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Fintech development, firm digitalization, and bank loan pricing[☆]

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ABSTRACT

Using loan-level data of Chinese listed companies from 2011 to 2018, this paper finds a significant decrease in bank loan prices due to the regional development level of financial technology (fintech). For small and medium-size regional commercial bank lenders, a 1% increase in the regional fintech development level can reduce the spread of bank loans for local firms by 1.13 basis points. The reduction effect is greater for enterprises with more binding financial constraints and those headquartered in regions with a lower level of banking competition. In addition, this study discusses the policy effect of firm digitalization. The results show that firm digitalization can reduce bank loan prices directly while weakening the policy effect of fintech in reducing loan prices indirectly. To promote the coordination between fintech development and firm digitalization in reducing corporate financing cost, fintech enterprises should take the role of helpers of commercial banks rather than competitors.

1. Introduction

Financial technology (fintech) comprehensively promotes innovation and transformation of the Chinese financial market and significantly impacts commercial banks. The Chinese fintech industry has gone through many stages, during which the relationships between fintech enterprises and commercial banks have deeply changed. A landmark event in Fintech's early development was the establishment of Zhejiang Alibaba Small Loan Co., Ltd. in June 2010, which started to provide small loans over the Internet. At that time, fintech development implies competition between technology companies, represented by Alibaba and Tencent, and traditional mainstream financial institutions, such as commercial banks. However, since the consolidation of Internet finance in March 2016, fintech development has shifted toward technology enterprises providing technical empowerment for financial institutions. In this process, leading fintech enterprises, represented by Ant and Tencent, have provided technical empowerment for a large number of regional small and medium-sized banks in China, gradually expanding the business scope of these financial institutions from their local areas to all of China.

Research on the competitive and cooperative relationships in lending activities between fintech companies and commercial banks has received extensive attention from scholars (Thakor, 2020). These studies focus on studying profitability (Phan et al., 2020), risk-taking level (Li et al., 2020; Wang et al., 2021a), client coverage scope (Philippon, 2019), and credit allocation efficiency (Tantri, 2021) of commercial banks affected by the development of fintech. The development of China's fintech has significantly impacted bank loans while having a smaller impact on deposits after the regulations on Yu'e Bao, Internet deposits, and other products.[1] Current literature studying the impact of fintech on bank lending has mainly focused on either mortgage lending (Buchak et al., 2018; Fuster et al., 2019), personal lending (Tang, 2019), or small business lending (Gopal and Schnabl, 2022; Beaumont et al., 2022). The policy effects of fintech on bank loans exist both in terms of price and amount. There has been little to no focus on lending to corporations. This paper aims to fill the research gap in understanding the impact of fintech development on corporate loan prices, which this study aims to fill.

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[1] In 2013, the launch of FinTech products, such as Yu'e Bao, pressured banks to absorb deposits, but then Chinese regulators took a series of normative measures to prevent Fintech innovation from raising the cost of bank deposits and thereby increased the financing cost of brick-and-mortar enterprises. Currently, the impact of fintech on bank deposits has been relatively small and the business innovation of fintech enterprises is mainly reflected on loans with obvious policy guidance to reduce the cost of corporate debt.

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Based on manually collected loan-level data of Chinese listed companies, this study finds that fintech development can effectively reduce the credit cost of enterprises: a 1% increase in the regional fintech development level can reduce the spread of bank loans for local firms by 0.193 basis points. Further studies show that the development of fintech will generate homogeneous effects on bank loan prices, both from different types of banks and loan contracts, as shown in this paper. The loan price decline effect exists only when the lender is a joint-stock commercial bank (JSB) or a small and medium-sized regional commercial bank (SMB) and is larger for an SMB lender. For an SMB lender, a 1% increase in the regional fintech development level can reduce the spread of bank loans for local firms by 1.13 basis points. Besides, the effect is only significant for loans with more than one year of maturity and is larger for long-term loans with maturity beyond five years. It is found that the impact channels of fintech development at reducing the credit cost of enterprises include both the alleviation of the external financing constraints of enterprises and the increase in the internal competition level of the banking system.

In addition, based on the leapfrog development of the digital economy, this study discusses the policy effect of firm digitalization in reducing loan prices. The results show that firm digitalization can reduce bank loan prices directly while weakening the policy effect of fintech in reducing loan prices indirectly. The widely existing regulatory arbitrage in the fintech industry may constitute a major obstacle to digitalization's enhancement of the policy effect of fintech development. To promote the coordination between fintech development and digital transformation in reducing the credit costs of enterprises, fintech enterprises should take the role of helpers of commercial banks rather than competitors, thus improving the efficiency of the banking sector in serving enterprise financing due to firm digitalization.

This paper makes three key contributions. First, this paper explores the impact of fintech development on bank loan prices with the use of loan-level data and develops a series of heterogeneous discussions based on bank types and loan contract terms, enriching the study of fintech's impact on banking. Second, this paper offers a pioneering discussion of the channels by which fintech affects bank loan prices. It is found that fintech enterprises both act as helpers and competitors to commercial banks, enhancing recognition of the relationships between fintech enterprises and commercial banks. Third, this paper identifies the substitutional relationship between enterprises' digital transformation and fintech development in reducing enterprise credit costs and deepens our understanding of how to effectively reduce enterprise credit costs in the digital era. It provides valuable insights into how digitalization on the firm side might be a substitute for digitalization on the bank side.

The remainder of this paper is organized as follows. Section 2 summarizes the existing relevant literature and proposes the hypotheses of the research. Section 3 describes the selected variables and data and introduces model specifications. Section 4 shows the empirical results of fintech development on bank loan prices. Section 5 explores the possible channels through which fintech development influences bank loan prices. Section 6 provides further discussions with the introduction of firm digitalization. Section 7 concludes this study.

2. Literature and hypotheses

Thakor (2020) suggests that "fintech is the use of technology to provide new and improved financial services", while the Financial Stability Board defines Fintech as "technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions, and the provision of financial services" (Vives, 2017). With regard to their expansion of the term fintech, these two definitions are inconsistent with each other. On the one hand, the narrow concept of fintech denotes the providers of financial services other than traditional financial intermediaries, such as banks. On the other hand, the broad concept represents financial innovation driven by technology, with implementers including both traditional intermediaries and emerging fintech enterprises (Allen et al., 2021). The narrow concept of fintech is adopted in this paper.

One promise of fintech enterprises is the unveiling of cheaper ways to overcome the frictions of financial contracting and lower the cost of financial services to improve consumer welfare (Thakor, 2020). The current research on the impact of fintech on commercial banks includes the following major dimensions. First, fintech development influences the performance of commercial banks. As a destructive innovation to the business model of commercial banks (Palmié et al., 2020), fintech innovation has a long-term impact on commercial banks' profit base. Because of the competitive relationship between external fintech enterprises and commercial banks, the growth of the fintech industry negatively influences bank performance (Phan et al., 2020; Zhao et al., 2021). Second, fintech development affects banks' risk-taking. The increased competition brought by fintech enterprises increases the risk appetite of commercial banks (Wang et al., 2021b). Third, fintech development improves the cost efficiency of banks (Lee et al., 2021). Fintech enterprises can enable banks by providing technology services and reducing the cost of bank services to enterprises (Tantri, 2021). The promoted efficiency in lending varies according to the degree to which banks cooperate with technology enterprises in China (Wang et al., 2021a). Fourth, fintech development changes the direction of bank credits. Fintech reduces the threshold of financial services and improves their availability (Bollaert et al., 2021), especially promoting the flow of financial funds to small and microenterprises (Sheng, 2021), which reduces the impact of credit discrimination on bank capital allocation (Philippon, 2019).

However, few studies have explored the impact of fintech on bank loan prices. For China's financial market, after the central government's cracking down on Internet finance, the direct competition between fintech enterprises and commercial banks has gradually decreased, and Fintech enterprises are positioned as enabling commercial banks. Fintech development has succeeded in disrupting the existing structure of the financial industry (Navaretti et al., 2017), increasing competition and efficiency of the financial system (Cortina and Schmukler, 2018), and deeply impacting bank loan pricing.

First, fintech development can reduce the information collection costs burdened by banks through technology empowerment and reduce loan prices. As technology has increased information exchange and reduced transaction costs, the production of financial services could become disaggregated (Feyen et al., 2021). Banks that apply digital technology in their operations can significantly reduce credit risk (Cheng and Qu, 2020). FinTech provides benefits relating to the information collection process and reduces the cost (Fasano and Cappa, 2022; Parlour et al., 2019), which would presumably lower loan pricing. It is pointed in Boot et al. (2021), the key new development is the abundance of non-financial data, including from digital footprints, which can be analyzed using machine learning and artificial intelligence, which gives rise to economies of scale in data usage and thus benefits information collection. In general, commercial banks with greater technology abilities empowered by fintech enterprises can face lower information asymmetry in the borrower–lender relationship and thus offer lower loan prices.

Second, fintech development can help enterprises reach banking services outside their region and enhance the competitiveness of regional banking markets. Fintech enterprises can efficiently collect enterprise data and share relevant information with banks outside their region, allowing enterprises to obtain loan services from banks of other regions, and their loan financing is no longer limited to local banks. In addition, fintech enterprises can effectively empower small banks and alleviate their weaker position when competing with large banks, thus greatly improving the degree of competition within the regional banking system. The literature on the banking sector structure largely supports the view that bank competition drives lower financing costs and reduces banks' monopoly rent (Boyd and De Nicolo, 2005; Berger and Black, 2011; Chong et al., 2013). Therefore, fintech development can reduce the price of bank loans by increasing the competitiveness of the banking industry.

Third, fintech development can bring no-bank financing opportunities and reduce enterprises' reliance on credit financing. Fintech innovation, such as blockchain finance, makes debt contracts more intelligent (Tinn, 2017), which makes bond financing more popular. Meanwhile, blockchain adoption increases the cost of debt financing (Chod et al., 2020). The substitution of bond financing for bank loans will reduce both the demand and loan prices of enterprises for bank loans. In addition, fintech is an important nonbank financing channel for enterprises (Temelkov and Gogova Samonikov, 2018). Nonbank lenders can secure soft information relating to creditworthiness (Jagtiani and Lemieux, 2018), directly competing with banks rather than addressing an unserviced market (Fuster et al., 2019; Cornelli et al., 2020). One of the typical no-bank fintech lenders is peer-to-peer (P2P) lending platforms. The use of alternative information sources by P2P lenders has allowed borrowers that would be classified as subprime clients by traditional banks to be slotted into "better" loan grades and therefore obtain lower-priced P2P loans (Jagtiani and Lemieux, 2017).

Based on the above analysis, this paper hypothesizes the following:

Hypothesis 1. Fintech development can reduce bank loan prices.

As mentioned above, the reason that fintech development can reduce bank loan prices may be due to the improved operating efficiency of lending banks through the digital empowerment of fintech enterprises (complementary effect) or the emergence of new financing channels for enterprises (substitution effect). In the digital economy, data resulting from digital transformation have formed an important basis for investment decisions by finance providers (Huang et al., 2021), reducing costly payments for banks' monitoring efforts to reduce the degree of information asymmetry (Krishnaswami et al., 1999).

When the impact mechanism is primarily of digital empowerment, enterprises can provide more data information by improving their digitalization. These data and information are increasingly relied on by banks for risk control with the help of fintech (Begenau et al., 2018). Therefore, higher degrees of firm digitalization relate to a more obvious policy effect of fintech development on reducing bank loan prices.

When the impact mechanism is primarily an increase in financing channels, the digital transformation of enterprises should break through regional restrictions on the financing and help enterprises obtain financing from banks outside their region (Huang et al., 2020). In addition, the increase in enterprise information transparency brought by digitalization also has a countervailing effect on the decrease in bank credit loan prices by improving firms' access to financing from other sources, such as improving their financing conditions in the equity market (Chen et al., 2014). This should reduce enterprises' bank loan prices, and it does not depend on regional fintech development. In this situation, higher enterprise digital transformation relates to a weaker influence of fintech development on commercial banks' monopoly power and a smaller decline in bank loan prices created by fintech development.

Based on the above analysis, the digital transformation of enterprises helps to reduce the cost of bank loans. However, there is uncertainty regarding the policy effect of the digital transformation of enterprises on fintech at reducing the cost of bank loans. Considering that there is a huge amount of regulatory arbitrage incentives in the development of China's fintech industry (Claessens et al., 2018; Chorzempa and Huang, 2022), it still plays an insignificant role in promoting the credit risk control of commercial banks. The development of fintech is more about offering new financing channels for enterprises, breaking the regulatory constraints of regional operations on financial services and improving the geographical coverage of financial institutions' expanding services (Muganyi et al., 2022). Therefore, firm digitalization and fintech development have certain substitutability effects in reducing the loan price of enterprises. Based on this understanding, the digital transformation of enterprises will reduce the policy effect of fintech development.

Thus, the following hypothesis is constructed:

Hypothesis 2. Improvement in firm digitalization reduces bank loan prices; however, it also reduces the policy effect of fintech in reducing bank loan prices.

3. Data and methodology

3.1. Model design

To test Hypothesis 1, regarding the impact of fintech development on bank loan prices, the following benchmark econometric model is constructed.

$$\begin{aligned} spread_{ijct} &= \alpha_0 + \alpha_1 \times LnFinTech_{ct} + \alpha \times X_{ijct} \\ &+ Year + Industry + Banktype + Loantype + \xi_{ijct} \end{aligned} \tag{1}$$

where $Spread_{ijct}$ is the level of interest margin for listed company i headquartered in city c to obtain loans from commercial bank j in year t. $LnFinTech_{ct}$ is the natural logarithm of city c's fintech development level at year t. X_{ijct} is the control variable. *Year*, *Industry*, *Banktype*, *Loantype* represent the year fixed effect, industry fixed effect, lending bank type fixed effect, and loan type fixed effect, respectively. In this paper, the types of lending banks mainly consist of large state-owned commercial banks, joint-stock commercial banks, urban commercial banks, rural commercial banks, rural cooperative banks, rural banks, urban credit cooperatives, and rural credit cooperatives. Loan types mainly consist of credit loans without any enhancement measures and loans with 12 types of enhancement measures, including "guarantee", "guarantee + security", "guarantee + mortgage", "guarantee + mortgage + pledge", "guarantee", "guarantee + mortgage", "guarantee + mortgage + pledge", "guarantee + mortgage + pledge", "mortgage", "mortgage + pledge" and "pledge".

If fintech development poses competitive pressure on commercial banks, α_1 is expected to be negative in Eq. (1). The absolute value of α_1 represents that a 1% increase in fintech development level will generate a α_1% (or $100 \times \alpha_1$ basic points) reduction in the level of loan interest margin.

Then, the following models are used to test the effect of digitization of enterprises on bank loan prices and its moderating effect on the relationship between fintech development and loan prices:

$$\begin{aligned} spread_{ijct} &= \alpha_0 + \alpha_1 \times Digital_{ijct} + \alpha \times X_{ijct} \\ &+ Year + Industry + Banktype + Loantype + \xi_{ijct} \end{aligned} \tag{2}$$

$$\begin{aligned} spread_{ijct} &= \alpha_0 + \alpha_1 \times LnFinTech_{ct} \\ &+ \alpha_2 \times LnFinTech_{ct} \cdot Digital_{ijct} + \alpha_3 \times Digital_{ijct} \\ &+ \alpha \times X_{ijct} + Year + Industry + Banktype + Loantype + \xi_{ijct} \end{aligned} \tag{3}$$

where $Digital_{ijct}$ is the level of firm digitalization. α_1 in Eq. (2) is expected to be negative, and α_2 in Eq. (3) is expected to be positive.

3.2. Variables

3.2.1. Bank loan price

The explained variable in this study is the level of interest rate spread of bank loan contracts. Referring to Kim et al. (2013) and Gu et al. (2019), the real loan price is calculated after eliminating the benchmark interest rate (*benchrate)* factor. Based on loan maturity matching,[2] the nominal loan interest rate (*nomrate*) minus *benchrate* for the corresponding maturity is used to calculate the degree of deviation of the *nomrate* from *benchrate*, denoted *spread*.

3.2.2. Fintech development

The level of fintech development is characterized by the Peking University Digital Financial Inclusive Index of the prefecture-level or above cities. As the underlying data come from Ant Technology Group, the largest fintech enterprise in China, the above index is widely used to measure the level of regional Fintech development in China (Zhang et al., 2020; Ding et al., 2022; Luo et al., 2022). The natural logarithm of the fintech development level (*LnFinTech*) is used as the key explanatory variable in this paper.

The underlying data related to the Peking University Digital Inclusive Finance Index comes from the business data of Ant Technology Group. Ant Technology Group is the largest fintech enterprise in China, started with the third-party payment business, competing with banks' retail payment business, and later ventured into financial businesses such as credit, insurance, and mutual funds. Ant Technology Group labeled itself as a competitor to commercial banks especially the national ones in its early stages of development. However, after the tightening of fintech regulation, Ant Technology Group began to focus on lending assistance and turned to cooperation with commercial banks. At the same time, Chinese commercial banks are also actively developing their fintech business. Mainstream Chinese commercial banks such as Industrial and Commercial Bank of China have established fintech subsidiaries to fully empower their banking business lines and compete with fintech enterprises.

The Peking University Digital Inclusive Finance Index includes 33 indicators in three categories: the breadth of digital finance coverage, the depth of digital finance use, and the degree of digitalization of inclusive finance. All indicators are translated into the regional development level of Ant Technology Group's fintech-related business, which includes both Ant's self-operating business and Ant's cooperative business with financial institutions. In terms of cooperation with other financial institutions, Ant Technology Group undertakes the output of technology, while most cooperative banks are more positioned as channels for funds. Thus, the fintech described by the index formed by Ant Technology Group's relevant data is narrowly defined.

3.2.3. Financial constraint

The SA index (Hadlock and Pierce, 2010), a commonly used financing constraint index to represent the financial constraint (*FC*), is a reverse index: larger SA index values represent weaker financial constraints, which is calculated as:

$$SA = -0.737 \times lnsize + 0.043 \times lnsize^2 - 0.040 \times Age \tag{4}$$

where *lnsize* is the natural logarithm of the total assets of the companies (in million yuan) and *Age* is how long the enterprise has been established.

3.2.4. Banking competition

Following Degryse and Steven (2007) and Chong et al. (2013), the number of bank branches in each prefecture-level city is used to develop a Herfindahl–Hirschman index (HHI) to measure banking competition (*BC*). The HHI for a city's banking sector is calculated as follows:

$$HHI_{c,t} = \sum_{k=1}^{N}\left(\frac{Branch_{k,c,t}}{TotalBranches_{c,t}}\right)^2 \tag{5}$$

where $Branch_{k,c,t}$ is the number of branches of bank k in prefecture-level city c in year t. $TotalBranches_{c,t}$ is the total number of different banks in city c in year t. The value of the HHI ranges from 0 to 1. A higher value of the HHI means a lower level of banking competition.

3.2.5. Firm digitalization

In this study, the explained variable is the degree of firm digitalization. Most existing descriptions of the degree of firm digitalization are based on the frequency of the text words related to digitalization in the annual reports of enterprises (Gal et al., 2019; Zhao et al., 2020; Chen, 2023). The China Digital Economy Research Database "Digitalization of Listed Companies" from the China Stock Market & Accounting Research (CSMAR) database portrays the degree of digital transformation of listed companies in five dimensions and mines the frequency of corresponding text words in the annual reports of listed companies. The five dimensions are artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and digital technology application. This study summed the word frequencies of these five dimensions and then logarithmically processed them after adding 1. The values were used to portray the level of digital transformation of enterprises. For the selection of specific text words, refer to Appendix 1.

3.2.6. Control variables

Referring to Beladi et al. (2018) and Gu et al. (2019), this study introduces a list of control variables, including the characteristic data of listed company i in year t and the characteristic data of bank loans. The firm-level data consist of the natural logarithm of the asset scale (*size*), the asset–liability ratio (*lev*), the return on assets (*roa*), Tobin's Q value (*q*), the ratio of fixed assets to total assets (*fixed*), and a dummy variable showing whether the company is a state-owned enterprise (*state*). The loan-level characteristic data contain the loan credit amount (*amount*) and the loan maturity (*maturity*). *amount* is measured by the ratio of the loan contract amount to the total operating revenue of the borrowing enterprise, and *maturity* is measured by the number of years from the loan start date to the maturity date.

3.3. Data source and descriptive statistics

All variables used in this study are defined in Table 1. The loan contract data are manually collected from the listed companies' annual reports, excluding the data of companies that belong to the financial sector or have been delisted. The fintech data are provided by a research team from the Institution of Digital Finance at Peking University and Ant Financial Services Group.

[2] Specifically, combined with the benchrate for different maturity tiers announced by the People's Bank of China, the actual maturity of a loan is divided into the following five levels before November 22, 2014: 6 months or less, between 6 months and 1 year (inclusive), between 1 year and 3 years (inclusive), between 3 years and 5 years (inclusive), and more than 5 years. It is divided into the following three levels after November 22, 2014: 1 year or less, between 1 year and 5 years (inclusive), and more than 5 years.

Table 1
Variables definition.

Variable symbols	Variable names	Variable definitions
spread	Bank loan price	The nominal loan interest rate – the benchmark interest rate for the corresponding maturity
floatingratio	Bank loan price (Alternative measure)	(The nominal loan interest rate – the benchmark interest rate for the corresponding maturity)/the benchmark interest rate for the corresponding maturity
LnFinTech	The natural logarithm of Fintech development level	The natural logarithm of the Peking University Digital Financial Inclusive Index
LnCredit	The natural logarithm of Fintech development level(Alternative measure)	The natural logarithm of the digital credit service level
ivFinTech	The instrumental variable of fintech development level	As defined in Section 4.3
FC	Financing constraints	As defined in Section 3.2.3
BC	Banking Competition Level	As defined in Section 3.2.4
Digital	The degree of enterprise digitalization	As defined in Section 3.2.5
size	Enterprise size	The natural logarithm of total assets
roa	Return on Assets	Operating profit/total assets
lev	The ratio of debt to asset	Total debt/total assets
q	Tobin's q ratio	Market value/Net assets
fixed	The proportion of fixed assets	Net fixed assets/total assets
state	The enterprise's ownership	State=1 if it is state-owned, State=0 if it is private-owned
amount	Loan credit amount	The loan contract amount/the total operating revenue of the borrowing enterprise
maturity	loan maturity	The number of years from the loan start date to the maturity date
lpgdp	Economic development level	Ln(Regional gross domestic product/population)
gov	Government intervention level	Local finance budget expenditures/regional gross domestic product
fid	Financial development level	(Balance of RMB deposits in banking institutions+ Balance of RMB loans in banking institutions)/regional gross domestic product
fdi	The level of economic openness	The amount of foreign capital actually utilized (adjusted by exchange rate)/regional gross domestic product

The remainder of the financial data of listed companies come from the Wind and CSMAR databases.

To avoid the interference of outliers, all continuous variables are tailed up and down by 1%. Descriptive statistics of these variables are shown in Table 2. The number of successfully matched loan contract samples is 7,132 for 866 listed companies from 2011 to 2018, including 421 state-owned enterprises and 445 private enterprises. As shown in Table 2, the bank loan prices of different enterprises vary widely. The mean values of *spread* and floating ratio are 0.0023 and 0.0432, respectively, which means that the average bank loan prices of the sample enterprises are 23 basis points higher than the benchmark loan interest rate, or up 4.32%. The minimum value of *the floating ratio* is −0.6530, and the maximum value is 0.8069, which means that the minimum loan interest rate of the sample enterprises is 65.30% lower than the benchmark interest rate and 80.69% higher than the benchmark interest rate. In terms of bank loan amount and maturity, the average bank loan scale of the sample enterprises is 0.0453 times the total operating income of the enterprises, and the average loan maturity is 3.3203 years. In addition, the development level of fintech widely varies, with its highest level ($e^{5.7137}$) at 6.6765 times its lowest level ($e^{3.8151}$).

Furthermore, we compare the sample used in this paper with the whole sample of Chinese A share-listed companies. The average asset size of the firms in our sample is 6.405 billion yuan ($e^{22.5804}$), while the average asset size of all Chinese A-share listed non-financial enterprises from 2011 to 2018 is 4.314 billion yuan ($e^{22.1851}$). The asset size of the firms involved in the empirical study is a little larger than the average level of the entire sample of listed companies. At the same time, the ratio of debt to asset of the sample is 0.5641, higher than 0.439 of the listed companies as a whole; The proportion of state-owned enterprises is 0.4905, higher than the overall 0.3792 of listed companies. Overall, the samples used in this article are representative and consistent with the basic acknowledge that Chinese commercial banks are more willing to serve larger enterprises, state-owned enterprises, etc. Although some listed companies have established subsidiaries outside the cities where they headquartered, as this article focuses on bank loans disclosed by the headquarters of listed companies, the bank loan prices of these enterprises are largely influenced by the regional financial markets.

4. Empirical results

4.1. Basic regression

As shown in columns (1)–(4) of Table 3, under different fixed-effect models, the coefficient of *LnFinTech* is always significantly negative at the 1% or 5% levels, meaning that fintech development can reduce the loan price charged by banks. As shown in column (4), a one percent increase in the regional fintech development level can reduce the spread of bank loans for local firms by 0.193 basis points.

For the loan-level control variables, as shown in columns (1)–(2), the larger the loan amount is, the higher the loan price, consistent with intuition. Although the coefficients of *amount* in columns (3)–(4) are not significant, they are still positive. As shown in columns (1)–(4), the longer the loan maturity is, the lower the loan price, which is consistent with Degryse and Ongena (2005). This is likely because commercial banks are willing

Table 2
Descriptive statistics.

Variables	N	Mean	Std. Dev	Min	Max
spread	7132	0.0023	0.0107	−0.0335	0.0431
floatingratio	7132	0.0432	0.1918	−0.6530	0.8069
LnFinTech	7132	4.9356	0.4793	3.8151	5.7137
LnCredit	7123	4.6672	0. 3808	3.6355	5.2336
ivFinTech	7103	0.00008	0.0001	0	0.0006
FC	7132	−3.7594	0.2314	−4.3111	−3.1973
BC	7103	6.7772	0.3047	6.2704	7.7982
Digital	7132	0. 6390	1.0685	0	4.8442
size	7132	22.5804	1.1596	19.3167	26.8963
roa	7132	0.0283	0.0509	−0. 2749	0. 2235
lev	7132	0.5646	0.1747	0.0572	0.9851
q	7132	1.2243	1.1046	0.1217	11.1624
fixed	7132	0.2271	0.1768	0.0015	0.6945
state	7132	0.4902	0.4999	0	1
amount	7132	0.0453	0. 1069	0. 00003	0.8149
maturity	7132	3.3203	2.6400	0. 4849	15.0082
lpgdp	7013	11.2506	0. 5847	9.814	13.0557
gov	7013	0.1575	0. 0592	0. 0760	0.4380
fid	7013	3.6179	1.5892	1.0708	7.436
fdi	7013	0.0289	0.0190	0.0006	0.1113

Table 3
Basic regression.

Variables	(1)	(2)	(3)	(4)
LnFinTech	−0.00276***	−0.00243***	−0.00171**	−0.00193**
	(0.000794)	(0.000894)	(0.000842)	(0.000854)
size	−0.000903***	−0.000998***	−0.000867***	−0.000652***
	(0.000141)	(0.000158)	(0.000149)	(0.000151)
roa	−0.00441*	−0.00861***	−0.00969***	−0.00991***
	(0.00246)	(0.00298)	(0.00285)	(0.00289)
lev	0.0103***	0.00901***	0.00747***	0.00666***
	(0.000864)	(0.000931)	(0.000886)	(0.000885)
q	0.000260	0.000600***	0.000403**	0.000427**
	(0.000160)	(0.000183)	(0.000168)	(0.000169)
fixed	−0.0104***	−0.00838***	−0.00732***	−0.00716***
	(0.000681)	(0.000907)	(0.000862)	(0.000856)
state	−0.00297***	−0.00310***	−0.00280***	−0.00260***
	(0.000262)	(0.000288)	(0.000274)	(0.000277)
amount	0.00667***	0.00261*	0.00124	0.00165
	(0.00146)	(0.00151)	(0.00146)	(0.00146)
maturity	−0.000696***	−0.000670***	−0.000577***	−0.000575***
	(0.000045)	(0.000046)	(0.000044)	(0.000044)
Constant	0.0341***	0.0338***	0.0250***	0.0193***
	(0.00463)	(0.00525)	(0.00488)	(0.00496)
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes
Bank Type FE	No	No	Yes	Yes
Loan Type FE	No	No	No	Yes
Observations	7,132	7,132	7,132	7,132
Adjusted R-squared	0.146	0.180	0.253	0.265

Note: This table reports the results of the effect of regional fintech development on corporate loan prices. The explained variable is bank loan price, calculated as " the nominal loan interest rate – the benchmark interest rate for the corresponding maturity". Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

to attract high-quality customers with relatively low loan costs and maintain long-term lending relationships.

4.2. Heterogeneous analysis

Table 4 shows the results of subsample regression based on the heterogeneity of bank types. Columns (1)–(3) list the regression results of subsamples when the lender is a large state-owned commercial bank (LSB), a JSB, and an SMB,[3] respectively. As shown, fintech development cannot reduce the loan price when the lender is an LSB. The main reasons include the following: First, the loan pricing strategy of LSBs operating in the whole nation is relatively less affected by regional markets, and regional fintech development has no significant impact on its loan price. Second, fintech enterprises are mainly empowering the lending activities of JSBs and SMBs and do little to help LSBs in business process transformation. Third, a LSB can provide customers with bundled integrated services, and its borrowers may be insensitive to loan prices. The loan price decline effect exists when the lender is a JSB or an SMB and is larger for an SMB lender. According to China's regulatory policies for commercial banks, SMBs can operate lending businesses only locally and are thus subjected to greater competitive pressure from local fintech development. However, Chinese fintech enterprises mainly collaborate with SMBs and have a more obvious effect on improving the quality and efficiency of the credit business of SMBs. As shown in column (3), a one percent increase in the regional fintech development level can reduce the spread of bank loans for local firms by 1.13 basis points.

[3] In this paper, the types of SMBs include urban commercial banks, rural commercial banks, rural cooperative banks, rural banks, urban credit cooperatives, and rural credit cooperatives.

Table 4
Heterogeneity analysis based on bank types.

Variables	(1) *LSBs*	(2) *JSBs*	(3) *SMBs*
LnFinTech	0.000705	−0.00525**	−0.0113***
	(0.000828)	(0.00238)	(0.00358)
size	−0.000752***	−0.000387	−0.000591
	(0.000183)	(0.000322)	(0.000563)
roa	−0.0145***	−0.00126	−0.00380
	(0.00378)	(0.00512)	(0.0117)
lev	0.00541***	0.00920***	0.00972***
	(0.000961)	(0.00208)	(0.00346)
q	0.000131	0.000692**	0.000812
	(0.000208)	(0.000321)	(0.000604)
fixed	−0.00573***	−0.0136***	−0.00583*
	(0.00104)	(0.00202)	(0.00317)
state	−0.00138***	−0.00366***	−0.00589***
	(0.000310)	(0.000617)	(0.00108)
amount	0.00458**	0.00687**	−0.00848**
	(0.00178)	(0.00345)	(0.00348)
maturity	−0.000443***	−0.000596***	−0.00107***
	(5.11e−05)	(9.06e−05)	(0.000206)
Constant	0.0143***	0.0309**	0.0724***
	(0.00523)	(0.0128)	(0.0188)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes
Observations	4,107	1,774	1,251
Adjusted R-squared	0.204	0.208	0.282

Note: This table reports the results of the heterogeneous effects of regional fintech development on corporate loan prices for different bank types. The explained variable is bank loan price, calculated as "the nominal loan interest rate − the benchmark interest rate for the corresponding maturity". Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5 shows the subsample regression results based on the heterogeneity of loan contracts. As shown in columns (1)–(2), the effect of reducing loan prices is significant only for unsecured loans and is not significant for secured loans because fintech largely provides unsecured loans (Thakor, 2020). As shown in columns (3)–(5), the effect is only significant for loans with more than one year of maturity and is larger for long-term loans with maturity beyond five years. For banks, the competition for transaction loans within one year is sufficient, and more competition from fintech cannot affect their pricing. However, because of the imperfect competition in relationship loans with a maturity of more than one year, outside competition from fintech may weaken the monopoly pricing power of banks, forcing them to reduce loan prices.

4.3. Robustness checks

Table 6 used multiple alternative methods to re-estimate the empirical model. As shown in column (1), this article re-designs the fixed effects model and introduces *Industry* × *Year*, *Bank Type* × *Year* and *Loan Type* × *Year* fixed effects are used to control the impact of unobservable factors that change year by year at the industry, bank type, and loan type levels on loan prices. In column (2), this article adds city fixed effects to column (1) to control for the impact of unobservable variables at city level on bank loan prices. In column (3), this article also adds some common control variables at city level on the model setting of column (2), such as economic development level (*lpgdp*), government intervention level (*gov*), financial development level (*fid*), and the level of economic openness (*fdi*). In column (4), this article re-designs the estimation model based on column (1), adding firm fixed effect. Overall, all the coefficients of *LFinTech* in columns (1)–(4) are significantly negative at the 1%, 5%, or 10% levels, indicating that the basic model's results are robust.

Table 7 shows the results of the robustness test. In column (1), *spread* divided by *benchrate* is used to calculate the degree of deviation of the *nomrate* from *benchrate*, denoted *floatingratio*, as the explained variable. As shown in the regression results in column (1), the coefficient of the *floating ratio* is significantly negative at the 10% level, which means that the basic regression result is robust. In column (2), the natural logarithm of the credit service level, which is a sub-indicator of the Peking University Digital Financial Inclusive Index and directly reflects the development level of fintech enterprises in the credit field, denoted *LnCredit*, is used as the explanatory variable. As shown in the regression results in column (2), the coefficient of *LnCredit* is significantly negative at the 1% level, which means that the basic regression results are robust.

In addition, this paper constructs an instrumental variable to solve potential endogeneity problems. The most prominent development of Chinese fintech innovation is paced by the rapid development of third-party payments. Thus, this study manually collected data on China's third-party payment market published by iResearch, identified the transaction amounts of internet payments and mobile payments and added the two together to form the total amount of third-party payment transactions at the national level. In addition, this paper also considers the impact of different cities' characteristics on the development level of fintech and constructs an instrumental variable based on urban geographical advantages. As the largest fintech enterprises in China are Ant Group and Tencent, headquartered in Hangzhou and Shenzhen, respectively, these two cities have become the cities with the highest degree of fintech development in China and have a great radiation effect on the fintech development of other cities. The closer a city is to Hangzhou and Shenzhen, the higher its fintech development level. Based on the longitude and dimension data of the city, this paper describes the geographical advantage of fintech development, calculated as follows. First, the geometric arithmetic average value of the absolute value of the longitude and latitude differences between the city and Hangzhou Shenzhen are calculated. Next, the geometric arithmetic average value is solved based on the above two values to obtain the variable *dlocation*. The smaller the value of *dlocation is*, the more prominent the geographical distance advantage of the city's fintech development. During the sample period, *dlocation* did not change with time. This paper constructs an instrumental variable $ivFinTech_{c,t} = \frac{dlocation_c}{third_t}$ for the core explanatory variable (*LnFinTech*), which is negatively correlated with Fintech development.

Table 8 lists the 2SLS regression results using the instrumental variable of *LnFinTech*. Columns (1) and (2) list the results based on the introduction of the industry, year, bank type, loan type fixed effects. Considering the possibility that the development of mobile payments may affect the cost of corporate loans by affecting local economies and other factors, this article re-designs the empirical estimation model in columns (3) and (4). This paper introduces *Industry* ×*Year*, *Bank Type*×*Year*, *Loan Type*×*Year* fixed effects, and adds some common control variables at city level.

As the regression results of the first stage of 2SLS in columns (1) and (3) of Table 8 show, the coefficient of *ivFinTech* is significantly negative at the 1% level, indicating a significant negative relationship between the instrumental variable and Fintech development, which is consistent with the prediction of the design description of the instrumental variable in this paper. The regression results of the second stage of 2SLS in columns (2) and (4) of Table 8 show that the coefficient of *LnFinTech* is significantly negative at the 1% level, indicating that the regression results based on the instrumental variable are robust and consistent with the prediction of Hypothesis 1. In addition, the instrumental variable designed in this paper passes the unidentifiable test and weak instrumental variable test.

Table 5
Heterogeneity analysis based on loan contract terms.

Variables	(1) *unsecured*	(2) *secured*	(3) *maturity<=1*	(4) *1<maturity<=5*	(5) *maturity>5*
LnFinTech	−0.00332***	0.00135	0.000798	−0.00189*	−0.00496**
	(0.00111)	(0.00141)	(0.00268)	(0.00105)	(0.00202)
size	−0.000545***	−0.00149***	−0.000920*	−0.000849***	−0.000447
	(0.000191)	(0.000287)	(0.000471)	(0.000183)	(0.000399)
roa	−0.00298	−0.0157***	−0.0159**	−0.0147***	−0.0109
	(0.00339)	(0.00484)	(0.00643)	(0.00400)	(0.0107)
lev	0.0111***	0.00316**	0.00583**	0.00437***	0.0102***
	(0.00131)	(0.00127)	(0.00242)	(0.00113)	(0.00295)
q	0.000798***	−0.000181	0.00141***	1.95e−06	0.000894**
	(0.000232)	(0.000250)	(0.000321)	(0.000233)	(0.000449)
fixed	−0.00946***	−0.00352**	−0.0172***	−0.00715***	−0.00175
	(0.00115)	(0.00137)	(0.00283)	(0.00108)	(0.00225)
state	−0.00342***	−0.00172***	−0.00299***	−0.00228***	−0.00246***
	(0.000381)	(0.000424)	(0.000881)	(0.000352)	(0.000779)
amount	0.00293	0.000796	−0.0113***	0.00140	0.00594**
	(0.00186)	(0.00248)	(0.00373)	(0.00186)	(0.00287)
maturity	−0.000504***	−0.000663***	0.00376**	−0.00123***	−0.000219*
	(0.000056)	(0.00007)	(0.00189)	(0.000142)	(0.000123)
Constant	0.0320***	0.0269***	0.0260*	0.0309***	0.0193
	(0.00612)	(0.00873)	(0.0151)	(0.00589)	(0.0125)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes
Observations	4,164	2,968	1,259	4,826	1,047
Adjusted R-squared	0.265	0.289	0.335	0.276	0.372

Note: This table reports the results of the heterogeneous effects of regional fintech development on corporate loan prices for different loan contract terms. The explained variable is bank loan price, calculated as "the nominal loan interest rate – the benchmark interest rate for the corresponding maturity". Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6
Robustness test: Alternative regression methods.

Variables	(1)	(2)	(3)	(4)
LFinTech	−0.00234***	−0.00548*	−0.00633**	−0.00900**
	(0.000839)	(0.00295)	(0.00313)	(0.00355)
size	−0.000720***	−0.000663***	−0.000633***	0.000310
	(0.000153)	(0.000174)	(0.000176)	(0.000812)
roa	−0.00955***	−0.00664**	−0.00708**	−0.00355
	(0.00314)	(0.00326)	(0.00330)	(0.00519)
lev	0.00601***	0.00304***	0.00300***	0.00466*
	(0.000991)	(0.00109)	(0.00110)	(0.00265)
q	0.000254	0.000319*	0.000342*	−0.000990***
	(0.000167)	(0.000179)	(0.000181)	(0.000366)
gdzc1	−0.00692***	−0.00477***	−0.00457***	−0.00224
	(0.00101)	(0.00113)	(0.00115)	(0.00288)
amount	−0.00267***	−0.00176***	−0.00171***	0.00244
	(0.000285)	(0.000335)	(0.000337)	(0.00235)
maturity	0.00221*	0.00477***	0.00475***	0.00430***
	(0.00115)	(0.00121)	(0.00121)	(0.00150)
lpgdp			−0.000173	
			(0.000873)	
gov			0.00113	
			(0.00803)	
fid			0.0000939	
			(0.000616)	
fdi			0.0349*	
			(0.0203)	
Constant	0.0338***	0.0518***	0.0530***	0.0391
	(0.00528)	(0.0151)	(0.0205)	(0.0256)
Industry × Year FE	Yes	Yes	Yes	Yes
Bank Type × Year FE	Yes	Yes	Yes	Yes
Loan Type × Year FE	Yes	Yes	Yes	Yes
City FE	No	Yes	Yes	No
Firm FE	No	No	No	Yes
Observations	7,089	7,074	6,953	6,924
Adjusted R-squared	0.337	0.423	0.426	0.6000

Note: This table reports the results of the effects of regional fintech development on corporate loan prices with alternative regression methods. The explained variable is bank loan price, calculated as "the nominal loan interest rate – the benchmark interest rate for the corresponding maturity". Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Singleton observations are dropped in regressions due to fixed effects.

Table 7
Robustness test: Replacement of key variables.

Variables	(1) *floatingratio*	(2) *spread*
LnFinTech	−0.0281*	
	(0.0146)	
LnCredit		−0.00255***
		(0.000674)
size	−0.00873***	−0.000648***
	(0.00267)	(0.000150)
roa	−0.219***	−0.00986***
	(0.0525)	(0.00289)
lev	0.121***	0.00643***
	(0.0158)	(0.000885)
q	0.0111***	0.000408**
	(0.00327)	(0.000168)
fixed	−0.126***	−0.00738***
	(0.0156)	(0.000850)
state	−0.0468***	−0.00266***
	(0.00494)	(0.000279)
amountr	0.0218	0.00136
	(0.0248)	(0.00146)
maturity	−0.0100***	−0.000572***
	(0.000778)	(0.0000445)
Constant	0.251***	0.0219***
	(0.0857)	(0.00466)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Bank Type FE	Yes	Yes
Loan Type FE	Yes	Yes
Observations	7,132	7,123
Adjusted R-squared	0.269	0.266

Note: This table reports the results of the effects of regional fintech development on corporate loan prices after replacing key variables. *floatingratio* is used as the explained variable in column (1), calculated as "(The nominal loan interest rate – the benchmark interest rate for the corresponding maturity)/the benchmark interest rate for the corresponding maturity". *spread* is used as the explained variable in column (2), calculated as "the nominal loan interest rate – the benchmark interest rate for the corresponding maturity". Observations in column (2) are reduced due to the lack of data. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5. Discussion of the potential channels

As pointed out in Section 2, fintech development exerts the policy effect of reducing loan prices, both on the demand side and on the supply side. From the perspective of the demand side, with the help of fintech companies, the financing channels of enterprises have been greatly broadened; that is, they can increase nonbank financing such as equity and bonds and can also have more loan links with banks outside the region, thus greatly reducing the financing constraints of enterprises and reducing their dependence on existing banks. From the perspective of the supply side, with the help of fintech companies, some local banks with weak lending capacity have made up for their weaknesses, and the competition among different banks has become more symmetrical, which has greatly increased the degree of competition in the regional banking market, and the loan prices of existing banks are facing downward pressure.

5.1. Financing constraint

This section examines the role of financial constraints. The financing availability of enterprises will affect the loan price of enterprises. For enterprises with poor financing availability, because of the lack of other financing channels, banks, especially relationship banks, will have stronger monopoly pricing abilities, resulting in high bank loan prices. As institutions that provide financial services offered by different commercial banks nationally, fintech enterprises provide new financing channels for enterprises, which reduces the monopoly pricing abilities of commercial banks in regional financial markets and pushes the loan price downward. Empirically, it is expected that enterprises with harder access to capital experience a relatively larger drop in bank loan prices brought by regional fintech development.

Referring to Amore and Bennedsen (2016), the following empirical model is constructed to test whether financial constraint constitutes a channel for fintech development that affects bank loan prices:

$$\begin{aligned} &spread_{ijct} = \alpha_0 + \alpha_1 \times LnFinTech_{ct} \\ &+\alpha_2 \times LnFinTech_{ct} \cdot FC_{ijct} + \alpha_3 \times FC_{ijct} \\ &+\alpha \times X_{ijct} + Year + Industry + Banktype + Loantype + \xi_{ijct} \end{aligned} \tag{6}$$

Column (1) of Table 9 shows that the coefficient of the interaction term *LnFinTech* ×*FC* is significantly positive at the 5% level, which means that fintech development can help reduce the loan cost of enterprises with more serious financing constraints, as it improves their financing conditions by offering new financing channels and reducing the monopoly pricing power of banks. As the development of fintech improves the financing situation of enterprises, it can weaken the monopoly pricing ability of banks from the demand side of loans, thus reducing bank loan prices.

5.2. Banking competition

This section explores the role of banking competition. Fierce banking competition reduces the bargaining power of banks and hence reduces bank loan prices. Fintech development enables commercial banks to offset the shortcomings of the loan granting capacity of SMBs and makes the competition between SMBs and LSBs more equal. According to the prospectus of Ant Group in 2020, Ant cooperated with approximately 100 banks, most of which are urban commercial banks and rural (commercial) banks. The main form of this cooperation is Ant using its well-developed fintech abilities to help these SMBs issue loans, which

Table 8
IV regression.

Variables	(1) *LnFinTech*	(2) *spread*	(1) *LnFinTech*	(2) *spread*
LnFinTech		−0.0121***		−0.0448***
		(0.00326)		(0.0134)
ivFinTech	−481.9***		−192.3***	
	(27.17)		(9.938)	
size	0.0154***	−0.000427***	0.000484	−0.000616***
	(0.00203)	(0.000165)	(0.000683)	(0.000178)
roa	−0.105***	−0.0110***	−0.0603***	−0.00895***
	(0.0386)	(0.00298)	(0.0129)	(0.00340)
lev	−0.0629***	0.00593***	−0.0198***	0.00234**
	(0.0128)	(0.000915)	(0.00428)	(0.00114)
q	0.00775***	0.000492***	0.00199***	0.000406**
	(0.00221)	(0.000171)	(0.000703)	(0.000184)
fixed	−0.126***	−0.00869***	−0.00512	−0.00467***
	(0.0138)	(0.00101)	(0.00446)	(0.00116)
state	0.0102**	−0.00271***	0.00791***	−0.00145***
	(0.00398)	(0.000280)	(0.00131)	(0.000352)
amountr	−0.0707***	0.000686	−0.0220***	0.00396***
	(0.0168)	(0.00148)	(0.00472)	(0.00126)
maturity	0.00267***	−0.000539***	−0.000184	−0.000611***
	(0.000587)	(0.000046)	(0.000189)	(4.94e−05)
lpgdp			−0.0253***	−0.00197**
			(0.00342)	(0.000993)
gov			−0.408***	−0.0386**
			(0.0490)	(0.0152)
fid			−0.00885***	0.000398
			(0.00245)	(0.000633)
fdi			0.399***	0.0559***
			(0.0784)	(0.0213)
Constant	4.131***	0.0585***	5.329***	
	(0.0486)	(0.0140)	(0.0440)	
Year FE	Yes	Yes		
Industry FE	Yes	Yes		
Bank Type FE	Yes	Yes		
Loan Type FE	Yes	Yes		
Industry FE × Year FE			Yes	Yes
Bank Type FE × Year FE			Yes	Yes
Loan Type FE × Year FE			Yes	Yes
City FE			Yes	Yes
Observations	7,013	7,013	6,953	6,953
Adjusted R-squared	0.930	0.250	0.996	0.0225
Kleibergen–Paap rk		563.207		
LM statistic		(0.0000)		
Anderson canon. corr.				385.774
LM statistic				(0.0000)
Cragg–Donald Wald F statistic		310.272		374.365

Note: This table reports the results of the effects of regional fintech development on corporate loan prices with the introduction of instrumental variable. The instrumental variable of fintech development level is defined in Section 4.3. The explained variable in columns (1) and (3) is LnFinTech. The explained variable in columns (2) and (4) is *spread*. Observations in columns (1)–(2) are reduced due to the lack of data. Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Singleton observations are dropped in regressions due to fixed effects in columns (3) and (4).

ultimately helps to reduce bank loan prices in regions lacking banking competition. Empirically, it is expected that enterprises in a region with a lower level of banking competition experience a relatively larger drop in bank loan prices brought by regional fintech development.

The following empirical model is constructed to test whether banking competition constitutes a channel for fintech development to affect bank loan prices:

$$\begin{aligned} &spread_{ijct} = \alpha_0 + \alpha_1 \times LnFinTech_{ct} \\ &+\alpha_2 \times LnFinTech_{ct} \cdot BC_{ct} + \alpha_3 \times BC_{ct} \\ &+\alpha \times X_{ijct} + Year + Industry + Banktype + Loantype + \xi_{ijct} \end{aligned} \tag{7}$$

As shown in Column (2) of Table 9, the coefficient of the interaction term $LnFinTech \times BC$ is significantly negative at the 5% level, which means that fintech development can help reduce the loan cost of enterprises in areas with less bank competition, as it improves bank competition by offering technological support for SMBs. As the development of fintech improves regional banking competition, it can weaken the monopoly pricing ability of banks from the supply side of loans, thus reducing bank loan prices.

By comparing the geographic location of the firm with that of the bank, we can learn more about the channel of the loan spread decrease. If the effect is only present when the bank is in the same geography as the firm, then the effect is about the impact of fintech development on local bank competition. If the effect is still present when the bank is in a different geography, then it is also partially driven by fintech development fostering better information transmission across geographies. In this latter case, the fintech development distance across the two geographic locations might also provide interesting variations to explore further.

To explore the above possibilities, this paper firstly divided the entire sample into two sub-sample groups, namely: one sub-sample with the borrower and lender headquartered in the same province,[4] the other sub-sample with the borrower and

[4] A large number of the annual reports of listed companies only disclosed the names of the lending banks without the information about their branches. Therefore, we match the locations of the lenders' headquarters with the locations of the borrowers' headquarters here.

Table 9
Potential channels.

Variables	(1) *spread*	(2) *spread*
LnFinTech	0.00459	0.00950
	(0.00301)	(0.00646)
LnFinTech × *FC*	0.00161**	
	(0.000755)	
FC	−0.0107***	
	(0.00373)	
LnFinTech × *BC*		−0.00188**
		(0.000949)
BC		0.00604
		(0.00461)
size	−0.000436***	−0.000622***
	(0.000156)	(0.000157)
roa	−0.0102***	−0.00827***
	(0.00291)	(0.00290)
lev	0.00611***	0.00660***
	(0.000886)	(0.000887)
q	0.000533***	0.000478***
	(0.000171)	(0.000170)
fixed	−0.00673***	−0.00687***
	(0.000850)	(0.000848)
state	−0.00275***	−0.00268***
	(0.000283)	(0.000279)
amount	0.00191	0.00188
	(0.00146)	(0.00146)
maturity	−0.000581***	−0.000588***
	(4.43e−05)	(4.54e−05)
Constant	−0.0270*	−0.0163
	(0.0152)	(0.0319)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Bank Type FE	Yes	Yes
Loan Type FE	Yes	Yes
Observations	7,132	7,013
Adjusted R-squared	0.267	0.272

Note: This table reports the results of the discussions of potential channels that regional fintech development affects corporate loan prices. The explained variable is *spread*. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

lender headquartered in different provinces. The corresponding regression results are shown in columns (1)–(2) of Table 10. Besides, this paper further divided the sub-sample with the borrower and lender headquartered in different provinces into two sub-samples, including one with the borrower and lender headquartered in a neighboring province, and the other one with the borrower and lender headquartered in the non-neighboring provinces. The corresponding regression results are shown in columns (3)–(4) of Table 10. As shown, the coefficients of *LnFintech* are significantly negative in columns (1)–(3), positive but not significant in column (4), and both the absolute values of the coefficient of *LnFintech* in columns (1) and (3) are greater than that in column (2). This means that compared to information transmission across geographies, the policy effect of fintech in promoting banking competition contributes more to reducing loan prices; at the same time, as geographic distance increases, the effect of fintech on promoting cross-regional information transmission and reducing bank loan prices weakens.

6. Digitalization of enterprises and its impact

On the one hand, the digital transformation of the economy contributes to the development of fintech. Theoretically, the digital transformation of the economy will promote the improvement of the policy effect of fintech development (Chen et al., 2022). On the other hand, the digital transformation of the economy reduces the degree of information asymmetry between banks and enterprises and weakens the unique information advantage of Fintech enterprises (Jagtiani and Lemieux, 2018). Thus, an improvement in the degree of digital transformation may reduce the policy effect of fintech development on bank loan pricing.

As shown in Column (1) of Table 11, the coefficient of *Digital* is significantly negative at the 1% level, which means that the digitalization of enterprises will drive down loan prices. As shown in Column (2) of Table 11, the coefficient of the interaction term *LnFinTech* × *Digital* is significantly positive at the 10% level, which means that firm digitalization and fintech development have substitution effects in reducing corporate loan prices, which means that the higher the degree of digital transformation of enterprises is, the smaller the policy effect of fintech development in reducing loan prices, supporting Hypothesis 2.

Furthermore, the sample of loan contracts is divided into a subsample of loan contracts offered by large state-owned banks and a subsample of loan contracts offered by other types of banks, and regression is conducted to test the heterogeneous impacts of digital transformation on reducing the policy effect of fintech development. As the business scope of a large state-owned bank covers the whole country, if an enterprise becomes a client of a large state-owned bank, due to the client information sharing mechanism of the bank's internal information, it will be able to obtain the loan services of the bank's nationwide branch network. Therefore, the value of firm digitalization to break the monopoly of regional banks is not prominent. As for the enterprises applying for other types of bank loans, as these banks are basically operating in the local region, the relevant credit information of enterprises cannot be transmitted outside the region. Therefore, enterprises' access to banks outside the region through digital transformation is expected to mitigate the financing constraints of enterprises and promote competition between banks outside the region and banks within the region. These are also the policy effects that fintech development can bring. Therefore, the digital transformation of enterprises and the improvement of regional fintech development have a certain substitution effect for these enterprises. As shown in Table 11, the coefficient of the interaction term *LnFinTech* × *Digital* is negative but not significant in column (3), while it is significantly positive at the 5% level in column (4), which means that the digitalization of enterprises and fintech development have substitution effects in reducing bank loan prices for the clients of JSBs and SMBs.

Considering that fintech development may affect the degree of firm digitalization, the estimation of the corresponding regulatory effect may be biased. To address this problem, this paper takes the construction of the National Big Data Comprehensive Pilot Zone from 2015 to 2016 as the exogenous impact to explore the impact of digitalization on bank loan prices and the impact on the policy effect of Fintech development. The construction of the National Big Data Comprehensive Pilot Zone is a major strategy for China's current digital economy development (Lu and Zhang, 2020). By undertaking the required tasks assigned by the central government, the pilot zone has promoted the development of the regional digital economy (Qiu and Zhou, 2021). Enterprises located in regions implementing the pilot zone are believed to embrace a more rapid digital transformation compared to those in regions not implementing the pilot zone. By evaluating the implementation effect of this policy, we can further verify the impact of digitalization on the relationship between fintech development and bank loan prices.

This paper designs a dummy variable as the adjustment variable based on whether the province where an enterprise is located is included in the pilot zone. During the sample period, China has 10 provinces (municipalities directly under the central government and autonomous regions) approved to build the National Big Data Comprehensive Pilot Zone in batches. Based on the time when relevant provinces are approved to build the

Table 10
Heterogeneity analysis based on the geographic locations of the borrower and lender.

Variables	(1) same	(2) different	(3) neighboring	(4) non-neighboring
LnFinTech	−0.0130***	−0.00184**	−0.00662***	0.000143
	(0.00465)	(0.000936)	(0.00233)	(0.000857)
size	−0.00201***	−0.000559***	−0.000390	−0.000641***
	(0.000434)	(0.000175)	(0.000360)	(0.000191)
roa	−0.00769	−0.00954***	0.000388	−0.0153***
	(0.00931)	(0.00329)	(0.00554)	(0.00386)
lev	0.0139***	0.00830***	0.00979***	0.00538***
	(0.00370)	(0.000980)	(0.00203)	(0.00101)
q	−0.0000887	0.000741***	0.000802**	0.000167
	(0.000395)	(0.000205)	(0.000353)	(0.000218)
fixed	−0.0135***	−0.00782***	−0.00930***	−0.00564***
	(0.00312)	(0.000973)	(0.00197)	(0.00106)
state	−0.00343***	−0.00280***	−0.00486***	−0.00140***
	(0.00104)	(0.000305)	(0.000593)	(0.000321)
amount	−0.00448	0.00427***	0.00192	0.00470**
	(0.00373)	(0.00161)	(0.00268)	(0.00192)
maturity	−0.000505***	−0.000644***	−0.000916***	−0.000419***
	(0.000145)	(4.95e−05)	(0.000107)	(5.12e−05)
Constant	0.0965***	0.0227***	0.0423***	0.0140**
	(0.0204)	(0.00554)	(0.0128)	(0.00556)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes
Observations	922	6,210	2,303	3,907
Adjusted R-squared	0.325	0.197	0.221	0.203

Note: This table reports the results of the heterogeneous effects of regional fintech development on corporate loan prices based on the matching of geographic locations of the borrower and lender. The explained variable is *spread*. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 11
The effect of digitalization.

Variables	(1) Full Sample *spread*	(2) Full Sample *spread*	(3) LSBs *spread*	(4) JSBs & SMBs *spread*
LnFinTech		−0.00202**	0.000740	−0.00704***
		(0.000852)	(0.000829)	(0.00187)
LnFinTech × *Digital*		0.000727*	−0.00006	0.00159**
		(0.000408)	(0.000540)	(0.000648)
Digital	−0.000514***	−0.00431**	−0.000263	−0.00860**
	(0.000142)	(0.00213)	(0.00281)	(0.00339)
size	−0.000633***	−0.000613***	−0.000694***	−0.000536*
	(0.000151)	(0.000150)	(0.000182)	(0.000274)
roa	−0.00954***	−0.00946***	−0.0145***	−0.00258
	(0.00289)	(0.00288)	(0.00378)	(0.00440)
lev	0.00680***	0.00662***	0.00543***	0.00748***
	(0.000879)	(0.000886)	(0.000969)	(0.00165)
q	0.000432**	0.000428**	0.000153	0.000521**
	(0.000169)	(0.000169)	(0.000209)	(0.000265)
fixed	−0.00724***	−0.00753***	−0.00615***	−0.0104***
	(0.000862)	(0.000878)	(0.00106)	(0.00156)
state	−0.00254***	−0.00255***	−0.00135***	−0.00407***
	(0.000279)	(0.000279)	(0.000312)	(0.000522)
amount	0.00170	0.00149	0.00446**	−0.00246
	(0.00145)	(0.00145)	(0.00178)	(0.00237)
maturity	−0.000584***	−0.000570***	−0.000451***	−0.000720***
	(0.000045)	(0.0000044)	(5.14e−05)	(8.16e−05)
Constant	0.0116***	0.0203***	0.0133**	0.0459***
	(0.00380)	(0.00498)	(0.00535)	(0.00998)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Bank Type FE	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes
Observations	7,132	7,132	4,107	3,025
Adjusted R-squared	0.265	0.266	0.206	0.277

Note: Column (1) reports the results of the effects of firm digitalization on corporate loan prices. Columns (2)–(4) report the results of the moderating effects of firm digitalization on the relationship between regional fintech development and corporate loan prices. The explained variable is *spread*. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

pilot zone, this paper takes 2015 as the policy time node of enterprises belonging to Guizhou and 2016 as the policy time node of enterprises belonging to Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Henan, Shanghai, Chongqing and Guangdong. For enterprise *i*, if it is included in the pilot zone at phase *t*, the dummy variable $Bigdata_{ijct}$ is set to 1 in phase t and subsequent phases, while $Bigdata_{i,t}$ for the remaining time is set to 0.

The following models are used to test the effect of the construction of the National Big Data Comprehensive Pilot Zone on bank loan prices and its moderating effect on the relationship between fintech development and loan prices:

$$spread_{ijct} = \alpha_0 + \alpha_1 \times Bigdata_{ijct} + \alpha \times X_{ijct} + Year + Industry + Banktype + Loantype + \xi_{ijct} \quad (8)$$

$$spread_{ijct} = \alpha_0 + \alpha_1 \times LnFinTech_{ct} + \alpha_2 \times LnFinTech_{ct} \cdot Bigdata_{ijct} + \alpha_3 \times Bigdata_{ijct} + \alpha \times X_{ijct} + Year + Industry + Banktype + Loantype + \xi_{ijct} \quad (9)$$

Column (1) of Table 12 shows that the coefficient of *Bigdata* is significantly negative at the 1% level, which means that the digitalization of the local economy will drive down the loan price of local enterprises. Column (2) of Table 12 shows that the coefficient of the interaction term *LnFinTech* × *Bigdata* is significantly positive at the 1% level, which means that the digitalization of enterprises and the development of fintech have substitution effects in reducing enterprises' loan prices, which means that the higher the degree of enterprises' digital transformation is, the smaller the policy effect of fintech development in reducing enterprises' loan prices, supporting Hypothesis 2.

The above results imply that increasing firm digitalization will help to directly reduce the loan prices of enterprises directly but may also reduce the policy effect of fintech development on reducing loan prices indirectly. The reason behind this is that digital transformation can reduce the degree of information asymmetry between enterprises and external banks and reduce incumbent banks' hold-up power, thus reducing the value of fintech development in increasing banking competition. This provides empirical evidence that the role of fintech development in reducing bank loan prices may be driven more by its role of bringing more financing opportunities to enterprises rather than by changes in credit technology. Therefore, to reduce enterprise financing, policymakers can either promote the digital transformation of enterprises or develop external fintech enterprises. Considering the previous chaos in China's fintech industry, promoting the digitalization of enterprises rather than cultivating external market troublemakers may be useful guidance for policymakers.

Table 12
The effect of the big data pilot.

Variables	(1) *spread*	(2) *spread*
LnFinTech		−0.00217**
		(0.000856)
LnFinTech × *Bigdata*		0.0135***
		(0.00419)
Bigdata	−0.00142***	−0.0756***
	(0.000534)	(0.0230)
size	−0.000650***	−0.000647***
	(0.000152)	(0.000152)
roa	−0.0104***	−0.00967***
	(0.00291)	(0.00294)
lev	0.00660***	0.00644***
	(0.000881)	(0.000886)
q	0.000433**	0.000436**
	(0.000170)	(0.000171)
fixed	−0.00688***	−0.00725***
	(0.000842)	(0.000850)
state	−0.00257***	−0.00255***
	(0.000277)	(0.000276)
amount	0.00183	0.00157
	(0.00145)	(0.00145)
maturity	−0.000588***	−0.000573***
	(0.000044)	(0.0000044)
Constant	0.0113***	0.0204***
	(0.00384)	(0.00497)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Bank Type FE	Yes	Yes
Loan Type FE	Yes	Yes
Observations	7,132	7,132
Adjusted R-squared	0.265	0.267

Note: Column (1) reports the results of the effects of the construction of the National Big Data Comprehensive Pilot Zone on bank loan prices on corporate loan prices. Columns (2)–(4) report results of the moderating effects of the construction of the National Big Data Comprehensive Pilot Zone on the relationship between regional fintech development and corporate loan prices. The explained variable is *spread*. Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Further research shows that the digital transformation of enterprises and the development of the fintech industry have substitution effects in reducing bank loan prices, which means that firm digitalization weakens the policy effect of fintech development. This discovery may mean that the current development of fintech is more likely to only promote the cross-regional operation of regional financial institutions, which still belongs to the category of regulatory arbitrage to a certain extent. To realize the complementary effect of fintech development and firm digitalization in promoting the reduction of enterprises' credit financing costs, it is necessary to further enhance the technical empowerment of fintech to commercial banks to continuously improve the operating efficiency of commercial banks.

7. Conclusion

This paper empirically identifies the role of regional fintech development in reducing bank loan prices. The decline in loan prices exists only when the lender is a JSB or an SMB, and the reduction effect is larger when the lender is an SMB. In addition, the reduction in loan price only exists in unsecured loans and loans with more than one-year maturity. The instrumental variable test based on urban geographical advantages also supports the robustness of this conclusion. In addition, this paper empirically finds that fintech development contributes to a larger drop in bank loan prices for enterprises with binding financing constraints and regions with a lower level of banking competition. It is believed that alleviating financing constraints and increasing banking competition are two important channels for the policy effect of fintech development.

CRediT authorship contribution statement

Wen Chen: Conceptualization, Writing – original draft, Formal analysis, Supervision, Funding acquisition. **Weili Wu:** Methodology, Writing – review & editing. **Tonghui Zhang:** Writing – revising, Language editing.

Appendix

See Table A.1.

Table A.1
Specific text words related to firm digitalization.

Dimensions of digitalization	Corresponding text word
Artificial intelligence technology	machine learning, artificial intelligence, face recognition, business intelligence, identity verification, deep learning, biometrics, image understanding, semantic search, voice recognition, intelligent robotics, intelligent data analysis, autonomous driving, natural voice processing
Blockchain technology	bitcoin, distributed computing, consensus mechanism, federated chain, decentralization. The terms of cloud computing technology include: EB-level storage, multiparty secure computing, brain-like computing, stream computing, green computing, in-memory computing, cognitive computing, converged architecture, graph computing, Internet of Things, information physical systems, billion concurrency, cloud computing
Cloud computing technology	EB-level storage, multiparty secure computing, brain-like computing, stream computing, green computing, in-memory computing, cognitive computing, converged architecture, graph computing, Internet of Things, information physical systems, billion concurrency, cloud computing
Big data technology	mixed reality, data visualization, data mining, text mining, virtual reality, heterogeneous data, augmented reality, credit investigation.
Digital technology applications	B2B, B2C, C2B, C2C, Fintech, NFC payment, O2O, third-party payment, e-commerce, industrial internet, internet finance, internet healthcare, fintech, open banking, quantitative finance, digital finance, digital marketing, netlink, unmanned retail, mobile internet, mobile payment, smart agriculture, smart wear, smart grid, smart environmental protection, smart home, smart transportation, smart customer service, smart energy, smart investment, smart cultural travel, smart medical, smart marketing

References

Allen, F., Gu, X., Jagtiani, J., 2021. A survey of fintech research and policy discussion. Rev. Corp. Financ. 1, 259–339.

Amore, M.D., Bennedsen, M., 2016. Corporate governance and green innovation. J. Environ. Econ. Manag. 75, 54–72.

Beaumont, P., Tang, H., Vansteenberghe, E., 2022. The role of fintech in small business lending. Available at SSRN 4260842.

Begenau, J., Farboodi, M., Veldkamp, L., 2018. Big data in finance and the growth of large firms. J. Monetary Econ. 97, 71–87.

Beladi, H., Chao, C.C., Hu, M., 2018. Does tax avoidance behavior affect bank loan contracts for Chinese listed firms? Int. Rev. Financ. Anal. 58, 104–116.

Berger, A.N., Black, L.K., 2011. Bank size, lending technologies, and small business finance. J. Bank. Financ. 35 (3), 724–735.

Bollaert, H., de Silanes, F.L., Schwienbacher, A., 2021. Fintech and access to finance. J. Corp. Financ. 101941.

Boot, A., Hoffmann, P., Laeven, L., Ratnovski, L., 2021. Fintech: what's old, what's new? J. Financ. Stab. 53, 100836.

Boyd, J.H., De Nicolo, G., 2005. The theory of bank risk taking and competition revisited. J. Finance 60 (3), 1329–1343.

Buchak, G., Matvos, G., Piskorski, T., Seru, A., 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. J. Financ. Econ. 130 (3), 453–483.

Chen, W., 2023. Can low-carbon development force enterprises to make digital transformation? Bus. Strategy Environ. 32 (4), 1292–1307.

Chen, T.Y., Dasgupta, S., Yu, Y., 2014. Transparency and financing choices of family firms. J. Financ. Quant. Anal. 49 (2), 381–408.

Chen, X., Yan, D., Chen, W., 2022. Can the digital economy promote FinTech development? Growth Change 53 (1), 221–247.

Cheng, M., Qu, Y., 2020. Does bank FinTech reduce credit risk? Evidence from China. Pac.-Basin Finance J. 63, 101398.

Chod, J., Trichakis, N., Tsoukalas, G., Aspegren, H., Weber, M., 2020. On the financing benefits of supply chain transparency and blockchain adoption. Manage. Sci. 66 (10), 4378–4396.

Chong, T.L., Lu, L., Ongena, S., 2013. Does banking competition alleviate or worsen credit constraints faced by small- and medium-sized enterprises? Evidence from China. J. Bank. Financ. 37 (9), 3412–3424.

Chorzempa, M., Huang, Y., 2022. Chinese fintech innovation and regulation. Asian Econ. Policy Rev. 12384.

Claessens, S., Frost, J., Turner, G., Zhu, F., 2018. Fintech credit markets around the world: size, drivers and policy issues. BIS Q. Rev. September.

Cornelli, Giulio, Frost, Jon, Gambacorta, Leonardo, Rau, P. Raghavendra, Wardrop, Robert, Ziegler, Tania, 2020. Fintech and Big Tech Credit: A New Database. BIS Working Paper, No. 887.

Cortina, J.J., Schmukler, S.L., 2018. The fintech revolution: A threat to global banking? In: World Bank Research and Policy Briefs. 125038.

Degryse, H., Ongena, S., 2005. Distance, lending relationships, and competition. J. Finance 60 (1), 231–266.

Degryse, H., Steven, O., 2007. The impact of competition on bank orientation. J. Financ. Intermediation 16 (3), 399–424.

Fasano, F., Cappa, F., 2022. How do banking fintech services affect SME debt? J. Econ. Bus. 121, 106070.

Feyen, E., Frost, J., Gambacorta, L., Natarajan, H., Saal, M., 2021. Fintech and the Digital Transformation of Financial Services: Implications for Market Structure and Public Policy. BIS Papers, No. 117.

Fuster, A., Plosser, M., Schnabl, P., Vickery, J., 2019. The role of technology in mortgage lending. Rev. Financ. Stud. 32 (5), 1854–1899.

Gal, P., Nicoletti, G., von Rüden, C., OECD, S.S., Renault, T., 2019. Digitalization and productivity: In search of the holy grail-firm-level empirical evidence from European countries. Int. Prod. Monit. (37), 39–71.

Gopal, M., Schnabl, P., 2022. The rise of finance companies and fintech lenders in small business lending. Rev. Financ. Stud. 35 (11), 4859–4901.

Gu, X., Xin, Y., Xu, L., 2019. Expected stock price crash risk and bank loan pricing: Evidence from China's listed firms. Pac.-Basin Finance J. 57, 101166.

Hadlock, C.J., Pierce, J.R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. Rev. Financ. Stud. 23 (5), 1909–1940.

Huang, Y., Pagano, M., Panizza, U., 2020. Local crowding-out in China. J. Finance 75 (6), 2855–2898.

Huang, S., Xiong, Y., Yang, L., 2021. Skill acquisition and data sales. Manage. Sci. http://dx.doi.org/10.1287/mnsc.2021.4117.

Jagtiani, J., Lemieux, C., 2017. Fintech Lending: Financial Inclusion, Risk Pricing, and Alternative Information. Federal Reserve Bank of Philadelphia Working Paper, No. 17-17.

Jagtiani, J., Lemieux, C., 2018. Do fintech lenders penetrate areas that are underserved by traditional banks? J. Econ. Bus. 100, 43–54.

Kim, J.B., Song, B.Y., Tsui, J.S., 2013. Auditor size, tenure, and bank loan pricing. Rev. Quant. Financ. Account. 40 (1), 75–99.

Krishnaswami, S., Spindt, P.A., Subramaniam, V., 1999. Information asymmetry, monitoring, and the placement structure of corporate debt. J. Financ. Econ. 51 (3), 407–434.

Lee, C.C., Li, X., Yu, C.H., Zhao, J., 2021. Does fintech innovation improve bank efficiency? Evidence from China's banking industry. Int. Rev. Econ. Finance 74, 468–483.

Li, J., Li, J., Zhu, X., Yao, Y., Casu, B., 2020. Risk spillovers between FinTech and traditional financial institutions: Evidence from the US. Int. Rev. Financ. Anal. 71, 101544.

Lu, J., Zhang, M., 2020. The harmonious development of big data industry and financial agglomeration in Guizhou. J. Risk Anal. Crisis Response 9 (4), 163–167.

Luo, S., Sun, Y., Zhou, R., 2022. Can fintech innovation promote household consumption? Evidence from China family panel studies. Int. Rev. Financ. Anal. 82, 102137.

Muganyi, T., Yan, L., Yin, Y., Sun, H., Gong, X., Taghizadeh-Hesary, F., 2022. Fintech, regtech, and financial development: evidence from China. Financ. Innov. 8 (1), 1–20.

Navaretti, G.B., Calzolari, G., Pozzolo, A.F., 2017. FinTech and banks: Friends or foes? Eur. Econ. (2), 9–30.

Palmié, M., Wincent, J., Parida, V., Caglar, U., 2020. The evolution of the financial technology ecosystem: An introduction and agenda for future research on disruptive innovations in ecosystems. Technol. Forecast. Soc. Change 151, 119779.

Parlour, C.A., Rajan, U., Zhu, H., 2019. Fintech Disruption, Payment Data, and Bank Information. NBER Working Paper, 22476.

Phan, D.H.B., Narayan, P.K., Rahman, R.E., Hutabarat, A.R., 2020. Do financial technology firms influence bank performance? Pac.-Basin Finance J. 62, 101210.

Philippon, T., 2019. On Fintech and Financial Inclusion. Working Paper 26330, National Bureau of Economic Research.

Qiu, Z., Zhou, Y., 2021. Development of digital economy and regional total factor productivity: An analysis based on national big data comprehensive pilot zone. J. Financ. Econ. 47 (07), 4–17.

Sheng, T., 2021. The effect of fintech on banks' credit provision to SMEs: Evidence from China. Finance Res. Lett. 39, 101558.

Tang, H., 2019. Peer-to-peer lenders versus banks: substitutes or complements? Rev. Financ. Stud. 32 (5), 1900–1938.

Tantri, P., 2021. Fintech for the poor: Financial intermediation without discrimination. Rev. Financ. 25 (2), 561–593.

Temelkov, Z., Gogova Samonikov, M., 2018. The need for fintech companies as non-bank financing alternatives for sme in developing economies. Int. J. Inf. Bus. Manag. 10 (3), 25–33.

Thakor, A.V., 2020. Fintech and banking: What do we know? J. Financ. Intermediation 41, 100833.

Tinn, K., 2017. Blockchain and the future of optimal financing contracts. Available at SSRN 3061532.

Vives, X., 2017. The impact of FinTech on banking. Eur. Econ. (2), 97–105.

Wang, R., Liu, J., Luo, H., 2021a. Fintech development and bank risk taking in China. Eur. J. Finance 27 (4–5), 397–418.

Wang, Y., Xiuping, S., Zhang, Q., 2021b. Can fintech improve the efficiency of commercial banks?—An analysis based on big data. Res. Int. Bus. Finance 55, 101338.

Zhang, X., Tan, Y., Hu, Z., Wang, C., Wan, G., 2020. The trickle-down effect of fintech development: From the perspective of urbanization. China World Econ. 28 (1), 23–40.

Zhao, J., Li, X., Yu, C.H., Chen, S., Lee, C.C., 2021. Riding the FinTech innovation wave: FinTech, patents and bank performance. J. Int. Money Finance 102552.

Zhao, T., Zhang, Z., Liang, S.K., 2020. Digital economy, entrepreneurship, and high-quality economic development: Empirical evidence from urban China. Manag. World 36 (10), 65–76.