-taking, and there may be heterogeneity over time. Moreover, considering that we use panel data, the above four situations are more appropriate for the following dynamic forms:

Situation 1. $\left.\frac{\partial \varepsilon}{\partial FT}\right|_{i,t} < \left.\frac{\partial MC_{\xi}^{AD}}{\partial FT}\right|_{i,t}, \left.\frac{\partial MC_{\xi}^{AD}}{\partial \xi}\right|_{i,t} > 0.$

Situation 2. $\left.\frac{\partial \varepsilon}{\partial FT}\right|_{i,t} > \left.\frac{\partial MC_{\xi}^{AD}}{\partial FT}\right|_{i,t}, \left.\frac{\partial MC_{\xi}^{AD}}{\partial \xi}\right|_{i,t} < 0$

Situation 3. $\left.\frac{\partial \varepsilon}{\partial FT}\right|_{i,t} > \left.\frac{\partial MC_{\xi}^{AD}}{\partial FT}\right|_{i,t}, \left.\frac{\partial MC_{\xi}^{AD}}{\partial \xi}\right|_{i,t} > 0$

Situation 4. $\left.\frac{\partial \varepsilon}{\partial FT}\right|_{i,t} < \left.\frac{\partial MC_{\xi}^{AD}}{\partial FT}\right|_{i,t}, \left.\frac{\partial MC_{\xi}^{AD}}{\partial \xi}\right|_{i,t} < 0$

The above analysis can help us understand the relationship between bank FinTech and credit risk.

Measurement of the FinTech index

We employ the text mining method and the Baidu search engine to build the bank FinTech index (FT_{it}). Text mining is a systematic process that uses data mining techniques to extract understandable and usable knowledge from a large number of unstructured and heterogeneous text information resources. The common techniques of text mining include word frequency statistics, text clustering, text classification, and so on. The text mining method based on word frequency statistics technology covers mainly the following four steps: text segmentation, text extraction, text dimension reduction, and text evaluation. Through these steps, the original text can be successively transformed into source text, structured data, knowledge, or a model and can ultimately create effective knowledge.

We build the bank FinTech index following the following four steps.

First, we indicate that the initial search items are composed of three parts. The first part is the year, the second is the bank name, and the last is our keywords. The reason we set the items in this way is that we focus on the application of bank FinTech at the bank-year level. We classify Chinese bank FinTech into the following five main categories: artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and internet technology. We establish the original keywords for these five main categories in Table B1. By doing so, we can effectively categorize the bank FinTech types and cover all the important words related to bank FinTech.

Second, we calculate the original keywords' frequency with the help of the Baidu search engine.[10] First, we use news articles containing the original keywords in Table B1 as target articles and employ the Baidu database to search for the number of target articles that were released for each bank from 2008 to 2017. Then, we count the total number of news articles released each year and calculate the frequency of the original keywords at the bank-year level.[11] The rationale for this approach is that the number of news items is highly correlated with many socioeconomic phenomena (Askitas and Zimmermann, 2009). The amount of bank FinTech news is positively related to bank FinTech input and development. Therefore, in an era when the network acts as the main medium of information transmission, as the amount of network news containing the original keywords in Table B1 increases, the better the development of bank FinTech.

Third, we choose the factor analysis method to construct the FinTech index (FT). From the previous two steps, we obtained new numbers for 20 different items for 60 banks in 10 years. (1) Based on the original keywords in each dimension, we construct the artificial intelligence technology index (FTA_{it}), blockchain technology index (FTB_{it}), cloud computing technology index (FTC_{it}), big data technology index (FTD_{it}), and internet technology index (FTI_{it}) in succession. First and foremost, pretests are carried out to determine whether there are shared elements among the original keywords in each dimension. The KMO tests and the approximate chi-square values of the Bartlett test of sphericity significantly reject the null hypothesis that the correlation coefficient matrix is a unit matrix, which indicates that there are shared factors among the original keywords. Thus, these keywords are appropriate for factor analysis. Second, the common factors are extracted following the principle that the eigenvalue should be greater than 1. The results show that the variance contribution rate of the extracted common factors exceeds 60%, indicating that the extracted factors can reflect the information contained in the keywords. Finally, to ensure that the indexes are positive, the maximum-minimum processing is applied to standardize data between 0 and 1, and FTA_{it}, FTB_{it}, FTC_{it}, FTD_{it}, and FTI_{it} are obtained. (2) Based on FTA_{it}, FTB_{it}, FTC_{it}, FTD_{it}, and FTI_{it}, we construct FT_{it} in a similar process as described above.

Finally, considering the real context of China, this paper evaluates the constructed result of the FT. Figs. 1 and 2 in the main text body demonstrate how the average FT and its subindexes change over the 2008–2017 period. The results show that bank FinTech was in continuous development during this period, and the development of internet technology is ahead of artificial intelligence technology, blockchain technology, cloud computing technology, and big data technology. These advancements are all highly consistent with the growth processes of Chinese bank FinTech.

[10] Baidu, founded in 2000, is the world's largest and most popular Chinese website and search engine.

[11] Given that the Baidu database does not disclose the total number of yearly news articles, we follow the research by Hou et al. (2016) and take the total number of news articles including the top ten commonly used Chinese idioms as the proxy variable of the total number of yearly news articles. The information on the top ten most commonly used Chinese idioms comes from the "Language Situation Report in China" issued by the Ministry of Education of the People's Republic of China.

Table B1
Initial lexicons for the FinTech index.

Field dimensions	A detailed description of the keywords			
Artificial intelligence	Intelligent	Face recognition	Live detection	Fingerprint recognition
Block-chain-related	Blockchain	Alliance chain	Test chain	Interconnected chain
Cloud technology	Cloud computing	Cloud architecture	Cloud service	Cloud finance
Data technology	Big data	Data layer	Dataset	Data flow
Internet technology	Mobile	Internet	Network	Online

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