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# FinTech development and commercial bank efficiency in China

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ABSTRACT

The rapid development of financial technology (FinTech) is challenging the business of commercial banks. This research analyzes the impact mechanisms of FinTech on the efficiency of commercial banks in China, drawing from the principles of consumer theory, disruptive innovation theory, and technology spillover theory. We apply the DEA–Malmquist model to calculate the total factor productivity of 74 commercial banks from 2012 to 2019 and utilize the text mining method to construct the FinTech development index during the same period. Finally, this study investigates FinTech's effects on commercial bank efficiency in China through the dynamic panel-generalized model of moments. The results show the following. First, FinTech development reduces the commercial bank efficiency for the overall effect. Second, its development affects the debt side of commercial banks, which becomes less efficient because of the rising debt cost. Third, various types of commercial banks are impacted differently by FinTech; urban commercial and rural commercial banks are the most influenced by FinTech, while joint-stock banks are the least influenced. Fourth, regional commercial banks are impacted more by FinTech, with those in the east region more affected. The research conclusions offer theoretical and practical values for deepening the reform of commercial banks and for developing and applying FinTech.

## 1. Introduction

Financial technology (FinTech) has developed rapidly in recent years, as represented by artificial intelligence, big data, blockchain, and cloud computing. With such technical advantages, FinTech companies have attracted extensive attention from regulators, consumers, investors, and academic circles by providing services that have significantly changed the original financial ecology. FinTech initially applied information technology (IT) to non-bank payment transactions and then harnessed information and computer technology such as big data for brokerage firms, bank credits, and insurance products. One generally accepted definition of FinTech in academic circles is that of the Financial Stability Board (FSB), which released its Analysis Framework Report in March 2016. According

*Abbreviations:* CAR, Capital adequacy ratio; FE, Fixed effect; FSB, Financial Stability Board; GMM, Generalized model of moments; IoT, Internet of Things; IT, Information technology; R&D, Research and development; RE, Random effect; ROE, Return on equity; SEA, South-East Asian; SFA, Stochastic frontier approach; SME, Small- to medium-size enterprises; TFP, Total factor productivity; VIF, Variance inflation factor; BvD, Bureau van Dijk; CNY, Chinese Yuan; DEA, Data envelopment analysis; GARCH, Generalized AutoRegressive Conditional Heteroskedasticity; GDP, Gross domestic product; L.C, Lag term of Cost; L.R, Lag term of ROE; L.S, Lag term of SFA; LI, Bank liquidity level; L.M, Lag term of M; OLS, Ordinary Least Squares; RC, Actual total cost.

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to FSB (2016), FinTech refers to the promotion of financial innovation through technical means to form a business model that significantly impacts financial markets, institutions, financial services, technology applications and processes, and products. The Basel Committee on Banking Supervision (2018) divides the FinTech business model into five categories: payment and settlement; deposits, loans, and capital raising; investment management; market facilities; and others. Among them, the Internet of Things (IoT), robo-advice, and blockchain can bring value to innovators (Chen, Wu, & Yang, 2019; Hsieh & Lee, 2020; Lee, Wang, & Ho, 2020a; Wu, Lee, Lee, & Peng, 2022).

Domestic commercial banks have increased their application of FinTech, which has developed rapidly in China over the past decade. From 2009 to 2019, investment in the cloud computing industry rose from 5.59 billion Chinese yuan (CNY) to 9.12 billion CNY. The scale of the IoT market also continues to expand, from 489.65 billion CNY in 2013 to 1.68 trillion CNY in 2019, making China the largest IoT market in the world.

Commercial banks have increased their investment in digital transformation. In 2019, the market scale of IT solutions in China's banking industry reached 42.58 billion yuan, marking a 23% year-on-year increase. Banks have accelerated the layout of FinTech in terms of constructing the ecological scene and optimizing service channels. This study considers the rapid development of FinTech in China and its application by commercial banks (Goldstein, Jiang, & Karolyi, 2019; Hsieh, Lee, & Lin, 2022; Lee & Wang, 2022; Zhang, Liang, & Lee, 2023), taking China's commercial banks as samples for empirical analysis.

From an efficiency standpoint, FinTech development has impacted China's commercial banks in two ways. First, FinTech companies compete with commercial banks by providing cross-border financial services that improve the debt cost of commercial banks, reduce the income of their assets, and lower their efficiency. Regarding liability factors, the solid inclusive nature of FinTech has attracted long-tail customers of commercial banks, accelerated financial disintermediation, and created new customer needs. In the asset business, the loan cost of commercial banks is high, and income is low. FinTech companies can more accurately describe customers' trading habits, investment and financing needs, and other behavioral characteristics with the help of intelligent decision-making, marketing, and risk control systems and models that optimize loan and consumer evaluations (Aslan & Sensoy, 2020; Bartlett, Morse, Stanton, & Wallace, 2022; Nie & Lee, 2023; Wan & Lee, 2023). Thus, convenient and low-cost loan services can be provided to the market. The Internet enables FinTech companies to provide loan services that cover a more comprehensive range of objects and to give differentiated loan interest rates to different groups with the help of a big data model. In areas with more FinTech lending, borrowers refinance more (Buchak, Matvos, Piskorski, & Seru, 2018; Jiang et al., 2021; Liu, Choo, Lee, & Lee, 2023).

The second avenue of impact is that FinTech supports financial sector development by enhancing access (loans), depth (deposits), and savings within China's financial institutions (Muganyi et al., 2022; Wang, Lee, & Wu, 2023). Commercial banks continue to reshape their business with the aid of FinTech, helping reduce their debt cost, increase the income of their assets, and ultimately improve their efficiency. First, these banks can directly learn the operation mode of FinTech companies and their specific products and services, make use of the companies' strong financial advantages, increase capital investment, imitate their product types, absorb their service ideas and realize the diversification of products and services (Berger, 2003; Sun, Zhang, & Fang, 2021; Zhang, Liu, Zhang, & Pang, 2021; Sokhanvar, Çiftçioğlu, & Lee, 2023). Second, commercial banks can actively compete with FinTech companies, create a flexible organizational structure and incentive mechanism, attract many financial science and technology talents, conduct technology research and development (R&D), and achieve their profit objectives.

The total effect of FinTech on commercial bank efficiency is still being debated. Some researchers have noted that it improves such efficiency by reducing commercial banks' operating costs and improving their service efficiency (Wang et al., 2021; Lee et al., 2020a; Lee, Wang, & Ho, 2020b; Chen, Cheng, Lee, & Wang, 2021; Chen, You, & Chang, 2021). In contrast, Jagtiani and Lemieux (2018) found that the lending activities of FinTech companies erode the market of traditional commercial banks. Through empirical research on 41 commercial banks in Indonesia, Phan, Narayan, Rahman, and Hutabarat (2020) concluded that FinTech development cuts the efficiency of commercial banks. Nonetheless, a question remains concerning whether the total effect is beneficial or harmful; thus, based on the existing literature, this research explores such an impact and analyzes the influence of regional and equity differences of commercial banks on this relationship, offering theoretical and practical significance. The paper's innovations are as follows.

First, we investigate the impact of FinTech companies providing financial services and examine this technology's overall impact on efficiency from an empirical perspective by using the principles of consumer theory, disruptive innovation theory, and technology spillover theory.

Second, based on investigating the overall effect of FinTech on commercial banks, we study the ways that FinTech influences commercial banks from their asset and liability sides and present the impactful ways that it improves the debt cost and reduces their efficiency.

Third, from the perspective of efficiency, this study provides a comprehensive viewpoint for investigating the impact of FinTech on commercial banks. We also examine whether commercial banks of different types and regional properties exhibit heterogeneity under the impact of FinTech.

The remainder of the paper runs as follows. Section 2 develops three hypotheses, Section 3 presents the data and the model, and Section 4 provides empirical results and analyses. Finally, Section 5 summarizes the main findings and gives suggestions.

## 2. Hypotheses development

### 2.1. FinTech and commercial bank efficiency

The impact of FinTech on the efficiency of commercial banks is complex, and the conclusions obtained when applying relevant theories for logical analysis are also ambiguous. Fig. 1 illustrates a brief impact path of FinTech on the efficiency of commercial banks.

Consumer theory (Aaker & Keller, 1990) holds that if a new service can better meet the needs of consumers, then it can replace the old service. Suppose FinTech companies provide consumers with better financial services in specific businesses (e.g., deposits, loans, payments, and remittances). In that case, consumers can reduce their use of commercial banks' traditional financial services, accelerate financial disintermediation, lower the profitability of commercial banks, and decrease commercial bank efficiency when the short-term cost is fixed. Conversely, when providing financial services, FinTech companies are affected by specific regulations and the inclusive nature of FinTech, and their target customer groups are long-tail customers of commercial banks. These customers demand financial services, but their risk level is high within the risk control system of commercial banks; thus, commercial banks often refuse to provide them with financial services. As the income of these long-tail customers only accounts for a minimal share of commercial banks' profits, their loss hardly reduces the profitability of commercial banks and will not significantly affect their efficiency.

Disruptive innovation theory (Christensen, 1997) maintains the following argument: when emerging enterprises that provide more convenient and lower-cost products and services through innovative technologies enter a specific market, they improve the degree of market competition. When financial products absorb residents' funds and participate in the interbank market in the form of money market funds, it becomes difficult for banks to obtain funds from the traditional deposit market. If they obtain funds through the interest rate competition, their debt cost will likely rise, and their efficiency will decline when short-term profits remain unchanged. At the same time, when FinTech companies provide financial services to residents, they carry out consumer education to a certain extent. Residents who are unwilling or inept at using financial services may begin to use financial services or use them more. This outcome also stimulates the demand of all consumers for financial services. The usage of technological services contributes to better access to external credit facilities by small- to medium-size enterprises (SMEs) (Agyekum, Reddy, Wallace, & Wellalage, 2022; Hsieh, Lee, & Shen, 2023). Given that higher levels of competition in the Chinese banking industry lead to higher levels of credit risk (Tan, Lau, & Gozgor, 2021), commercial banks extend more loans to the public. The market capacity of the financial industry will then increase, and existing commercial banks can provide more financial services. Competition from new non-bank FinTech companies makes the least efficient banks unprofitable and subsequently, moves out of the banking industry; thus, the efficiency of existing commercial banks will rise.

Hornuf, Klus, Lohwasser, and Schwienbacher (2021) started with the technology spillover theory to discuss the channel of competition and cooperation between FinTech and commercial banks. They believed that commercial banks could vigorously develop and apply FinTech to significantly improve their total factor productivity (TFP). In contrast, in the short term, no matter which of the above methods are utilized, commercial banks need to invest certain funds, personnel, and other resources before they can build financial technologies such as big data risk control systems, distributed ledger systems, and intelligent investment advisory systems. Indeed, banks using FinTech may invest more in green projects, and the risks may offset profitability (Del Gaudio, Previtali, Sampagnaro, Verdoliva, & Vigne, 2022); hence, commercial banks' costs will increase, and TFP will theoretically decrease.

In conclusion, the overall impact of FinTech on the efficiency of commercial banks is unknown; therefore, this paper proposes the following two hypotheses.

**H1a.** FinTech increases the efficiency of commercial banks, and there is a positive correlation between them.

**H1b.** FinTech reduces the efficiency of commercial banks, and there is a negative correlation between them.

### *2.2. FinTech and efficiency of commercial banks classified by ownership*

In China's banking industry, large commercial banks, joint-stock banks, urban commercial banks, and rural commercial banks provide the main bulk of financial services. Owing to diverse profit objectives, resource endowments, and business models, different commercial banks exhibit distinct behaviors in the face of FinTech, but eventually, they will all be affected. As a result, it is necessary to distinguish different types of commercial banks when analyzing the impact of FinTech on their efficiency.

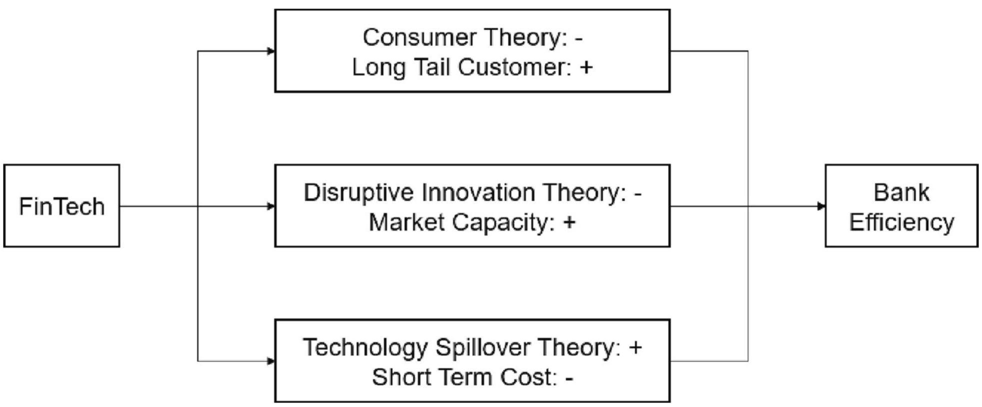


**Fig. 1.** Path of the impact of financial technology on the efficiency of commercial banks.
Note: + or –indicates the positive or negative impact of FinTech on bank efficiency from a specific theory.

Although large commercial banks have absolute advantages in terms of asset scale and customers and can develop and apply FinTech, their principal–agent chain is too long, the incentive mechanism is not perfect, and the motivation for developing and applying FinTech is insufficient (Caprio, Fiechter, Litan, & Pomerleano, 2010; Jiang, Yao, & Feng, 2013). On the one hand, problems such as the long principal–agent chain of China's commercial banks have subsided after the joint-stock reform; however, the soft budget constraint still causes commercial banks to be less affected by the demonstration and competition effects. When facing the impact of FinTech on their asset and liability sides, commercial banks often rely on federal assistance rather than developing and applying technology to adapt to changes (Megginson, 2005; Wang, Lee, & Chen, 2022). On the other hand, despite many branches being critical drivers of profitability (Kumar, Thrikawala, & Acharya, 2022), the management mechanism of large commercial banks is relatively solid. In the face of new technologies or development trends, they often choose complacency rather than a positive response. Such financial inclusion negatively affects commercial bank efficiency (Abakah, Nasreen, Tiwari, & Lee, 2023; Le, Chuc, & Taghizadeh-Hesary, 2019).

Compared to commercial banks, which are limited by profit objectives and budget constraints, joint-stock banks are further along in terms of their property rights definition and corporate governance due to their self-financing mode of operation; therefore, joint-stock banks have the motivation to develop FinTech (Jiang et al., 2013; Shen, Li, & Lee, 2023). At the same time, they have considerable financial strength, a flexible organizational structure, an incentive mechanism in management, and the ability to develop and apply FinTech.

In contrast, urban and rural commercial banks are limited by their resource endowment and talent team, a relatively backward technical infrastructure, and insufficient scientific and technological R&D capacity. At the same time, their main customers are local SMEs and individuals, who also happen to be the target customers of FinTech companies; thus, the living space of urban and rural commercial banks is becoming increasingly constricted. Although these banks can actively perceive market changes, they cannot develop and apply FinTech. In summation, this paper puts forward the following research hypotheses.

**H2a**. Joint-stock banks are less impacted by FinTech.

**H2b**. Large commercial banks and urban and rural commercial banks are significantly impacted by FinTech.

### *2.3. FinTech and efficiency of commercial banks classified by location*

From the standpoint of economic location, compared with the east region of China, the central and west regions are relatively backward in their market-oriented level, financial industry chain, and talent flow. At the same time, most of China's FinTech enterprises are concentrated in the east region. The influence of digital finance is more significant in cities with more developed economies (Ren, Zeng, & Gozgor, 2023); therefore, large commercial banks and joint-stock banks operating across regions have more opportunities to communicate and cooperate with FinTech companies in the east region through alliances, incubation, and joint ventures. The cost of R&D-related FinTech is low, and R&D can be applied to various branches at a small marginal cost to provide financial services for the central and west regions. Urban and rural commercial banks operating in limited areas are also affected by their economic locations. Compared to urban and rural commercial banks in the west region, such banks in the east region are seriously squeezed by FinTech companies and are thus more impacted by FinTech. Based on the above reasons, this paper puts forward the following hypotheses.

**H3a**. Regional commercial banks are more impacted by FinTech.

**H3b**. Among regional commercial banks, commercial banks with different regional characteristics incur different impacts from FinTech.

## 3. Data and model

### *3.1. Sample*

Considering the rapid development of China's FinTech, this research takes 74 commercial banks from 2012 to 2019 as a sample to investigate the impact of FinTech on their efficiency. The relevant data for calculating the efficiency of commercial banks in this paper are from the BvD BankFocus database, the annual public reports of banks, and the data for calculating the FinTech development index are from the Baidu Index. The empirical test uses a multiple regression model to identify the relationship between FinTech and the efficiency of commercial banks and investigate the impact of different banks and locations on the relationship.

### *3.2. Variables*

#### *3.2.1. Efficiency*

This paper's explanatory variable is the efficiency of commercial banks, represented by total factor productivity (M). Many calculation methods are available for their efficiency. This research uses the Malmquist index of the DEA model to calculate the TFP of commercial banks (Lee & Lee, 2023; Lee, Wang, Hsieh, & Chen, 2023; Lv, Fan, & Lee, 2023; Wen, Chen, & Lee, 2023). In terms of input and output, this paper believes that commercial banks are intermediaries; their main goal is to turn deposits (liabilities) into loans (assets) and further turn absorbed deposits into loans through the labor force to collect interest income. Therefore, we select deposits and labor as input indicators and loans and net interest as output indicators. Table 1 lists these details.

**Table 1**
TFP index selection of commercial banks and FinTech index thesaurus.

| | Direction | Index name | Financial indicators for measurement |
|---|---|---|---|
| Total factor productivity index selection of commercial banks | Input index | Total deposits | Resident deposits + interbank deposits |
| | | Labor force | Labor force |
| | Output index | Total loans | Total loan size |
| | | Net interest income | Interest income –interest expense |

| | Dimension | Specific description | | | | |
|---|---|---|---|---|---|---|
| FinTech index thesaurus | Payment settlement | Third-party payment | Digital currency | Mobile payment | Online payment | |
| | Deposits and loans and capital raising | Crowd-funding | Online financing | Network investment | Online banking service | |
| | Investment management | Electronic transaction | Internet finance | Internet insurance | Online finance | |
| | Market facilities | Big Data | Cloud computing | Artificial intelligence | Blockchain | Biometrics |

Notes: This first part of the table shows the input and output index measurement used in this paper under the DEA model. The second part reports the vocabulary chosen when constructing the FinTech index.

**Table 2**
Total factor productivity of China's commercial banks from 2011 to 2019.

| Method | Year | Large commercial banks | Joint-stock banks | Urban commercial banks, rural commercial banks | All banks |
|---|---|---|---|---|---|
| DEA | 2011–2012 | 1.0242 | 0.9603 | 1.3334 | 1.2520 |
| | 2012–2013 | 1.0408 | 1.0163 | 1.0011 | 1.0063 |
| | 2013–2014 | 1.0302 | 1.0036 | 1.0664 | 1.0538 |
| | 2014–2015 | 0.9918 | 1.0333 | 0.9915 | 0.9983 |
| | 2015–2016 | 0.9972 | 1.0228 | 0.9392 | 0.9567 |
| | 2016–2017 | 1.0326 | 1.1162 | 1.0466 | 1.0569 |
| | 2017–2018 | 1.0128 | 1.1010 | 1.0966 | 1.0916 |
| | 2018–2019 | 1.0318 | 1.0157 | 0.9888 | 0.9960 |
| | Average | 1.0202 | 1.0336 | 1.0579 | 1.0514 |
| SFA | 2011 | 0.8200 | 0.6966 | 0.3394 | 0.4298 |
| | 2012 | 0.8920 | 0.7608 | 0.3987 | 0.4908 |
| | 2013 | 0.8880 | 0.7791 | 0.4022 | 0.4962 |
| | 2014 | 0.9160 | 0.8091 | 0.4189 | 0.4962 |
| | 2015 | 0.9140 | 0.7600 | 0.4168 | 0.5158 |
| | 2016 | 0.9280 | 0.7383 | 0.4175 | 0.5040 |
| | 2017 | 0.9480 | 0.7958 | 0.5107 | 0.5864 |
| | 2018 | 0.9500 | 0.8033 | 0.5177 | 0.5932 |
| | 2019 | 0.9560 | 0.7925 | 0.5078 | 0.5843 |
| | Average | 0.9124 | 0.7706 | 0.4366 | 0.5229 |

Notes: This first part of the table shows the total factor productivity of large commercial banks, joint commercial banks, and urban and rural commercial banks from 2011 to 2019 by the DEA method. The second part shows the cost efficiency of large commercial banks, joint commercial banks, and urban and rural commercial banks from 2011 to 2019 by the SFA method.

We employ deap2.1 software to calculate the TFP values of 74 commercial banks in China, based on which they are divided into 5 large commercial banks, 12 joint-stock banks, and 57 urban and rural commercial banks. After classification and calculation, the average annual TFP value of each type of commercial bank is obtained. The results appear in Table 2. From the perspective of the time dimension, the TFP values of large commercial and joint-stock banks remained unchanged from 2012 to 2019, while those of urban and rural commercial banks decreased. Overall, the efficiency of urban and rural commercial banks is slightly higher than that of joint-stock commercial banks, whose efficiency is slightly higher than that of large commercial banks.

### *3.2.2. FinTech development index*

The core explanatory variable of this paper is FinTech. The literature has three main methods to measure the financial science and technology development index. The first one is text mining, which uses the number of entries searched by Baidu to construct the FinTech development index (Alarab & Prakoonwit, 2022; Cheng & Qu, 2020; Wang et al., 2021; Hao, Shen, & Lee, 2023). The second is the China Digital Inclusive Finance Index compiled by the Digital Finance Research Center of Peking University (Qiu, Huang, & Ji, 2018). The third method is the ratio of the scale of third-party payment to the scale of online payment transactions as the proxy index of the Internet finance index (Liu & Yang, 2017; Zhu & Lee, 2022; Yahya, Abbas, & Lee, 2023). In the empirical part, the current study uses the first method to construct the FinTech index and the second and third methods to replace the explanatory variables in the robustness test.

The steps for constructing the FinTech index using the text mining method are as follows. First, when combined with the classification of FinTech models by the Basel Committee, the initial thesaurus of FinTech is constructed in Table 1. Second, with the help of the Baidu search engine, we collected the monthly frequency of each word from 2012 to 2019 and the annual word frequency after the annualized average. Finally, factor analysis allows us to estimate the coefficient matrix and take the variance percentage of each factor as the weight. After the weighted average and standardization, the annual FinTech index is obtained.

#### 3.2.3. Control variables

This paper also selects the control variables that can affect the efficiency of commercial banks from the macro level, industry level, and company level. At the macro level, this paper selects the GDP growth rate (Ggdp) and the ratio of total stock market value to GDP (GS) to control the impact of economic aggregate and capital market development. At the industry level, market concentration (CR4) helps to control the impact of market structure. At the bank level, we select capital adequacy ratio (CAR), liquidity ratio (LI), and whether listed (SS) to control the impact of a bank's risk-taking and liquidity level. Appendix Table a1 presents an explanation of all variables. The variable definitions and descriptive statistics appear in Table 3. Among them, there are 592 observed values of TFP, with a mean value of 1.0514 and a standard deviation of 0.4969. There are nine observed values of the FinTech development index, the proxy variable of FinTech, whose mean value is 0.5016, and its standard deviation is 0.3513. There were 592 observed values for other control variables.

This research first uses the following panel data model to explore the impact of FinTech on the efficiency of commercial banks.

$$M_{i,t} = \beta_0 + \beta_1 {}^* FinTech_t + \sum_{k=2}^{5} \beta_k {}^* Controls_{k,t} + \beta_6 {}^* LI_{i,t} + \beta_7 {}^* SS_{i,t} + \mu_i + \varepsilon_{i,t} \tag{1}$$

$$M_{i,t} = \beta_0 + \beta_1 {}^* M_{i,t-1} + \beta_2 FinTech_t + \sum\nolimits_{k=3}^{6} \beta_{\mathrm{k}} Controls_{k,t} + \beta_7 {}^* LI_{i,t} + \beta_8 {}^* SS_{i,t} + u_i + \varepsilon_{i,t} \tag{2}$$

Subscript $i$ is the i$^{th}$ bank, $t$ is the t$^{th}$ year, and $M$ is the total factor productivity of the banks. $FinTech_t$ denotes the degree of its development. $Controls_{k,t}$ represent control variables at the macro level and industry level, $\mu_i$ is the fixed effect (FE) of banks and $\varepsilon_{i,t}$ represents the error term.

When testing Hypothesis 1, this paper brings the whole sample data into Eqs. (1) and (2). When testing Hypothesis 2, the commercial bank-type dummy variable and its cross-item with the FinTech index can quickly produce multicollinearity and other problems. Therefore, this paper adopts the subsampling method, eliminates large commercial banks, joint-stock banks, and urban and rural commercial banks from the whole sample, forms subsamples 1, 2, and 3, and brings them into Eq. (2). When testing Hypothesis 3, the sample is divided into cross-regional and regional commercial banks according to the geographical location. The sample is then brought into Eq. (2) to test the relationship between FinTech and commercial bank efficiency. Regional commercial banks are divided into eastern and non-eastern banks and then brought into Eq. (2) to test the relationship between FinTech and commercial bank efficiency.

For the choice of the estimation method, considering that the data in this paper are short panel data, we use mixed OLS (P_OLS), panel FE, and random effect (RE) models. Furthermore, Eq. (2) introduces the lag term of the explained variable and how the related explanatory variables and the efficiency of commercial banks cause and affect each other, leading to endogenous problems for the model. Therefore, Eq. (2) uses the differential generalized model of moments (GMM).

## 4. Empirical analysis

### 4.1. Correlation test and stability test

We first conduct the correlation test for each variable. Table 4 presents the results, indicating that the correlation coefficients of FinTech and GDP, GS, Cr4, and GDP were greater than 0.5. The variance inflation factor (VIF) test shows that the VIF values of each explanatory variable are less than 10, indicating no severe multicollinearity problem in this paper. The stationarity test is conducted around each variable. The results are in the last row of Table 4, indicating no unit root between the explained and explanatory variables, and there is no pseudo regression in the empirical results. Finally, this research adopts robust standard error in the empirical process to avoid the influence of heteroscedasticity in the empirical results.

### 4.2. Test of the influence of FinTech on commercial bank efficiency

This paper uses the P_ OLS, FE, and RE estimation Eq. (1); the results are shown in Table 5. First, the mixed OLS estimation Eq. (1) is applied, but the F test set by the model rejects the mixed estimation at the 1% level. The RE estimation Eq. (1) is then used, and the LM test of this equation is conducted. The results show that there was no individual RE. At the same time, the Hausman test was carried out. The test results reject that the random disturbance term is unrelated to the explanatory variable. Therefore, this paper further applies the FE estimation Eq. (1); however, the significance of the explanatory variable coefficient in the FE regression results is poor, indicating that the explanatory variable and the error term are not independent and that Eq. (1) may be endogenous. The Hausman test is performed next on the OLS and IV estimation results, and we find that endogeneity exists. The differential GMM estimation method is used to regress Eq. (2).

**Table 3**
Variable design and descriptive statistics.

| Type | Variable | Symbol | Variable design | Minimum | First quartile | Mean | Medium | The third quartile | Maximum | Standard deviation |
|---|---|---|---|---|---|---|---|---|---|---|
| Explained variable | Total factor productivity | M | DEA–Malmquist | 0.4790 | 0.9503 | 1.0514 | 1.0175 | 1.0868 | 1.11830 | 0.4969 |
| Core explanatory variable | FinTech | FinTech | FinTech development index | 0.0000 | 0.2552 | 0.5016 | 0.4536 | 0.7431 | 1.0000 | 0.3513 |
| Control variables | Macroeconomic level | Ggdp | GDP growth rate | 0.060000 | 0.5143 | 0.0706 | 0.5277 | 0.5709 | 0.07900 | 0.0058 |
| | Stock market development | GS | Ratio of total stock market value to GDP | 0.4202 | 0.4508 | 0.5837 | 0.5905 | 0.6843 | 0.7850 | 0.1222 |
| | Banking concentration | CR4 | Asset proportion of the top four banks * 100 | −9.4273 | −6.730 | −2.5196 | −2.6205 | 2.2809 | 3.4512 | 4.3585 |
| | Bank risk-taking | CAR | Capital adequacy ratio | 0.0000 | 11.8100 | 14.0118 | 12.7750 | 14.0056 | 560.5850 | 22.6126 |
| | Bank liquidity level | LI | Proportion of liquid assets * 100 | 1.0000 | 12.1145 | 20.0516 | 18.7481 | 26.4355 | 63.5794 | 10.7200 |
| | Bank listing | SS | Virtual variable of “bank listing” | 0.0000 | 0.0000 | 0.3328 | 0.0000 | 1.0000 | 1.0000 | 0.7098 |

Note: This table shows the explanation and descriptive statistics of all variables.

**Table 4**
Correlation test and stability test for each variable.

| Variable | M | FinTech | Ggdp | GS | CR4 | CAR | lI | SS |
|---|---|---|---|---|---|---|---|---|
| M | 1.000 | | | | | | | |
| FinTech | −0.114*** | 1.000 | | | | | | |
| Ggdp | 0.089** | −0.509*** | 1.000 | | | | | |
| GS | −0.094** | 0.501*** | −0.461*** | 1.000 | | | | |
| CR4 | −0.061 | 0.263*** | −0.604*** | 0.215*** | 1.000 | | | |
| CAR | −0.011 | −0.047 | 0.045 | −0.059 | −0.001 | 1.000 | | |
| LI | −0.139*** | −0.371*** | 0.346*** | −0.289*** | −0.125*** | 0.145*** | 1.000 | |
| SS | −0.042 | 0.054 | −0.107*** | 0.037 | 0.058 | −0.034 | −0.095** | 1.000 |

Notes: This table shows the Pearson correlation coefficient matrix for the variables used in our baseline regression. M is the total factor productivity calculated by the DEA model, FinTech is the FinTech development index, Ggdp is the GDP growth rate, GS is the ratio of total stock market value to GDP, and CR4 is 100 times the asset proportion of the top four banks. CAR is the capital adequacy ratio, LI is 100 times the proportion of liquid assets, and SS is the virtual variable of "bank listing." *, **, and *** are significant at the 10%, 5%, and 1% confidence levels, respectively.

The regression results are in the last column of Table 5. The *p*-value of AR(2) is greater than 0.1, indicating no second-order sequence correlation in the difference in the disturbance term. The p-value of the Sargan test is also greater than 0.1, indicating that all instrumental variables are exogenous. This result shows that the dynamic model based on empirical analysis and the selected instrumental variables are reasonable.

The regression results of differential GMM indicate that the estimated coefficient of FinTech is significantly negative, meaning it reduces the efficiency of commercial banks (Phan et al., 2020; Hussain & Lee, 2022); thus, H1b is supported, but H1a is not. This conclusion is contrary to that of Lee, Li, Yu, and Zhao (2021), potentially because of different methods for calculating the efficiency of commercial banks and differences in samples. This paper's results show that consumer theory and disruptive innovation theory may better explain the impact of FinTech on commercial banks compared with the technology spillover theory. From the specific approach, FinTech may affect the asset side of commercial banks, reduce their profitability, and thus lower their efficiency. It may simultaneously affect the liability side of commercial banks, increase their liability cost, and reduce their efficiency. Therefore, this paper proposes the

**Table 5**
Impact of FinTech on the efficiency of commercial banks in the whole sample.

| Variable | P_OLS | FE | RE | D_GMM |
|---|---|---|---|---|
| FinTech | −0.2661 | −0.3544 | −0.2661 | −0.3393** |
| | (0.1827) | (0.2270) | (0.1827) | (0.1379) |
| Ggdp | 1.3164 | 2.2697 | 1.3164 | 5.6434*** |
| | (1.0358) | (1.5475) | (1.0358) | (1.3335) |
| GS | 0.0427 | 0.1082 | 0.0427 | −0.0289 |
| | (0.1569) | (0.1911) | (0.1569) | (0.2268) |
| CR4 | 0.0009 | 0.0032 | 0.0009 | 0.0112** |
| | (0.0035) | (0.0046) | (0.0035) | (0.0045) |
| CAR | 0.0002 | 0.0004 | 0.0002 | −0.0351 |
| | (0.0003) | (0.0004) | (0.0003) | (0.0569) |
| LI | −0.0108* | −0.0183* | −0.0108* | −0.0327** |
| | (0.0058) | (0.0101) | (0.0058) | (0.0152) |
| SS | −0.0486 | 0.1197* | −0.0486 | 1.9053** |
| | (0.0303) | (0.0672) | (0.0303) | (0.8304) |
| L.M | | | | −0.0812* |
| | | | | (0.0477) |
| _Cons | 0.7021* | 0.3026 | 0.7021* | |
| | (0.4032) | (0.6300) | (0.4032) | |
| F | 3.47***[0.003] | 6.79***[0.001] | | |
| $R^2$ | 0.0477 | 0.0477 | 0.0477 | |
| LM | | | 0.00[1.000] | |
| Hausman | | | 15.17***[0.002] | |
| AR(1) | | | | 0.66[0.511] |
| AR(2) | | | | −0.26[0.797] |
| Sargan | | | | 6.46[0.775] |

Notes: The table shows the impact of FinTech on the efficiency of all commercial banks in China. The first three columns report the regression results based on Pool OLS, Fixed effect, and random effect estimates, respectively, and the last column shows the regression results based on differential GMM estimates. M is the total factor productivity calculated by the DEA model, FinTech is the FinTech development index, Ggdp is the GDP growth rate, GS is the ratio of total stock market value to GDP, and CR4 is 100 times the asset proportion of the top four banks. CAR is the capital adequacy ratio, LI is 100 times the proportion of liquid assets, and SS is the virtual variable of "bank listing." LM is the lagged term of the variable M, and _Cons is the constant term. F is the F test of equality of variance, $R^2$ is the coefficient of determination, LM is the Pagan Lagrange multiplier test, Hausman is the Hausman test, AR(1) and AR(2) are first-order and second-order serial correlation tests, respectively, and Sargan is the Sargan test for the GMM model. The value in parenthesis below the regression coefficient is the robust standard error. The model setting tests the corresponding *p*-value in brackets on the right. *, **, and *** are significant at the 10%, 5%, and 1% confidence levels, respectively.

following hypotheses.

**H4a.** FinTech reduces the profitability of commercial banks by affecting their asset side, thus lowering their efficiency.

**H4b.** FinTech improves the debt level of commercial banks by affecting their debt side, thus reducing their efficiency.

This paper further uses the intermediary effect model to explore the impact path of FinTech on commercial banks from the asset and liability sides. The mediating effect model is shown in Eqs. (3)–(5).

$$M_{i,t} = \beta_0 + \beta_1 M_{i,t-1} + \beta_2 FinTech_t + \sum\nolimits_{k=3}^{6} \beta_k Controls_{k,t} + \beta_7 {}^* LI_{i,t} + \beta_8 {}^* SS_{i,t} + u_i + \varepsilon_{i,t} \tag{3}$$

$$Mediator_{i,t} = \beta_0 + \beta_1 Mediator_{i,t-1} + \beta_2 FinTech_t + \sum\nolimits_{k=3}^{6} \beta_k Controls_{k,t} + \beta_7 LI_{i,t} + \beta_8 {}^* SS_{i,t} + u_i + \varepsilon_{i,t} \tag{4}$$

$$M_{i,t} = \beta_0 + \beta_1 M_{i,t-1} + \beta_2 Mediator_{i,t} + \beta_3 FinTech_t + \sum\nolimits_{k=4}^{7} \beta_k Controls_{k,t} + \beta_8 {}^* LI_{i,t} + \beta_9 {}^* SS_{i,t} + u_i + \varepsilon_{i,t} \tag{5}$$

This paper constructs intermediary transmission variables from commercial banks' asset and liability sides. On the one hand, commercial banks' rate of return on equity (ROE) is used as an intermediary variable to represent the change on the asset side and reflect the impact of FinTech on the profitability of commercial banks. On the other hand, commercial banks' cost of loanable funds (cost = interest expense / total deposit) is used as another intermediary variable to represent the change on the liability side and reflect the impact of FinTech on the liability cost of commercial banks. The differential GMM estimation is applied to regress Eqs. (3)–(5), and the results are in Table 6.

As shown in the third and fourth columns of Table 6, the FinTech item in model (3) is significantly positive, but the ROE item in model (4) is not significant. The Sobel test finds that the result is insignificant, and the original hypothesis cannot be rejected, indicating that FinTech does not affect commercial banks' profitability or efficiency. The last two columns of Table 6 present that the FinTech term in model (3) is significantly negative, the FinTech term in model (4) is significantly negative, and the cost term is

**Table 6**
Mechanism of financial technology's impact on commercial banks.

| Model | (2) | (3) | (4) | (3) | (4) |
|---|---|---|---|---|---|
| Explained variable | M | ROE | M | Cost | M |
| L.M | −0.0812* | | −0.0900 | | −0.0751 |
| | (0.0477) | | (0.0590) | | (0.0556) |
| FinTech | −0.3393** | 0.1382*** | −0.3115** | 0.1558*** | −0.2112* |
| | (0.1379) | (0.0464) | (0.1454) | (0.0559) | (0.1247) |
| Ggdp | 5.6434*** | −1.1854 | 5.9294*** | −1.6562* | 5.5787*** |
| | (1.3335) | (0.8977) | (1.3387) | (0.9418) | (1.1115) |
| GS | −0.0289 | −0.1061 | −0.0022 | −0.1689 | 0.0881 |
| | (0.2268) | (0.1013) | (0.2191) | (0.1346) | (0.2154) |
| CR4 | 0.0112** | −0.0040** | 0.0104** | −0.0008 | 0.0109*** |
| | (0.0045) | (0.0017) | (0.0048) | (0.0018) | (0.0035) |
| CAR | −0.0351 | 0.0003 | −0.0388 | 0.0005 | −0.0275 |
| | (0.0569) | (0.0014) | (0.0654) | (0.0020) | (0.0500) |
| LI | −0.0327** | 0.0136** | −0.0286 | −0.0135** | −0.0238* |
| | (0.0152) | (0.0059) | (0.0176) | (0.0068) | (0.0130) |
| SS | 1.9053** | −1.2376** | 1.7176** | −1.4334* | 1.9141** |
| | (0.8304) | (0.6128) | (0.7960) | (0.7597) | (0.8590) |
| ROE | | | −0.4927 | | |
| | | | (0.6814) | | |
| L.ROE | | −0.1223 | | | |
| | | (0.1430) | | | |
| Cost | | | | | −0.8578** |
| | | | | | (0.3976) |
| L.Cost | | | | −0.1252 | |
| | | | | (0.1577) | |
| AR(1) | 0.66[0.511] | −0.90[0.368] | 0.58[0.562] | −1.02[0.309] | 0.73[0.466] |
| AR(2) | −0.26[0.797] | 0.35[0.730] | −0.07[0.947] | −1.10[0.271] | 0.04[0.968] |
| Sargan | 6.46[0.775] | 17.94[0.160] | 6.50[0.689] | 10.64[0.641] | 6.43[0.696] |

Notes: This table shows the regression results of the mediation effect; the first three columns report how FinTech affects the efficiency of commercial banks by affecting their profitability, and the last two columns report how FinTech affects the efficiency of commercial banks via their cost. M is total factor productivity; ROE is the rate of return on common stockholders' equity, and Cost equals interest expense / total deposit. LM is the lagged term of the variable M, FinTech is the FinTech development index, Ggdp is the GDP growth rate, GS is the ratio of the total stock market value to GDP, and CR4 is 100 times the assets proportion of the top four banks. CAR is the capital adequacy ratio, LI is 100 times the proportion of liquid assets, SS is a virtual variable of "bank listing," _Cons is the constant term, and L.ROE and L.Cost are the lag items of variables ROE and Cost, respectively. AR(1) and AR(2) are first-order and second-order serial correlation tests, respectively, and Sargan is the Sargan test for the GMM model. The value in parenthesis below the regression coefficient is the robust standard error. The model setting tests the corresponding *p*-value in brackets on the right. *, **, and *** are significant at the 10%, 5%, and 1% confidence levels, respectively.

significantly positive. This finding means that FinTech development increases the debt cost of commercial banks, and a higher debt cost leads to a lower TFP of commercial banks; therefore, H4b is supported.

To a certain extent, when FinTech companies enter the financial market with the help of innovative technology, they target the long-tail customers of commercial banks. Initially, these customers used the financial services provided by commercial banks. The increased convenience and lower cost of similar financial services provided by FinTech companies then likely persuade customers to use their financial services more and reduce their use of commercial banks' financial services. The loss of customers in commercial banks increases the cost of obtaining funds from the traditional deposit market, and the profitability of commercial banks decreases quickly, resulting in lower efficiency. Furthermore, FinTech companies conduct consumer education when providing financial services, which stimulates the demand of all consumers for financial services and increases the market capacity of the financial industry; therefore, most consumers still choose the channels provided by FinTech companies rather than those provided by commercial banks when they demand financial services. The marginal income brought by the increase in market capacity to commercial banks is less than the marginal cost brought by FinTech companies entering the financial industry; thus, the efficiency of commercial banks drops. Although the high level of competition may push some least efficient banks out of the industry, this outcome also negatively impacts all commercial banks. The market capacity of the financial industry increases, but existing commercial banks extend fewer loans to the public and provide fewer financial services; hence, the whole industry's efficiency level decreases when we measure it.

While commercial banks can develop and apply FinTech from the perspective of technology spillover, they need to invest significant human and financial resources in early hardware construction, channel construction, and publicity, which reduce their efficiency. In the short term, as long-tail customers shift from commercial banks to FinTech companies, the profitability of commercial banks declines, resulting in a decrease in efficiency. In the long run, the relatively low level of risk control of FinTech companies and the provision of financial services for a large number of long-tail customers causes their liquidity risk to become relatively high. This increase implies an injection of unstable factors into the financial system; therefore, the regulatory authorities should establish corresponding laws and regulations to supervise the relevant business of FinTech companies.

### *4.3. Empirical evidence on FinTech and commercial bank efficiency classified by type*

This study empirically tests Hypothesis 2 by using the identification strategy of Zhu (2012). First, we divide the whole sample into three subsamples for dynamic regression. Subsample 1 excludes large commercial banks from the whole sample, subsample 2 excludes joint-stock banks from the whole sample, and subsample 3 excludes urban and rural commercial banks. Second, the regression results of the subsamples and total samples were compared. A decrease in the coefficient of the explanatory variable of the FinTech development index in the subsample indicates that the excluded commercial banks are less affected by FinTech than all banks. Furthermore, a more significant decline in the regression coefficient indicates that excluded commercial banks are less affected by FinTech. Finally,

**Table 7**
Efficiency of FinTech and different types and locations of commercial banks.

| Variable | Subsample 1 | Subsample 2 | Subsample 3 | Subsample 4 | Subsample 5 | Subsample 6 |
|---|---|---|---|---|---|---|
| L.M | −0.0846* | −0.0818** | −0.2017** | −0.0870** | −0.1557*** | −0.0663** |
| | (0.0459) | (0.0393) | (0.0924) | (0.0379) | (0.0579) | (0.0275) |
| FinTech | −0.3868*** | −0.4570*** | −0.0387 | −0.5263*** | −0.8379*** | −0.1556 |
| | (0.1448) | (0.1573) | (0.0869) | (0.1622) | (0.2819) | (0.1467) |
| Ggdp | 6.3249*** | 7.3915*** | 2.6978* | 8.3615*** | 7.7550*** | 4.5356*** |
| | (1.3810) | (1.6261) | (1.4170) | (1.6498) | (2.5609) | (1.0236) |
| GS | −0.0053 | 0.0017 | −0.0720 | 0.0445 | 0.3095 | 0.1016 |
| | (0.2380) | (0.2556) | (0.0876) | (0.2665) | (0.2704) | (0.2826) |
| CR4 | 0.0132*** | 0.0147*** | 0.0019 | 0.0174*** | 0.0222*** | 0.0081 |
| | (0.0048) | (0.0054) | (0.0022) | (0.0057) | (0.0067) | (0.0062) |
| CAR | −0.0379 | −0.0375 | 0.0720 | −0.0399 | −0.0107 | −0.1300* |
| | (0.0594) | (0.0557) | (0.0526) | (0.0569) | (0.0146) | (0.0730) |
| LI | −0.0336** | −0.0445** | −0.0128 | −0.0453*** | −0.0585*** | −0.0109 |
| | (0.0150) | (0.0177) | (0.0110) | (0.0170) | (0.0216) | (0.0087) |
| SS | 1.8502** | 1.9753** | | 1.9052** | 1.7399 | 1.2079 |
| | (0.7937) | (0.8378) | | (0.7851) | (1.1709) | (0.8970) |
| AR(1) | 0.66[0.507] | 0.71[0.475] | −1.23[0.217] | 0.71[0.479] | 0.92[0.358] | −1.79[0.073] |
| AR(2) | −0.33[0.741] | −0.43[0.668] | −1.45[0.147] | −0.58[0.110] | −1.08[0.279] | −1.11[0.268] |
| Sargan | 5.72[0.838] | 5.02[0.890] | 41.43[0.001] | 5.95[0.203] | 9.42[0.493] | 54.98[0.001] |

Notes: This table reports the impact of FinTech on commercial banks of different types and locations. This paper eliminates large commercial banks, joint-stock banks, and urban and rural commercial banks from the whole sample and forms subsample 1, subsample 2, and subsample 3, respectively. Subsample 4 only contains urban and rural commercial banks, subsample 5 includes commercial banks in the east region from subsample 4, and subsample 6 excludes commercial banks in the east region from subsample 4. M is total factor productivity, LM is the lagged term of the variable M, FinTech is the FinTech development index, Ggdp is the GDP growth rate, GS is the ratio of total stock market value to GDP, and CR4 is 100 times the assets proportion of the top four banks. CAR is the capital adequacy ratio, LI is 100 times the proportion of liquid assets, SS is the virtual variable of "bank listing," and _Cons is the constant term. AR(1) and AR(2) are first-order and second-order serial correlation tests, respectively. Sargan is the Sargan test for the GMM model. The value in parenthesis below the regression coefficient is the robust standard error. The model setting tests the corresponding p-value in brackets on the right. *, **, and *** are significant at the 10%, 5%, and 1% confidence levels, respectively.

this paper tests whether there are significant differences in the coefficients of grouped regression.

Differential GMM estimation is used to bring three subsamples into Eq. (2); the regression results are in Table 7. The results of the AR(2) test and Sargan test of subsamples 1 and 2 show that the setting of the regression model and the selection of instrumental variables are reasonable. The coefficients of FinTech for subsamples 1 and 2 are −0.3868 and − 0.4570, respectively. Compared with the regression results of the whole sample, the subsample results 1 and 2 fall by 14.00% and 20.69%, respectively. These findings indicate that the impact of FinTech on large commercial banks and joint-stock banks is less than the average level, and the impact of FinTech on joint-stock banks is less than that of large commercial banks. The impact of FinTech on large commercial banks and joint-stock banks is less than the average level, but the impact of FinTech on urban and rural commercial banks is greater than average. Therefore, urban and rural commercial banks are the most impacted by FinTech, followed by large commercial banks, while joint-stock banks are the least impacted.

To further verify Hypothesis 2, we compare the estimation results of FinTech in the whole sample regression and grouping regression with the intergroup difference *t*-test method proposed by Acquaah (2012). The results show different coefficients of the FinTech index between the full sample and subsample 1 and between the full sample and subsample 2, at 0.0475 and 0.0702, respectively. The original assumption that "there is no deviation in the estimated coefficient" is rejected at the significance levels of 5% and 1%, showing that the impact of FinTech on large commercial banks is significantly less than the average level. Therefore, the impact of FinTech on joint-stock banks is significantly less than that of large commercial banks.

After excluding urban and rural commercial banks, the dynamic regression instrument variables of subsample 3 become unreasonable, and the coefficients of FinTech variables are insignificant. Thus, this paper constructs subsample 4, which only includes urban and rural commercial banks. The differential GMM estimation method is applied to bring the four subsamples into Eq. (2), and the results appear in the fourth column of Table 8. The results of the AR(2) test and Sargan test of subsample 4 denote that the setting of the regression model and the selection of instrumental variables are reasonable. The results are negative when comparing the coefficients of FinTech with the full sample regression; however, the coefficients of subsample 4 are smaller, indicating that the impact of FinTech

**Table 8**

Mechanism of FinTech's impact on commercial banks under subsamples 1, 2, and 4.

| Sample<br>Model | 1<br>(3) | 1<br>(4) | 1<br>(5) | 2<br>(3) | 2<br>(4) | 2<br>(5) | 4<br>(3) | 4<br>(4) | 4<br>(5) |
|---|---|---|---|---|---|---|---|---|---|
| Explained variable | M | Cost | M | M | Cost | M | M | Cost | M |
| L.M | −0.0846* | | −0.0775 | −0.0818** | | −0.0726 | −0.0870** | | −0.0764 |
| | (0.0459) | | (0.0536) | (0.0393) | | (0.0498) | (0.0379) | | (0.0482) |
| FinTech | −0.3868*** | 0.1584*** | −0.2554* | −0.4570*** | 0.1157* | −0.2873* | −0.5263*** | 0.1191* | −0.3532** |
| | (0.1448) | (0.0576) | (0.1390) | (0.1573) | (0.0620) | (0.1482) | (0.1622) | (0.0655) | (0.1667) |
| Ggdp | 6.3249*** | −1.5650 | 6.1149*** | 7.3915*** | −1.1565 | 6.5594*** | 8.3615*** | −1.0873 | 7.3264*** |
| | (1.3810) | (0.9658) | (1.1559) | (1.6261) | (0.8671) | (1.4038) | (1.6498) | (0.9068) | (1.5308) |
| GS | −0.0053 | −0.1761 | 0.1086 | 0.0017 | −0.1041 | 0.0814 | 0.0445 | −0.1191 | 0.1196 |
| | (0.2380) | (0.1363) | (0.2294) | (0.2556) | (0.1382) | (0.2313) | (0.2665) | (0.1422) | (0.2451) |
| CR4 | 0.0132*** | −0.0005 | 0.0124*** | 0.0147*** | −0.0013 | 0.0132*** | 0.0174*** | −0.0010 | 0.0151*** |
| | (0.0048) | (0.0020) | (0.0039) | (0.0054) | (0.0021) | (0.0041) | (0.0057) | (0.0023) | (0.0047) |
| CAR | −0.0379 | 0.0005 | −0.0289 | −0.0375 | 0.0005 | −0.0270 | −0.0399 | 0.0005 | −0.0283 |
| | (0.0594) | (0.0019) | (0.0510) | (0.0557) | (0.0022) | (0.0452) | (0.0569) | (0.0021) | (0.0461) |
| LI | −0.0336** | −0.0132** | −0.0247* | −0.0445** | −0.0103 | −0.0316** | −0.0453*** | −0.0105 | −0.0330** |
| | (0.0150) | (0.0066) | (0.0133) | (0.0177) | (0.0069) | (0.0160) | (0.0170) | (0.0068) | (0.0165) |
| SS | 1.8502** | −1.2692* | 1.8318** | 1.9753** | −0.8149 | 1.8541** | 1.9052** | −0.7144 | 1.7642** |
| | (0.7937) | (0.7083) | (0.8222) | (0.8378) | (0.5688) | (0.8197) | (0.7851) | (0.5170) | (0.7749) |
| Cost | | | −0.7848* | | | −1.0228** | | | −0.9204* |
| | | | (0.4178) | | | (0.4462) | | | (0.4846) |
| L.Cost | | −0.1383 | | | −0.2176 | | | −0.2317 | |
| | | (0.1585) | | | (0.1553) | | | (0.1572) | |
| AR(1) | 0.66 | −1.15 | 0.71 | 0.71 | −1.47 | 0.79 | −1.23 | −0.72 | −1.42 |
| | [0.507] | [0.248] | [0.480] | [0.475] | [0.141] | [0.428] | [0.217] | [0.470] | [0.155] |
| AR(2) | −0.33 | −1.17 | −0.11 | −0.43 | −1.29 | −0.09 | −0.58 | −1.41 | −0.31 |
| | [0.741] | [0.243] | [0.991] | [0.668] | [0.198] | [0.929] | [0.110] | [0.159] | [0.753] |
| Sargan | 5.72 | 12.66 | 5.79 | 5.02 | 11.72 | 4.88 | 5,95 | 13.42 | 4.30 |
| | [0.838] | [0475] | [0.761] | [0.890] | [0.55] | [0.845] | [0.203] | [0.416] | [0.891] |

Notes: This table reports the regression results of the mediation effect with subsamples. The first three columns report how FinTech affects the efficiency of commercial banks in subsample 1 via their cost, the medium three columns report how FinTech affects the efficiency of commercial banks in subsample 2 by affecting their cost, and the last three columns report how f = FinTech affects the efficiency of commercial banks in subsample 3 by affecting their cost. This paper eliminates large commercial banks and joint-stock banks from the whole sample and forms subsamples 1 and subsample 2, respectively. Subsample 4 only contains urban and rural commercial banks. Subsample 5 includes commercial banks in the east region from subsample 4, and subsample 6 excludes commercial banks in the east region from subsample 4. M is total factor productivity, L.M is the lagged term of the variable M, FinTech is the FinTech development index, Ggdp is the GDP growth rate, GS is the ratio of the total stock market value to GDP, and CR4 is 100 times the assets proportion of the top four banks. CAR is the capital adequacy ratio, LI is 100 times the proportion of liquid assets, SS is the virtual variable of "bank listing," and _Cons is the constant term. AR(1) and AR(2) are first-order and second-order serial correlation tests, respectively; Sargan is the Sargan test for the GMM model. The value in parenthesis below the regression coefficient is the robust standard error. The model setting tests the corresponding *p*-value in brackets on the right. *, **, and *** are significant at the 10%, 5%, and 1% confidence levels, respectively.

on urban and rural commercial banks is greater than the average level.

The t-test method of intergroup difference proposed by Acquaah (2012) is used to compare the estimation results of FinTech in the full sample regression and four subsample regressions. The difference coefficient was 0.1870. The original assumption that "there is no deviation in the estimated coefficient" is rejected at the 1% significance level, suggesting that the impact of FinTech on urban and rural commercial banks is significantly greater than the average level.

Subsamples 1, 2, and 4 are also brought into Eqs. (3)–(5) to test whether the type of commercial bank affects the channel through which FinTech impacts efficiency. Table 8 shows the regression results, indicating that the FinTech coefficients in model (3) are significantly negative, the FinTech coefficients in model (4) are significantly positive, and the cost coefficients in model (5) are significantly negative. This finding means that FinTech development increases the debt cost of commercial banks, and a higher debt cost leads to a lower TFP of commercial banks in these subsamples; therefore, the channel through which FinTech affects the efficiency of commercial banks is consistent when splitting the samples.

In summation, the statement that "different types of commercial banks are significantly impacted by FinTech" in Hypothesis 2 is supported; urban and rural commercial banks are most impacted by FinTech, followed by large commercial banks, while joint-stock banks are the least impacted by FinTech. This result implies that while urban and rural commercial banks are incentivized to develop and apply FinTech, their living space is squeezed due to resource endowment and talent team restrictions. Although large commercial banks have insufficient incentives and are slow to act, with their absolute advantages in asset scale and customers, it is only a matter of time before they develop and apply FinTech. Owing to the limitations of profit objectives and budget constraints, joint-stock banks have sufficient incentives to develop and apply FinTech, and their relatively strong financial advantages are necessary for their FinTech development.

### *4.4. Empirical evidence on the impact of FinTech on commercial bank efficiency classified by location*

The whole sample was first divided into three subsamples for dynamic regression. The first is subsample 4, a regional commercial bank group that includes urban and rural commercial banks. The second is subsample 5, which includes commercial banks in the east region from subsample 4, and the third is subsample 6, which excludes commercial banks in the east region from subsample 4. Next, we compared the regression results of the subsamples and full samples. If the coefficient of the explanatory variable of FinTech in the subsample decreases, then the commercial banks in the sample will be affected more by FinTech than all the banks. Moreover, the more significant the decline in the regression coefficient is, the greater the impact of FinTech on the proposed commercial banks. Finally, this paper tests for significant differences in the coefficients of the grouped regression.

Differential GMM estimation brings three subsamples into Eq. (2). The regression results are in Table 8. The results of the AR(2) test and Sargan test of subsamples 4 and 5 show that the setting of the regression model and the selection of instrumental variables are reasonable. In subsample 4, the coefficient of FinTech is −0.5263, or a decrease of 55.11% compared with the regression results of the whole sample, indicating that its impact on regional commercial banks is higher than the average level. In subsample 5, the coefficient of FinTech is −0.8379, 146.95% lower than the regression result of subsample 4. This result indicates that its impact on regional commercial banks in the east region is higher than the average of FinTech's impact on regional commercial banks. The result also showed that the impact of FinTech on non-eastern regional commercial banks is lower than the average level of its impact on regional commercial banks.

To further verify Hypothesis 3, the intergroup difference *t*-test method proposed by Acquaah (2012) was used to compare the estimation results of FinTech in the full sample regression and four subsample regressions. The difference coefficient was 0.1870. The original hypothesis that "there is no deviation in the estimated coefficient" is rejected at the significance level of 1%, which shows that the impact of FinTech on regional commercial banks is significantly greater than the average level. We compare the estimated results of FinTech in the regressions of subsamples 4 and 5. The difference coefficient was 0.3116. Under the significance level of 1%, the original assumption that "there is no deviation in the estimated coefficient" is rejected, indicating that the impact of FinTech on regional commercial banks in the east region is higher than the average level of its impact on regional commercial banks.

Hypothesis 3 states that "regional commercial banks are more impacted by FinTech, and among regional commercial banks, commercial banks with different regional characteristics are differently impacted by FinTech." This statement is supported, and FinTech impacts regional commercial banks more in the east region than in other regions. This result may be because regional commercial banks can only provide financial services in a specific region, and their main customer groups are local enterprises and residents. The main profits of these regional commercial banks come from providing financial services to local enterprises, as they have a strong customer relationship with these enterprises. Therefore, when FinTech companies enter the local area to provide financial services, they steal the institutional customers of regional commercial banks but instead attract individual customers. To maintain customer relationships with some individual customers, regional commercial banks spend considerable resources and workforce to develop and apply FinTech. The income is small, so FinTech impacts their efficiency more than average. At the same time, because most of China's FinTech enterprises are concentrated in the east region, the regional commercial banks face more significant challenges. In particular, these banks lose more personal customers or have greater costs to develop FinTech, so FinTech impacts their efficiency more than other regions.

### *4.5. Robustness test*

#### *4.5.1. Using the digital inclusive finance index of Peking University to represent the FinTech development index*

The second recognized method to measure FinTech development in academia is the Peking University Digital Inclusive Finance

Index. This research employs this index as the core explanatory variable to represent the degree of FinTech development, brings it into Eq. (2), and re-examines the above three hypotheses using the system GMM estimation.

$$M_{i,t} = \beta_0 + \beta_1{}^*M_{i,t-1} + \beta_2 FinTech_{i,t} + \sum\nolimits_{k=3}^{6}\beta_k Controls_{k,t} + \beta_7{}^*LI_{i,t} + \beta_8{}^*SS_{i,t} + u_i + \varepsilon_{i,t} \tag{6}$$

The regression results appear in Table 9, which indicate that the estimated coefficient of FinTech is significantly negative, suggesting that it reduces the efficiency of commercial banks and supports H1b rather than H1a. This finding is consistent with the above conclusion. According to Table 9, compared with the whole sample, the estimated coefficients of FinTech in subsamples 1 and 3 are larger, while the estimated coefficient of FinTech in subsample 2 is smaller than others. This result shows that the impact of FinTech on large commercial banks and urban and rural commercial banks is greater than the average level, while its impact on joint-stock banks is less than the average level. According to the *t*-test method of intergroup difference, the estimated coefficients of FinTech of the whole sample and subsample 1, the whole sample and subsample 3, and subsamples 1 and 3 differ at the confidence levels of 10%, 1%, and 1%, respectively, indicating that FinTech significantly impacts different types of commercial banks and that urban and rural commercial banks are the most impacted. Large commercial banks take second place; joint-stock banks are the least impacted by FinTech. These findings are consistent with the above conclusion.

Table 9 also shows that the estimated coefficient of FinTech in subsample 4 is smaller than the whole sample and subsample 4, indicating that the impact of FinTech on regional commercial banks is greater than the average level. A comparison reveals that the estimated coefficient of FinTech in subsample 5 is smaller than in subsample 4, signifying that the impact of FinTech on regional commercial banks in the east region is higher than the average level of its impact on regional commercial banks. When the *t*-test method of intergroup difference is used, the estimated coefficients of FinTech of the whole sample and subsample 4 are significantly different, and so are the estimated coefficients of FinTech of subsamples 4 and 5, indicating that regional commercial banks are more affected by FinTech. Commercial banks with different regional characteristics are dissimilar, and FinTech impacts regional commercial banks more in the east region. These findings are consistent with the above conclusion.

#### *4.5.2. Using the ratio of third-party payment scale to online banking transaction scale to represent the degree of FinTech development*

Other scholars (Liu & Yang, 2017) used the ratio of a third-party payment scale to an online banking transaction scale to describe the degree of FinTech development. As the core explanatory variable, the current study brings the proxy for the degree of FinTech development after the ratio is standardized into Eq. (2). The above three hypotheses are then re-tested by using the system GMM estimation.

**Table 9**
Efficiency of FinTech and different types and locations of commercial banks—robustness test 1.

| Variable | Full sample | Subsample 1 | Subsample 2 | Subsample 3 | Subsample 4 | Subsample 5 | Subsample 6 |
|---|---|---|---|---|---|---|---|
| L.M | −0.0879* | −0.0902* | −0.0909* | −0.3999*** | −0.0924* | −0.1461** | −0.0340** |
| | (0.0507) | (0.0522) | (0.0482) | (0.1528) | (0.0492) | (0.0598) | (0.0157) |
| FinTech | −0.4477*** | −0.4080** | −0.4815*** | −0.3125** | −0.4630** | −0.5506** | −0.3618 |
| | (0.1353) | (0.1689) | (0.1469) | (0.1302) | (0.1873) | (0.2429) | (0.4905) |
| Ggdp | 1.8339** | 2.0842** | 1.8336** | 2.4066* | 2.2433** | 2.0224 | 2.2245 |
| | (0.7480) | (0.8101) | (0.8817) | (1.4472) | (1.0004) | (1.4864) | (1.8846) |
| GS | −0.2206** | −0.2453** | −0.2978*** | 0.0745 | −0.3298*** | −0.2453* | −0.2425 |
| | (0.0945) | (0.1044) | (0.1136) | (0.0808) | (0.1266) | (0.1369) | (0.2207) |
| CR4 | −0.0006 | −0.0002 | −0.0003 | −0.0012 | 0.0004 | −0.0005 | −0.0017 |
| | (0.0022) | (0.0024) | (0.0025) | (0.0015) | (0.0028) | (0.0030) | (0.0068) |
| CAR | −0.0209 | −0.0212 | −0.0191 | 0.0031 | −0.0191 | −0.0102 | −0.0122 |
| | (0.0157) | (0.0159) | (0.0158) | (0.0097) | (0.0157) | (0.0104) | (0.0423) |
| LI | 0.0018 | 0.0018 | 0.0029 | 0.0016 | 0.0034 | 0.0014 | −0.0031 |
| | (0.0044) | (0.0045) | (0.0048) | (0.0030) | (0.0048) | (0.0053) | (0.0076) |
| SS | −0.0705 | −0.0698 | −0.0747 | −0.1575 | −0.0674 | −0.1228 | −0.0036 |
| | (0.0767) | (0.0974) | (0.0842) | (0.1083) | (0.1155) | (0.2354) | (0.1397) |
| _Cons | 0.2677 | 0.1340 | 0.2959 | −0.2286 | 0.0572 | 0.0325 | 0.0508 |
| | (0.5736) | (0.6227) | (0.6675) | (0.9763) | (0.7486) | (1.0041) | (1.7220) |
| AR(1) | 0.42[[0.379] | −0.54[0.233] | −0.65[0.294] | −1.83[0.068] | 0.64[0.403] | −0.43[0.849] | −2.02[0.334] |
| AR(2) | 0.33[0.742] | 0.36[0.721] | 0.24[0.812] | −1.40[0.161] | 0.25[0.799] | 0.31[0.760] | −1.31[0.189] |
| Sargan | 5.20[0.636] | 5.95[0.546] | 4.53[0.717] | 10.78[0.868] | 5.21[0.634] | 5.07[0.652] | 6.75[0.693] |

Notes: This paper employs the Peking University Digital Inclusive Finance Index as the core explanatory variable to represent the degree of FinTech development in robustness test 1. This table reports the impact of FinTech on commercial banks of different types and locations. The paper eliminates large commercial banks, joint-stock banks, and urban and rural commercial banks from the whole sample and forms subsample 1, subsample 2, and subsample 3, respectively. Subsample 4 only contains urban and rural commercial banks, subsample 5 includes commercial banks in the east region from subsample 4, and subsample 6 excludes commercial banks in the east region from subsample 4. M is total factor productivity, L.M is the lagged term of the variable M, FinTech is the FinTech development index, Ggdp is the GDP growth rate, GS is the ratio of the total stock market value to GDP, and CR4 is 100 times the assets proportion of the top four banks. CAR is the capital adequacy ratio, LI is 100 times the proportion of liquid assets, SS is the virtual variable of "bank listing," and _Cons is the constant term. AR(1) and AR(2) are first-order and second-order serial correlation tests, respectively. Sargan is the Sargan test for the GMM model. The value in parenthesis below the regression coefficient is the robust standard error. The model setting tests the corresponding *p*-value in brackets on the right. *, **, and *** are significant at the 10%, 5%, and 1% confidence levels, respectively.

The regression results are in Table 10, which shows that the estimated coefficient of FinTech in the whole sample group is significantly negative, indicating that FinTech reduces the efficiency of commercial banks, which is consistent with the above conclusion. Compared with the whole sample, the estimated coefficient of FinTech of subsample 3 is larger, while the estimated coefficients of FinTech of subsamples 1 and 2 are smaller. This outcome means that the impact of FinTech on urban and rural commercial banks is greater than the average level, and its impact on large commercial and joint-stock banks is less than the average level. According to the t-test method of intergroup difference, the estimated coefficients of FinTech of the whole sample and subsample 1, the whole sample and subsample 2, the whole sample and subsample 3, and subsamples 1 and 2 are different at the confidence levels of 5%, 1%, 1%, and 1%, respectively. These results indicate that different types of commercial banks are significantly affected by FinTech. Urban and rural commercial banks are the most impacted by FinTech, followed by large commercial banks, whereas joint-stock banks are the least impacted by FinTech. These findings are also consistent with the above conclusion.

Table 10 also shows that between the whole sample and subsample 4, the estimated coefficient of FinTech of subsample 4 is smaller, suggesting that the impact of FinTech on regional commercial banks is greater than the average level. Furthermore, the estimated coefficient of FinTech in subsample 5 is smaller than in subsample 4, indicating that the impact of FinTech on regional commercial banks in the east region is higher than the average level of its impact on regional commercial banks. When the intergroup difference t-test method is used, the estimated coefficients of FinTech of the whole sample and subsample 4, and subsamples 4 and 5, differ at a confidence level of 1%. This result means that regional commercial banks are more affected by FinTech. Among regional commercial banks, commercial banks with varying regional characteristics are differently impacted by FinTech, and FinTech impacts regional commercial banks more in the east region. These findings are again consistent with the above conclusion.

#### 4.5.3. Using cost efficiency modeled by SFA to represent commercial bank efficiency

The stochastic frontier approach (SFA) is used to measure the efficiency of commercial banks; thus, this paper applies SFA to measure the cost efficiency of commercial banks (Berger, Hasan, & Zhou, 2009; Lensink, Meesters, & Naaborg, 2008). In model selection, the transcendental logarithm production function is used, and the function form is

$$Ln\left(\frac{RC}{W_2}\right) = A + BLn(K) + \sum\nolimits_{i=1}^{3} C_i{*}Ln(Y_i) + D{*}Ln(K)^2 + \sum\nolimits_{i=1}^{3} Ln(Y_i)^2 + E_{12}{*}Ln(Y_1)Ln(Y_2) + E_{13}{*}Ln(Y_1)Ln(Y_3) + E_{23}{*}Ln(Y_2)Ln(Y_3) + \sum\nolimits_{i=1}^{3} F_i Ln(K)Ln(Y_i) + \varepsilon_{i,t} + \mu_{i,t} \tag{7}$$

**Table 10**
FinTech and efficiency of different types of commercial banks—robustness test 2.

| Variable | Full sample | Subsample 1 | Subsample 2 | Subsample 3 | Subsample 4 | Subsample 5 | Subsample 6 |
|---|---|---|---|---|---|---|---|
| L.M | −0.0902* | −0.0896* | −0.0889* | −0.2051** | −0.0891* | −0.1501** | −0.0312*** |
| | (0.0548) | (0.0538) | (0.0501) | (0.0954) | (0.0496) | (0.0669) | (0.0100) |
| FinTech | −0.2058*** | −0.2147*** | −0.2272*** | −0.1601** | −0.2444*** | −0.2767*** | −0.2276 |
| | (0.0594) | (0.0721) | (0.0646) | (0.0637) | (0.0797) | (0.0972) | (0.1690) |
| Ggdp | 2.3810*** | 2.7222*** | 2.6196** | 1.1085 | 3.0968** | 2.4594* | 3.5454* |
| | (0.8445) | (0.9159) | (1.0960) | (0.8747) | (1.2160) | (1.3981) | (1.9332) |
| GS | −0.1698* | −0.1823* | −0.2125* | 0.0704 | −0.2313* | −0.1233 | −0.1404 |
| | (0.0936) | (0.1035) | (0.1142) | (0.0796) | (0.1280) | (0.1391) | (0.3365) |
| CR4 | 0.0007 | 0.0012 | 0.0007 | −0.0012 | 0.0014 | 0.0008 | −0.0013 |
| | (0.0021) | (0.0022) | (0.0025) | (0.0015) | (0.0028) | (0.0027) | (0.0047) |
| CAR | −0.0183 | −0.0196 | −0.0199 | −0.0138 | −0.0213 | −0.0090 | −0.0134 |
| | (0.0152) | (0.0164) | (0.0155) | (0.0125) | (0.0160) | (0.0090) | (0.0337) |
| LI | −0.0028 | −0.0031 | −0.0010 | −0.0029 | −0.0011 | 0.0001 | −0.0043 |
| | (0.0046) | (0.0046) | (0.0051) | (0.0042) | (0.0051) | (0.0053) | (0.0058) |
| SS | −0.0648 | −0.0827 | −0.0681 | 0.0564 | −0.0915 | −0.0576 | 0.0170 |
| | (0.0708) | (0.0897) | (0.0852) | (0.0659) | (0.1213) | (0.1844) | (0.1549) |
| _Cons | 0.2179 | 0.0606 | 0.0961 | 0.7438 | −0.1367 | 0.0017 | −0.5604 |
| | (0.5531) | (0.6122) | (0.6904) | (0.5294) | (0.7720) | (0.8436) | (1.2360) |
| AR(1) | 0.42[0.592] | −1.21[0.883] | −0.54[0.438] | 0.23[0.534] | 0.62[0.556] | 0.32[0.839] | 0.42[0.785] |
| AR(2) | 0.23[0.819] | 0.30[0.767] | 0.25[0.804] | −0.51[0.612] | 0.30[0.761] | 0.15[0.884] | −1.31[0.258] |
| Sargan | 4.66[0.702] | 4.91[0.671] | 4.14[0.764] | 12.69[0.392] | 4.77[0.688] | 3.17[0.869] | 6.97[0.728] |

Notes: This paper employs the ratio of third-party payment scale to online banking transaction scale as the core explanatory variable to represent the degree of FinTech development in robustness test 2. This table reports the impact of FinTech on commercial banks of different types and locations. The paper eliminates large commercial banks, joint-stock banks, and urban and rural commercial banks from the whole sample and forms subsample 1, subsample 2, and subsample 3, respectively. Subsample 4 only contains urban and rural commercial banks, subsample 5 includes commercial banks in the east region from subsample 4, and subsample 6 excludes commercial banks in the east region from subsample 4. M is total factor productivity, L.M is the lagged term of the variable M, FinTech is the FinTech development index, Ggdp is the GDP growth rate, GS is the ratio of the total stock market value to GDP, and CR4 is 100 times the assets proportion of the top four banks. CAR is the capital adequacy ratio, LI is 100 times the proportion of liquid assets, SS is the virtual variable of "bank listing," and _Cons is the constant term. AR(1) and AR(2) are first-order and second-order serial correlation tests, respectively. Sargan is the Sargan test for the GMM model. The value in parenthesis below the regression coefficient is the robust standard error. The model setting tests the corresponding p-value in brackets on the right. *, **, and *** are significant at the 10%, 5%, and 1% confidence levels, respectively.

where $RC$ is the actual total cost = interest expense + operating expenses. Input index $W_1$ is the price of loanable funds = interest expense / loanable funds; $W_2$ is the operating input price = operating expenses / total assets, reflecting the expenditure of human resources and operating expenses, and K is $W_1$ / $W_2$. The output indicators are loan balances $Y_1$, non-interest income $Y_2$, and investment and securities $Y_3$. Here $\varepsilon_{i,t}$ is a random interference term, subject to $N(0, \sigma_\varepsilon^2)$, and $\mu_{i,t}$ is a non-negative non-efficiency term subject to $N^+\left(0\ ,\ \sigma_\mu^2\right)$.

We obtain the cost efficiencies of 74 commercial banks in China from 2011 to 2019 using the frontier 4.1 operation model (6), as shown in Table 2. We observe the cost efficiency of different commercial banks and find that large commercial banks have the highest cost efficiency, followed by joint-stock banks; urban and rural commercial banks have the lowest cost efficiency. From the perspective of time, from 2011 to 2019, the cost efficiency of China's large commercial banks increased yearly, and the cost efficiencies of joint-stock banks and urban and rural commercial banks show an overall upward trend.

Cost efficiency is applied to represent the efficiency of commercial banks. Specifically, the data are brought into Eq. (2), and system GMM estimation is used to test the above four assumptions. The regression results are in Tables 11 and 12. Table 11 shows that the estimated coefficient of FinTech in the whole sample group is significantly negative, indicating that FinTech reduces the efficiency of commercial banks and supports H1b rather than H1a, which is consistent with the above conclusion. According to models (3) and (4) in Table 11, the estimated coefficient of FinTech in model (3) is significantly positive, the estimated coefficient of the cost intermediary variable in model (4) is significantly negative, and the debt cost of commercial banks play a part of the intermediary effect in the process of FinTech reducing commercial banks' efficiency. In other words, FinTech development increases commercial banks' debt cost, reducing their efficiency, which is consistent with the above conclusion.

Table 12 shows that the estimated coefficient of FinTech of subsample 3 is larger than the whole sample, while those of subsamples 1 and 2 are smaller. This result indicates that the impact of FinTech on urban and rural commercial banks is greater than the average level, while its impact on large commercial banks and joint-stock banks is less than the average level. According to the *t*-test method of intergroup difference, the estimated coefficients of FinTech for the full sample and subsample 1, full sample and subsample 2, full sample and subsample 3, and subsamples 1 and 2 differ at the 1% confidence level. This result indicates that different types of commercial banks are significantly affected by FinTech, and urban and rural commercial banks are the most affected by FinTech. Large commercial banks take second place; joint-stock banks are the least impacted by FinTech. These findings are consistent with the above

**Table 11**
Efficiency of FinTech and commercial banks—robustness test 3.

| Model | (2) | (3) | (4) |
|---|---|---|---|
| Explained variable | SFA_M | Cost | SFA_M |
| L.SFA_M | 0.5621*** | | −0.1238 |
| | (0.2025) | | (0.0918) |
| FinTech | −0.0567* | 0.1558*** | −0.0293 |
| | (0.0316) | (0.0559) | (0.0333) |
| Ggdp | −0.2077 | −1.6562* | −0.8594*** |
| | (0.2373) | (0.9418) | (0.3098) |
| Gs | 0.0180 | −0.1689 | −0.0496 |
| | (0.0582) | (0.1346) | (0.0437) |
| Cr4 | −0.0038** | −0.0008 | −0.0017 |
| | (0.0016) | (0.0018) | (0.0011) |
| Car | −0.0000 | 0.0005 | 0.0002 |
| | (0.0015) | (0.0020) | (0.0012) |
| Li | −0.0026 | −0.0135** | −0.0060 |
| | (0.0023) | (0.0068) | (0.0037) |
| Ss | 0.1971** | −1.4334* | −0.2416 |
| | (0.0941) | (0.7597) | (0.1639) |
| Cost | | | 0.4797*** |
| | | | (0.1455) |
| L.cost | | −0.1252 | |
| | | (0.1577) | |
| _Cons | 0.3566** | | |
| | (0.1782) | | |
| AR(1) | −2.27[0.023] | −1.02[0.309] | −0.52[0.602] |
| AR(2) | 0.29[0.770] | −1.10[0.271] | 0.12[0.904] |
| Sargan | 5.32[0.621] | 10.64[0.641] | 8.20[0.224] |

Notes: This paper applies SFA to measure the cost efficiency of commercial banks in the robustness test 3. This table shows the regression results for the mediation effect. It reports how FinTech affects the efficiency of commercial banks by affecting their cost. SFA_M is the cost efficiency of commercial banks calculated by the SFA model, cost equals interest expense / total deposit, and L.SFA_M and L.Cost are the lag items of variables SFA _M and Cost, respectively. FinTech is the FinTech development index, Ggdp is the GDP growth rate, GS is the total stock market value to GDP ratio, and CR4 is 100 times the assets proportion of the top four banks. CAR is the capital adequacy ratio, LI is 100 times the proportion of liquid assets, SS is the virtual variable of "bank listing," and _Cons is the constant term. AR(1) and AR(2) are first-order and second-order serial correlation tests, respectively, and Sargan is the Sargan test for the GMM model. The value in parenthesis below the regression coefficient is the robust standard error. The model setting tests the corresponding p-value in brackets on the right. *, **, and *** are significant at the 10%, 5%, and 1% confidence levels, respectively.

**Table 12**
FinTech and efficiency of different types of commercial banks—robustness test 3.

| Variable | Subsample 1 | Subsample 2 | Subsample 3 | Subsample 4 | Subsample 5 | Subsample 6 |
|---|---|---|---|---|---|---|
| L.M | 0.5747*** | 0.4781** | 0.4406*** | 0.5545** | 0.7617*** | 0.5423 |
| | (0.2084) | (0.1939) | (0.1609) | (0.2554) | (0.1866) | (0.5180) |
| FinTech | −0.0607* | −0.1065*** | −0.0473* | −0.0611* | −0.0683* | −0.0464** |
| | (0.0332) | (0.0413) | (0.0280) | (0.0328) | (0.0409) | (0.0211) |
| Ggdp | −0.2367 | 0.1842 | 0.3225 | −0.3895 | −0.1026 | −0.2866 |
| | (0.2545) | (0.3639) | (0.3267) | (0.3134) | (0.3565) | (0.7514) |
| GS | 0.0228 | 0.0518 | −0.0112 | 0.0399 | 0.1022 | −0.0757 |
| | (0.0631) | (0.0749) | (0.0477) | (0.0858) | (0.1018) | (0.2027) |
| CR4 | −0.0043** | −0.0018 | −0.0027*** | −0.0044*** | −0.0052*** | −0.0029 |
| | (0.0017) | (0.0015) | (0.0007) | (0.0017) | (0.0015) | (0.0037) |
| CAR | 0.0002 | 0.0002 | 0.0138* | 0.0003 | −0.0000 | 0.0073 |
| | (0.0015) | (0.0014) | (0.0082) | (0.0016) | (0.0015) | (0.0176) |
| LI | −0.0027 | −0.0072** | −0.0053* | −0.0021 | −0.0014 | −0.0056 |
| | (0.0022) | (0.0033) | (0.0029) | (0.0017) | (0.0017) | (0.0048) |
| SS | 0.1742* | 0.2090** | 0.1617** | 0.1456** | 0.1515** | 0.0669 |
| | (0.0912) | (0.0833) | (0.0716) | (0.0736) | (0.0625) | (0.0824) |
| _Cons | 0.3648* | 0.2843 | 0.1157 | 0.4242 | 0.1466 | 0.4253 |
| | (0.1874) | (0.2215) | (0.3156) | (0.2776) | (0.2788) | (0.5087) |
| AR(1) | −2.29[0.12] | −0.45[0.324] | −0.95[0.343] | −2.12[0.198] | −2.33[0.21] | −1.18[0.239] |
| AR(2) | 0.39[0.695] | −0.11[0.910] | −2.06[0.139] | 0.51[0.613] | 0.90[0.369] | −1.75[0.180] |
| Sargan | 5.65[5.81] | 5.22[0.517] | 24.96[0.162] | 4.23[0.753] | 3.62[0.823] | 16.94[0.390] |

Notes: This paper applies SFA to measure the cost efficiency of commercial banks in the robustness test 3. This table reports the impact of FinTech on commercial banks of different types and locations. This paper eliminates large commercial banks, joint-stock banks, and urban and rural commercial banks from the whole sample and forms subsample 1, subsample 2, and subsample 3, respectively. Subsample 4 only contains urban and rural commercial banks, subsample 5 includes commercial banks in the east region from subsample 4, and subsample 6 excludes commercial banks in the east region from subsample 4. M is total factor productivity, L.M is the lagged term of the variable M, FinTech is the FinTech development index, Ggdp is the GDP growth rate, GS is the ratio of the total stock market value to GDP, and CR4 is 100 times the assets proportion of the top four banks. CAR is the capital adequacy ratio, LI is 100 times the proportion of liquid assets, SS is the virtual variable of "bank listing," and _Cons is the constant term. AR (1) and AR(2) are first-order and second-order serial correlation tests, respectively, and Sargan is the Sargan test for the GMM model. The value in parenthesis below the regression coefficient is the robust standard error. The model setting tests the corresponding p-value in brackets on the right. *, **, and *** are significant at the 10%, 5%, and 1% confidence levels, respectively.

conclusion.

Table 12 also shows that compared with the whole sample and subsample 4, the estimated coefficient of FinTech in subsample 4 is smaller, indicating that the impact of FinTech on regional commercial banks is greater than the average level. A comparison of subsamples 4 and 5 indicates that the estimated coefficient of FinTech in subsample 5 is smaller, showing that the impact of FinTech on regional commercial banks in the east region is higher than the average level of its impact on regional commercial banks. The t-test method of intergroup difference, the estimated coefficients for FinTech of the whole sample and subsample 4, subsamples 4 and 5, and subsamples 4 and 6 are different at a confidence level of 1%, indicating that FinTech has a greater impact on regional commercial banks. Finally, commercial banks with varying regional characteristics are affected by FinTech differently, and regional commercial banks in the east region are more affected by FinTech. These findings are also consistent with the above conclusion.

## 5. Conclusion and policy recommendations

Represented by artificial intelligence, big data, blockchain, and cloud computing, FinTech has developed rapidly in recent years and greatly impacted the business model of the traditional banking industry. This research investigates the effect of FinTech on commercial banks from the perspective of efficiency by using the principles of consumer theory, disruptive innovation theory, and technology spillover theory. Our paper takes 74 commercial banks from 2012 to 2019 as samples, takes the TFP of commercial banks measured by the DEA method as the explanatory variable, and uses the FinTech index constructed by the text mining method as the core explanatory variable. The conclusions are as follows.

First, overall FinTech development reduces the efficiency of commercial banks. Second, FinTech development affects the liability side of commercial banks, as commercial banks' liability cost increases and efficiency decreases. Third, various types of commercial banks are impacted differently by FinTech. Urban and rural commercial banks are the most impacted by FinTech, followed by large commercial banks, while joint-stock banks are the least impacted by FinTech. Fourth, regional commercial banks are more impacted by FinTech. Among regional commercial banks, those in the east are more impacted by FinTech.

We study how FinTech affects commercial banks from the perspectives of their asset side and liability side and present the impactful ways that it improves commercial banks' debt cost and reduces their efficiency; however, the relationship and mechanism between the efficiency of commercial banks and risk are still unknown when risk is simultaneously affected by FinTech. Future research can observe the influence mechanism of how commercial bank efficiency and risk affect each other under FinTech development and examine the extent of their effect. As the systematic financial risk in China mainly originates from the banking industry (Zhang, Wei, Lee, & Tian, 2023), such a topic could contribute immensely to these areas.

From the research conclusions, this paper proposes relevant suggestions to commercial banks, FinTech companies, and regulators, as presented below.

First, as the product of the combination of the information revolution and financial services, FinTech has greatly impacted commercial banks' business model and production process. Facing the rapid development of FinTech, commercial banks should diverge from their traditional thinking mode, focus on customers, and effectively identify and solve customers' needs. Large commercial and joint-stock banks should accept the challenge from FinTech companies, use their immense capital and customer advantages, compete and cooperate with FinTech enterprises, and explore new paths and business development models. For example, these banks can build a digital support system based on the mobile Internet, big data, cloud computing, and other technologies. Small- and medium-sized banks can accelerate the construction of their high-end financial science and technology talent teams, strengthen independent R&D of critical technologies, and promote high-quality services. Such banks can also actively follow the trends in financial science and technology development and application through demonstration, competition, personnel mobility, and connection effects to improve operation and management ability and performance level. Cross-regional commercial banks can combine physical outlets with Internet virtual online stores, realize asset-light operations in some regions, and finally reduce costs and improve profitability. Regional commercial banks in the east region should also use their local advantages to provide financial services with regional characteristics and integrate their development into regional economic development. Local governments of the central and west regions should vigorously promote financial science and technology development, encourage policies and guiding laws and regulations, focus on hardware construction and talent introduction, and achieve breakthrough development.

Second, FinTech companies should seek a balance between their own and social benefits when providing cross-border financial services. In the past five years, FinTech companies' financial services have provided great convenience for residents and enterprises in payments, deposits, loans, and financial management, allowing them to obtain huge profits. However, when FinTech companies conduct financial services, Internet financial enterprises should clarify the bottom line, refuse data monopoly, give full play to their advantages in obtaining transaction data and information based on legal and compliant operations, innovate constantly, and provide richer and diversified financial services for residents and enterprises.

Finally, the provision of financial services by FinTech companies has brought new risks and problems, such as the abuse of customer information and illegal securities activities; thus, regulators should adhere to substantive supervision according to the essence of the financial business. Regulators should further pay close attention to and analyze the potential impact of FinTech to lay a proper foundation and prepare for improving the supervision mode and preventing financial risks. Market access and continuous supervision of FinTech companies should be implemented under the framework of current laws and regulations, and FinTech companies should be required to follow the same business rules and risk management mandates. Relevant authorities should also participate actively in research on the development, impact, and supervision of FinTech by international organizations, such as FSB and the Basel Committee. The authorities should also jointly explore regulatory rules that keep pace with the times, ensure the effectiveness of supervision, and prevent and ably resolve significant financial risks.

## Disclosure statement

The authors declare that we have no relevant or material financial interests that relate to the research described in this paper.

## Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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## CRediT authorship contribution statement

**Chien-Chiang Lee:** Conceptualization, Supervision, Project administration, Writing – review & editing. **Wenjie Ni:** Software, Data curation, Methodology, Writing – original draft. **Xiaoming Zhang:** Funding acquisition, Investigation, Project administration, Writing – original draft.

## Declaration of Competing Interest

The authors declare no conflicts of interest.

## Data availability

Data will be made available on request.

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## Appendix A. Appendix

**Table A1**
Explanation of all variables.

| Type | Variable | Sym | Variable design | Sources |
|---|---|---|---|---|
| Explained variable | Total factor productivity | M | DEA–Malmquist (1) | Bank Focus |
| | | SFA_M | SFA (2) | Bank Focus; Annual report |
| Core explanatory variable | FinTech | FinTech | FinTech development index | Baidu Index |
| | | | Digital Inclusive Finance Index | Reports from Peking University |
| | | | Ratio of third-party payment scale to online banking transaction scale | Office for National Statistics |
| Mediator variables | Profitability | ROE | ROE | |
| | | | | Bank Focus |
| | Liability Cost | Cost | Interest expense / total deposit | |
| Control variables | Macroeconomic level | Ggdp | GDP growth | |
| | Stock market development | GS | Ratio of total stock market value to GDP | Office for National Statistics |
| | | CR4 | Growth rate | |
| | | | Asset proportion of the top four banks * 100 | Bank Focus |
| | Banking concentration | | | |
| | Bank risk-taking | CAR | Capital adequacy ratio | |
| | Bank liquidity level | LI | Proportion of liquid assets * 100 | Bank Focus |
| | | | | Bank Focus |
| | | SS | Virtual variable of "bank listing" | Company official website |
| | Bank listing | | | |

Notes: (1) The input and output variables selected in the DEA–Malmquist appear in Table 1. (2) The concrete way to calculate the efficiency under the SFA method is in part 4.5.3.

## References


Aaker, D. A., & Keller, K. L. (1990). Consumer evaluations of brand extensions. *Journal of Marketing, 54*(1), 27–41. https://doi.org/10.1177/002224299005400102

Abakah, E. J. A., Nasreen, S., Tiwari, A. K., & Lee, C. C. (2023). U.S. leveraged loan and debt markets: Implications for optimal portfolio and hedging. *International Review of Financial Analysis, 87*, Article 102514. https://doi.org/10.1016/j.irfa.2023.102514

Acquaah, M. (2012). Social networking relationships, firm-specific managerial experience and firm performance in a transition economy: A comparative analysis of family owned and nonfamily firms. *Strategic Management Journal, 33*(10), 1215–1228. https://doi.org/10.1002/smj.1973

Agyekum, F. K., Reddy, K., Wallace, D., & Wellalage, N. H. (2022). Does technological inclusion promote financial inclusion among SMEs? Evidence from south-east Asian (SEA) countries. *Global Finance Journal, 53*, Article 100618. https://doi.org/10.1016/j.gfj.2021.100618

Alarab, I., & Prakoonwit, S. (2022). Effect of data resampling on feature importance in imbalanced blockchain data: Comparison studies of resampling techniques. *Data Science and Management, 5*(2), 66–76. https://doi.org/10.1016/j.dsm.2022.04.003

Aslan, A., & Sensoy, A. (2020). Intraday efficiency-frequency nexus in the cryptocurrency markets. *Finance Research Letters, 35*, Article 101298. https://doi.org/10.1016/j.frl.2019.09.013

Bartlett, R., Morse, R., Stanton, R., & Wallace, N. (2022). Consumer-lending discrimination in the FinTech era. *Journal of Financial Economics, 143*(1), 30–56. https://doi.org/10.1016/j.jfineco.2021.05.047

Berger, A. N. (2003). The economic effects of technological progress: Evidence from the banking industry. *Journal of Money, Credit, and Banking, 35*(2), 141–176. https://www.jstor.org/stable/3649852. https://doi.org/10.1353/mcb.2003.0009.

Berger, A. N., Hasan, I., & Zhou, M. M. (2009). Bank ownership and efficiency in China: What will happen in the world's largest nation? *Journal of Banking and Finance, 33*(1), 113–130. https://doi.org/10.1016/j.jbankfin.2007.05.016

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). FinTech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics, 130*(3), 453–483. https://doi.org/10.1016/j.jfineco.2018.03.011

Caprio, G., Fiechter, J. L., Litan, R., & Pomerleano, M. (2010). *The future of state-owned financial institutions*. Brookings Institution Press.

Chen, M. A., Wu, Q. X., & Yang, B. Z. (2019). How valuable is FinTech innovation? *Review of Financial Studies, 32*(5), 2062–2106. https://doi.org/10.1093/rfs/hhy130

Chen, X. H., You, X. Y., & Chang, V. (2021). FinTech and commercial banks' performance in China: A leap forward or survival of the fittest? *Technological Forecasting and Social Change, 166*, Article 120645. https://doi.org/10.1016/j.techfore.2021.120645

Chen, Y., Cheng, L., Lee, C. C., & Wang, C. S. (2021). The impact of regional banks on environmental pollution: Evidence from China's city commercial banks. *Energy Economics, 102*, Article 105492. https://doi.org/10.1016/j.eneco.2021.105492

Cheng, M. Y., & Qu, Y. (2020). Does bank FinTech reduce credit risk? Evidence from China. *Pacific-Basin Finance Journal, 63*, Article 101398. https://doi.org/10.1016/j.pacfin.2020.101398

Christensen, C. M. (1997). In *, 33. The innovator's dilemma: When new technologies cause great firms to fail* (p. 32465791). Harvard Business Review Press. https://doi.org/10.5465/amr.2008.32465791.

Del Gaudio, B. L., Previtali, D., Sampagnaro, G., Verdoliva, V., & Vigne, S. (2022). Syndicated green lending and lead bank performance. *Journal of International Financial Management and Accounting, 33*(3), 412–427. https://doi.org/10.1111/jifm.12151

FSB. (March 2016). *FinTech: Describing the landscape and a framework for analysis*.

Goldstein, I., Jiang, W., & Karolyi, G. A. (2019). To FinTech and beyond. *Review of Financial Studies, 32*(5), 1647–1661. https://doi.org/10.1093/rfs/hhz025

Hao, Q., Shen, J. H., & Lee, C. C. (2023). Risk Contagion of Bank-firm Loan Network: Evidence from China. *Eurasian Business Review, 13*, 341–361. https://doi.org/10.1007/s40821-022-00237-w

Hornuf, L., Klus, M. F., Lohwasser, T. S., & Schwienbacher, A. (2021). How do banks interact with FinTech startups? *Small Business Economics, 57*(3), 1505–1526. https://doi.org/10.1007/s11187-020-00359-3

Hsieh, M. F., & Lee, C. C. (2020). Foreign bank lending during a crisis: The impact of financial regulations. *Economic Systems, 44*(3), Article 100791. https://doi.org/10.1016/j.ecosys.2020.100791

Hsieh, M. F., Lee, C. C., & Lin, Y. C. (2022). New evidence on liquidity creation and bank capital: The roles of liquidity and political risk. *Economic Analysis and Policy, 73*, 778–794. https://doi.org/10.1016/j.eap.2022.01.002

Hsieh, M. F., Lee, C. C., & Shen, M. F. (2023). Ownership structure, diversification, and bank performance: International evidence. *Emerging Markets Finance and Trade, 59*(1), 90–112. https://doi.org/10.1080/1540496X.2022.2093103

Hussain, J., & Lee, C. C. (2022). A green path towards sustainable development: optimal behavior of the duopoly game model with carbon neutrality instruments. *Sustainable Development, 30*, 1523–1541. https://doi.org/10.1002/sd.2325

Jagtiani, J., & Lemieux, C. (2018). Do FinTech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business, 100*, 43–54. https://doi.org/10.1016/j.jeconbus.2018.03.001

Jiang, C. X., Yao, S. J., & Feng, G. F. (2013). Bank ownership, privatization, and performance: Evidence from a transition country. *Journal of Banking and Finance, 37*(9), 3364–3372. https://doi.org/10.1016/j.jbankfin.2013.05.009

Jiang, G., Liu, F., Liu, W., Liu, S., Chen, Y., & Xu, D. (2021). Effects of information quality on information adoption on social media review platforms: Moderating role of perceived risk. *Data Science and Management, 1*(1), 13–22. https://doi.org/10.1016/j.dsm.2021.02.004

Kumar, V., Thrikawala, S., & Acharya, S. (2022). Financial inclusion and bank profitability: Evidence from a developed market. *Global Finance Journal, 53*, Article 100609. https://doi.org/10.1016/j.gfj.2021.100609

Le, T. H., Chuc, A. T., & Taghizadeh-Hesary, F. (2019). Financial inclusion and its impact on financial efficiency and sustainability: Empirical evidence from Asia. *Borsa Istanbul Review, 19*(4), 310–322. https://doi.org/10.1016/j.bir.2019.07.002

Lee, C. C., & Lee, H. T. (2023). Optimal portfolio diversification with a multi-chain regime-switching spillover GARCH model. *Global Finance Journal, 55*, Article 100808. https://doi.org/10.1016/j.gfj.2023.100808

Lee, C. C., Li, X. R., Yu, C. H., & Zhao, J. S. (2021). Does FinTech innovation improve bank efficiency? Evidence from China's banking industry. *International Review of Economics and Finance, 74*, 468–483. https://doi.org/10.1016/j.iref.2021.03.009

Lee, C. C., & Wang, C. (2022). Financial development, technological innovation, and energy security evidence from Chinese provincial experience. *Energy Economics, 112*, Article 106161. https://doi.org/10.1016/j.eneco.2022.106161

Lee, C. C., Wang, C. W., & Ho, S. J. (2020a). Financial innovation and bank growth: The role of institutional environments. *North American Journal of Economics and Finance, 53*, Article 101195. https://doi.org/10.1016/j.najef.2020.101195

Lee, C. C., Wang, C. W., & Ho, S. J. (2020b). Financial inclusion, financial innovation, and firms' sales growth. *International Review of Economics and Finance, 66*, 189–205. https://doi.org/10.1016/j.iref.2019.11.021

Lee, C. C., Wang, C. W., Hsieh, H. Y., & Chen, W. L. (2023). The impact of central bank digital currency variation on firm's implied volatility. *Research in International Business and Finance, 64*, Article 101878. https://doi.org/10.1016/j.ribaf.2023.101878

Lensink, R., Meesters, A., & Naaborg, I. (2008). Bank efficiency and foreign ownership: Do good institutions matter? *Journal of Banking and Finance, 32*(5), 834–844. https://doi.org/10.1016/j.jbankfin.2007.06.001

Liu, M., Choo, W., Lee, C. C., & Lee, C. C. (2023). Trading volume and realized volatility forecasting: Evidence from the China stock market. *Journal of Forecasting, 42*(1), 76–100. https://doi.org/10.1002/for.2897

Liu, X. T., & Yang, D. Y. (2017). Research on the efficiency of M&a choice differences of commercial banks under the background of internet finance – An empirical analysis of Malmquist index based on the heterogeneity of commercial banks. *Studies of International Finance, 10*.

Lv, C., Fan, J., & Lee, C. C. (2023). Can green credit policies improve corporate green production efficiency? *Journal of Cleaner Production, 397*, Article 136573. https://doi.org/10.1016/j.jclepro.2023.136573

Megginson, W. L. (2005). The economics of bank privatization. *Journal of Banking and Finance, 29*(8–9), 1931–1980. https://doi.org/10.1016/j.jbankfin.2005.03.005

Muganyi, T., Yan, L., Yin, Y., Sun, H., Gong, X., & Taghizadeh-Hesary, F. (2022). FinTech, regtech, and financial development: Evidence from China. *Financial Innovation, 8*(1), Article 101186. https://doi.org/10.1186/s40854-021-00313-6

Nie, C., & Lee, C. C. (2023). Synergy of pollution control and carbon reduction in China: Spatial–temporal characteristics, regional differences, and convergence. *Environmental Impact Assessment Review, 101*, 107110. https://doi.org/10.1016/j.eiar.2023.107110

Phan, D. H. B., Narayan, P. L., Rahman, E., & Hutabarat, A. R. (2020). Do FinTech firms influence bank performance? *Pacific-Basin Finance Journal, 62*, Article 101210. https://doi.org/10.1016/j.pacfin.2019.101210

Qiu, H., Huang, Y. P., & Ji, Y. (2018). The impact of financial technology on traditional banking behavior-from the perspective of internet finance. *Journal of Financial Research, 11*.

Ren, X., Zeng, G., & Gozgor, G. (2023). How does digital finance affect industrial structure upgrading? Evidence from Chinese prefecture-level cities. *Journal of Environmental Management, 330*, Article 117125. https://doi.org/10.1016/j.jenvman.2022.117125

Shen, J. H., Li, W., & Lee, C. C. (2023). Unlocking the myths of size expansion in China's large state-owned enterprises: Theory and evidence. *Managerial and Decision Economics, 44*(2), 1264–1284. https://doi.org/10.1002/mde.3746

Sokhanvar, A., Çiftçioğlu, S., & Lee, C. C. (2023). The effect of energy price shocks on commodity currencies during the war in Ukraine. *Resources Policy, 82*, 103571. https://doi.org/10.1016/j.resourpol.2023.103571

Sun, L., Zhang, H., & Fang, C. (2021). Data security governance in the era of big data: Status, challenges, and prospects. *Data Science and Management, 2*, 41–44. https://doi.org/10.1016/j.dsm.2021.06.001

Tan, Y., Lau, M. C. K., & Gozgor, G. (2021). Competition and profitability: Impacts on stability in Chinese banking. *International Journal of the Economics of Business, 28*(2), 197–220. https://doi.org/10.1080/13571516.2020.1724009

Wan, J., & Lee, C. C. (2023). Corporate investment and the dilemma of the monetary policy: Evidence from China. *Economic Analysis and Policy, 78*, 106–121. https://doi.org/10.1016/j.eap.2023.03.002

Wang, C. W., Lee, C. C., & Chen, M. C. (2022). The effects of economic policy uncertainty and country governance on banks' liquidity creation: International evidence. *Pacific-Basin Finance Journal, 71*, Article 101708. https://doi.org/10.1016/j.pacfin.2022.101708

Wang, C. W., Lee, C. C., & Wu, L. T. (2023). The relationship between cash flow uncertainty and extreme risk: International evidence. *Pacific-Basin Finance Journal, 77*, Article 101927. https://doi.org/10.1016/j.pacfin.2022.101927

Wang, Y., Sui, X. P., Qi, Z., Wang, Y., Xiuping, S., & Zhang, Q. (2021). Can FinTech improve the efficiency of commercial banks? —An analysis based on big data. *Research in International Business and Finance, 55*, Article 101338. https://doi.org/10.1016/j.ribaf.2020.101338

Wen, H., Chen, S., & Lee, C. C. (2023). Impact of low-carbon city construction on financing, investment, and total factor productivity of energy-intensive enterprises. *The Energy Journal, 44*(2), 51–74. https://doi.org/10.5547/01956574.44.2.hwen

Wu, Y., Lee, C. C., Lee, C. C., & Peng, D. (2022). Geographic proximity and corporate investment efficiency: Evidence from high-speed rail construction in China. *Journal of Banking and Finance, 140*, Article 106510. https://doi.org/10.1016/j.jbankfin.2022.106510

Yahya, F., Abbas, G., & Lee, C. C. (2023). Asymmetric effects and volatility transmission from metals markets to solar energy stocks: Evidence from DCC, ADCC, and quantile regression approach. *Resources Policy, 82*, 103501. https://doi.org/10.1016/j.resourpol.2023.103501

Zhang, N., Liu, R., Zhang, X., & Pang, Z. (2021). The impact of consumer perceived value on repeat purchase intention based on online reviews: By the method of text mining. *Data Science and Management, 3*, 22–32. https://doi.org/10.1016/j.dsm.2021.09.001

Zhang, X. M., Liang, Q., & Lee, C. C. (2023). How does central bank transparency affect systemic risk? Evidence from developed and developing countries. *The Quarterly Review of Economics and Finance, 88*, 101–115. https://doi.org/10.1016/j.qref.2022.12.005

Zhang, X. M., Wei, C., Lee, C. C., & Tian, Y. M. (2023). Systemic risk of Chinese financial institutions and asset price bubbles. *North American Journal of Economics and Finance, 64*, Article 101880. https://doi.org/10.1016/j.najef.2023.101880

Zhu, C., & Lee, C. C. (2022). The effects of low-carbon pilot policy on technological innovation: Evidence from prefecture-level data in China. *Technological Forecasting and Social Change, 183*, Article 121955. https://doi.org/10.1016/j.techfore.2022.121955

Zhu, X. (2012). Understanding China's growth: Past, present, and future. *Journal of Economic Perspectives, 26*(4), 103–124. https://doi.org/10.1257/jep.26.4.103