International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 7728-7737

https://doi.org/10.70517/ijhsa464665

Monte Carlo Simulation-Driven Quantitative Model of Dual Effects of Bank Operational Efficiency and Risk Management in FinTech

Yujia Nie[1,*]
[1] Faculty of Economics and Management, College of Arts and Science, Hubei Normal University, Huangshi, Hubei, 435109, China
Corresponding authors: (e-mail: Julientte@163.com).

Abstract The rapid development of financial technology has had a profound impact on traditional banking, particularly in terms of improving operational efficiency. This paper collects publicly disclosed data from 35 listed banks between 2015 and 2024 and uses the EBM model to measure the operational efficiency of banks under fintech. Through literature review, appropriate input and output indicators are selected to calculate the Malquist index for the sample banks. Additionally, regression analysis is employed to conduct an empirical analysis of the impact of fintech on bank operational efficiency. The average total factor productivity of the sample banks from 2015 to 2024 was above 1, with an annual improvement rate of 19.44%, and technological efficiency was the primary factor driving this improvement. Additionally, state-owned large banks had the highest operational efficiency growth rate at 31.2%, while national joint-stock banks and city banks had growth rates of 17.7% and 9.3%, respectively. The intensity of fintech investment and the outcomes of fintech application significantly enhance banks' total factor productivity and technological progress. The coefficients of the impact of fintech application outcomes on the overall operational efficiency, technological progress index, and technical efficiency of state-owned large banks are 0.171, 0.164, and 0.017, respectively, indicating a significant positive effect.

Index Terms fintech, EBM model, Malquist index, regression analysis, bank operational efficiency

I. Introduction

In recent years, with the widespread adoption of mobile internet and advancements in digital technology, fintech has increasingly disrupted traditional finance. As new financial models such as blockchain, digital currencies, and online lending emerge, many traditional banking operations face significant challenges [1]. Against the backdrop of digital finance development, traditional banks have been broadly and profoundly impacted across multiple dimensions, including business models, operational domains, management capabilities, and profitability [2], [3]. On one hand, fintech leverages the efficient and convenient characteristics of modern science and technology in information and data processing to apply them to the financial sector, which requires handling complex information and conducting rapid and efficient data mining and processing [4]-[7]. Additionally, its coverage is more comprehensive and extensive. Traditional financial institutions can leverage the low-cost and high-efficiency advantages of digital finance to more effectively meet the service needs of all parties [8], [9]. On the other hand, in today's rapidly developing fintech landscape, many new financial business models have emerged. The development of electronic information technology has posed significant challenges to traditional financial institutions, undermining their dominant position in financial markets [10]-[13]. How to leverage fintech to enhance bank operational efficiency and core competitiveness is the key for banks to stand out in a competitive environment [14], [15]. Therefore, conducting research and analysis on the impact of fintech development on bank operational efficiency can provide valuable policy references for the long-term development of Chinese banks.

Academic circles generally recognize fintech as an emerging technology that can be effectively integrated with the financial industry, representing the successful application of technology in the information industry sector. Literature [16] outlines the positive impact of fintech on traditional banking operations, noting that it not only improves banks' profitability and financial innovation capabilities but also effectively controls financial risks, thereby enhancing the operational efficiency of the banking industry. Literature [17] measures the efficiency scores of China's banking sector under different equity structures, finding that banks supported by fintech can effectively improve their cost efficiency and technological innovation capabilities, which in turn manifests as enhanced service efficiency. Literature [18] uses accuracy, effectiveness, and efficiency as evaluation criteria for bank operational performance and combines intelligent PLS analysis methods to investigate the impact of fintech on banking operations. It finds that fintech can enhance banks' competitive advantages, improve customer experience, and reduce operational costs, thereby improving bank operational efficiency. Literature [19] indicates that increasing banks' investment in financial technology will significantly enhance their profitability while reducing their risk exposure levels, which has a positive impact on banks' financial performance and operational stability. Literature [20] explores the correlation between financial technology and internal cost efficiency in the banking industry, pointing out that banks' cost efficiency improves with the level of financial technology application, and that the impact varies significantly across different banking sectors. It can be seen that the above studies simply map bank operational efficiency to economic performance evaluations. Since banks cannot assess overall efficiency using a single or multiple indicators, the value of fintech in enhancing bank operational efficiency cannot be fully reflected.

This study provides a detailed introduction to the theoretical foundations of fintech in enhancing bank operational efficiency, employing a combination of quantitative and qualitative methods. It selected 35 representative listed banks in China, analyzed their annual and quarterly reports from 2015 to 2024, and utilized data envelopment analysis to measure the relationship between technological investment and operational efficiency. Additionally, by constructing a static short panel model, it conducted regression analysis using fintech investment intensity and fintech application outcomes as core explanatory variables to empirically study changes in the operational efficiency of the sample banks.

II. Theoretical foundations of financial technology

FinTech [21] is a new technology system that deeply integrates financial and technological elements and demonstrates its application in financial services. Generally speaking, the public's understanding of FinTech mainly comes from examples in daily life, such as convenient payments via smartphones, easy transfer transactions on mobile banking apps, and real-time account balance inquiries.

II. A.Platform Economy Theory

Platform economy theory refers to an economic model in the digital age that promotes transactions and value creation between suppliers and consumers through the establishment and operation of online platforms. Its core concept is that by building an intermediary platform, efficient connections between suppliers and consumers can be achieved, transaction costs can be reduced, transaction efficiency can be improved, and new value can be created.

In the fintech sector, fintech platforms integrate financial service providers and users to offer convenient and efficient financial services that meet users' diverse needs. Fintech companies leverage the mechanisms of the platform economy to achieve resource sharing and acquire more customer resources. Through multi-channel development, they can successfully establish their own financial service platforms and attract a certain number of customers. Once such a platform is established and a customer base is established, fintech companies can begin to launch their own financial products and services on the platform.

Through the financial services platforms of fintech companies, customers can enjoy more convenient and innovative financial products and services. These products and services may include online payments, personal investment consulting, and loans. Customers can apply and operate online through the platform without visiting traditional bank branches, thereby saving time and effort.

II. B.The Long Tail Theory

The long tail refers to a phenomenon in the market where a small number of popular products or services account for a large share of sales, while the majority of non-popular products or services have smaller sales volumes, yet the overall sales volume remains substantial. In traditional economies, due to limited resources, suppliers produce popular products or services based on market demand, while other non-popular products or services are neglected or marginalized. However, the advent of the internet has broken this constraint, leading to the emergence of a large number of long-tail products or services in the market.

The long tail theory has had a significant impact on the business model of banks. Traditional bank products have primarily focused on developing mass-market demand, such as loans and savings. However, the long tail theory posits that there are numerous niche demands in the market. Through fintech, banks can better address these niche demands and develop more personalized products and services. For example, some banks have launched financial products tailored to specific industries or groups, such as agricultural loans, further expanding their product lines.

II. C.Innovation Diffusion Theory

The theory of innovation diffusion posits that the diffusion process of new technologies depends on factors such as their relative advantage, compatibility, complexity, trialability, and observability. In the fintech sector, many innovations possess distinct advantages, such as superior user experience, higher efficiency, greater compatibility, lower transaction costs, and more personalized products, enabling them to spread rapidly in the market. Additionally, the diffusion of fintech also depends on factors such as the policy environment, market conditions, and user habits.

II. D.Network Effect Theory

The network effect theory posits that the value of a product or service is directly proportional to the number of users who utilize it. In the fintech sector, many products and services (such as mobile payments and social investing) can generate network effects, meaning that the more users there are, the greater the value of the service. For example, mobile payment services like Alipay and WeChat Pay become more valuable as the number of users increases, as more merchants are likely to accept them. Therefore, for fintech companies, the key to success lies in attracting more users through high-quality services and innovative business models.

III. Measurement and analysis of bank operational efficiency

III. A. Selection of Efficiency Measurement Models

Data Envelopment Analysis (DEA) is one of the primary methods for measuring bank efficiency. DEA can be used to set the model by adopting optimal weights, thereby calculating the relative efficiency between input factors and outputs [22]. The EBM model, as an extension of the DEA model, can address the issue of slackness between inputs and outputs and handle non-radial relationships that cannot be addressed by the CCR and BCC models. Additionally, the EBM model incorporates both unexpected outputs and super-efficiency into the model, resolving the issue of multiple efficient decision units being unable to be compared with one another.

To address the issue of slackness between input and output indicators, this paper introduces slack variables when calculating indices. Based on this, this paper selects the EBM model to measure bank operational efficiency. Additionally, to address the issue of inter-period comparability, this paper adopts the global reference method for measuring total factor productivity, using bank data from different periods as the global frontier, thereby resolving the issue of inter-period comparison.

III. A. 1) EBM-DEA model

The EBM-DEA model [23] assumes that the decision-making unit (DMU) is used to measure the operational efficiency of banks, with a total of n DMUs (j=1,2,…,n) to be measured. The DMUs to be measured are denoted as DMUK. The total factor productivity represented by DMUK is composed of m input indicators and s output indicators. The input indicators are denoted as $x_i(i=1,2,...,m)$ and the output indicators are denoted as $y_r(r=1,2,...,s)$ The super-efficiency EBM-DEA model constructed in this way is expressed as:

$$\begin{aligned}
&\min \rho = \frac{1+\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1-\frac{1}{s}(\sum_{r=1}^{s} s_r^+ / y_{rk})} \\
&s.t. \sum_{j=1, j\neq k}^{n} x_{ij}\ \lambda_j - s_i^- \le x_{ik} \\
&\lambda, s^-, s^+ \ge 0 \\
&i=1,2,...,m;\ r=1,2,...,q;\ j=1,2,...,n\ (j\neq k) \\
&\sum_{j=1}^{n}\lambda_j = 1
\end{aligned} \tag{1}$$

ρ is the final quantifiable comparable efficiency value; s^- is the relaxation variable introduced into the model for input indicators; s^+ is the relaxation variable for output indicators; the model converts panel data into interface data for h different periods, so the total number of decision units is nh, and the interface data for different periods is incorporated into a unified reference set S^g to enable inter-period comparison. The specific formula is as follows:

$$S^g = S^1 \cup S^2 \cup ......\cup S^h = \left\{(x_j^1, y_j^1)\right\} \cup \left\{(x_j^2, y_j^2)\right\} \cup ......\cup \left\{(x_j^h, y_j^h)\right\} \tag{2}$$

III. A. 2) EBM-DEA-Malmquist model

Unlike the EBM-DEA model, the EBM-DEA-Malmquist model focuses on measuring changes in efficiency.

The Malmquist total factor productivity model assumes that there are n decision-making units (DMUs) to be measured and p periods, so the total number of DMUs is np. All DMUs in all periods are distributed in a unified reference set P^g.

The single Malmquist total factor productivity index for the global reference can be expressed as:

$$M_g(y_j^{t+1}, x_j^{t+1}, x_j^t, y_j^t) = E_g(y_j^{t+1}, x_j^{t+1}) / E_g(x_j^t, y_j^t) \tag{3}$$

Among them, M_g represents the calculated Malmquist index, x_j^t represents the input indicator of category j in period t, and x_j^{t+1} represents the input indicator of the same category in the next period of x_j^t. y_j^t and y_j^{t+1} represent the output indicators for periods t and $t+1$ respectively.

Further decomposition of M_g yields efficiency change (EC) and technical change (TCg), whose intrinsic relationship is as follows:

$$M_g = EC \times TC_g \tag{4}$$

Efficiency changes can be calculated based on the frontier of input-output indicators, while technological changes mainly measure the changes in input-output indicators between two adjacent periods.

The specific calculation methods for efficiency changes (EC) and technological changes (TCg) are as follows:

$$\begin{aligned} EC &= E^{t+1}(x_j^{t+1}, y_j^{t+1}) / E^t(x_j^t, y_j^t) \\ TC_g &= \frac{E_g(x_j^{t+1}, y_j^{t+1}) / E_g(x_j^t, y_j^t)}{E^{t+1}(x_j^{t+1}, y_j^{t+1}) / E^t(x_j^t, y_j^t)} \end{aligned} \tag{5}$$

III. B. Data Sources and Indicator Selection

In terms of data selection, this paper is based on data availability and collects publicly disclosed data from 35 listed banks for the period from 2015 to 2024 through annual and quarterly reports of various banks, research institution reports, company announcements, and the WIND and CSMAR databases.

Based on the principles for selecting indicators, this paper references the research of domestic and international scholars and aligns with the direction of its own research. The following input indicators were selected: total deposits, fixed asset scale, number of employees, and operating expenses. These indicators respectively reflect the bank's inputs in terms of current assets, non-current assets, personnel, and expenses. Total loans, net profit, and net interest income were selected as output indicators, respectively reflecting the bank's loan business, operating revenue, and interest income. By incorporating the aforementioned four input indicators, three output indicators, and the non-desired output indicator of non-performing loan ratio into the indicator construction system, the EBM-DEA-Malquist index was ultimately measured.

III. C. Calculation of changes in total factor productivity of banks

Based on the input-output data collected from the sample banks, this paper calculates the total factor productivity (TFP) and its component efficiency indicators—technical efficiency (EC) and technical progress (TC)—for the selected 35 listed banks from 2015 to 2024, in accordance with the measurement principles outlined above. Additionally, the global score (G-Score) is calculated to measure the contribution of technical progress to efficiency for the sample banks. In the measurement of total factor productivity, the DEAP 2.1 software was used, and the results of the total factor productivity measurement for the sample banks are shown in Figure 1.

According to the calculation results in the figure, the final measurement results fluctuate around 1. When the measured index result is greater than 1, it indicates that total factor productivity and decomposed efficiency are currently in a state of progress. Similarly, a value equal to 1 or less than 1 indicates a state of stagnation or decline. Among them, the TFP of the sample banks showed a certain improvement between 2015 and 2024, with the mean values all above 1. Specifically, the annual average improvement rate of technical efficiency (EC) was 4.9%, the annual average improvement rate of technological progress (TC) was 13.1%, and the annual average improvement rate of TFP was 19.4%. Based on this, it can be concluded that the improvement in total factor productivity of the sample banks between 2015 and 2024 was primarily driven by technological progress. Additionally, after 2020, the global participation scores of the sample banks showed a sustained upward trend, indicating that the production efficiency of the sample banks is gradually reaching the industry's global optimal level.

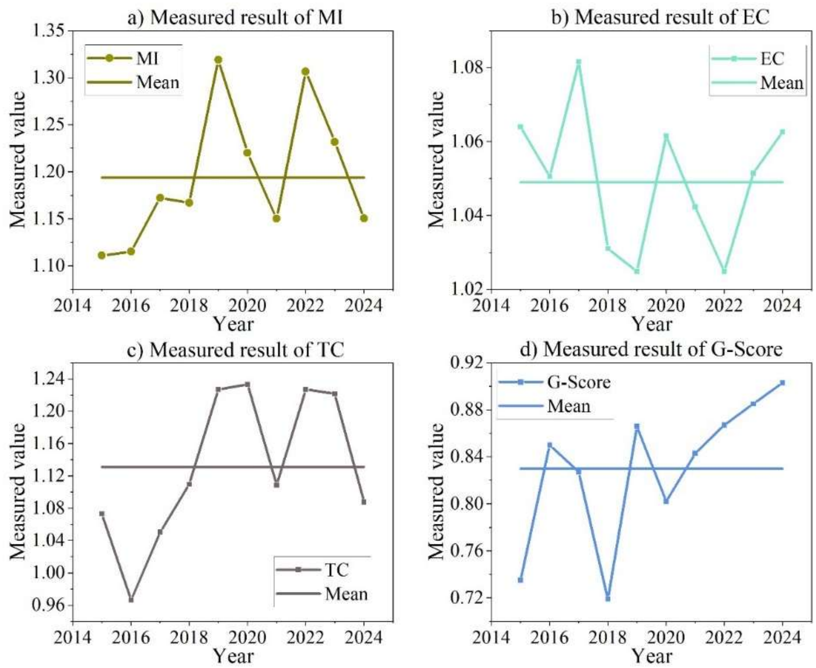

Figure 1: The total factor productivity measure of the sample bank

Based on the input-output data collected from the sample banks, this paper calculates the total factor productivity (TFP) and its component efficiency indicators—technical efficiency (EC) and technical progress (TC)—for the selected 35 listed banks from 2015 to 2024, in accordance with the measurement principles outlined above. Additionally, the global score (G-Score) is calculated to measure the contribution of technical progress to efficiency for the sample banks. In the measurement of total factor productivity, the DEAP 2.1 software was used, and the results of the total factor productivity measurement for the sample banks are shown in Figure 2.

According to the calculation results in the figure, the final measurement results fluctuate around 1. When the measured index result is greater than 1, it indicates that total factor productivity and decomposed efficiency are currently in a state of progress. Similarly, a value equal to 1 or less than 1 indicates a state of stagnation or decline. Among them, the TFP of the sample banks showed a certain improvement between 2015 and 2024, with the mean values all above 1. Specifically, the annual average improvement rate of technical efficiency (EC) was 4.9%, the annual average improvement rate of technological progress (TC) was 13.1%, and the annual average improvement rate of TFP was 19.4%. Based on this, it can be concluded that the improvement in total factor productivity of the sample banks between 2015 and 2024 was primarily driven by technological progress. Additionally, after 2020, the global participation scores of the sample banks showed a sustained upward trend, indicating that the production efficiency of the sample banks is gradually reaching the industry's global optimal level.

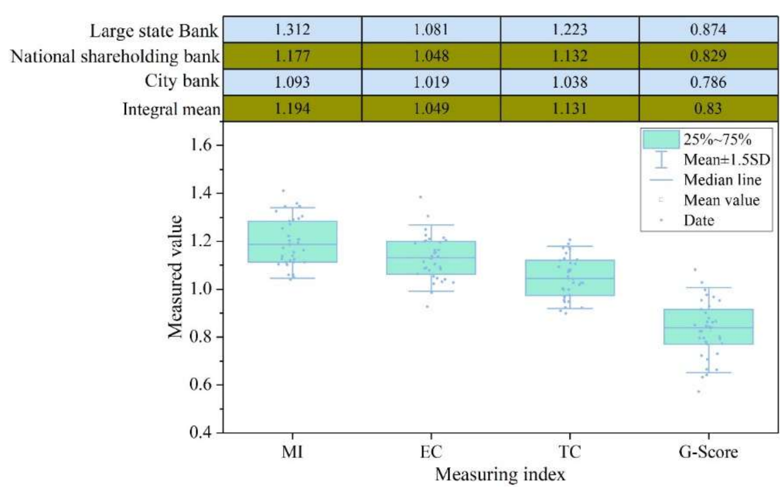

Figure 2: Total factor productivity and its decomposition results

IV. Empirical analysis of the impact of financial technology on banking operational efficiency

IV. A. Variable Selection

IV. A. 1) Dependent variable

The above text uses the EBM model to calculate the operational efficiency of banks. Total factor productivity, the technological progress index, and the technological efficiency change index are selected as explanatory variables, each reflecting different aspects of business efficiency, and the impact of different explanatory factors on bank operational efficiency is explored.

IV. A. 2) Core explanatory variables

To more accurately reflect the development of fintech, this paper selects fintech investment intensity and fintech application outcomes as the main explanatory variables. Fintech investment intensity refers to the level of investment made by banks in fintech development, while fintech application outcomes refer to the productivity gains achieved by banks through the use of fintech.

(1) Fintech investment intensity. This indicator directly reflects banks' investment in and emphasis on fintech, as well as their level of development in fintech. It is calculated by dividing the total fintech investment of different banks by their business revenue.

(2) Fintech application outcomes. This indicator directly reflects the profitability of fintech products for banks.

This paper evaluates the outcomes of banks' use of fintech using the number of updates to mobile application software as an indicator. Mobile application software is used for online transactions, expanding marketing channels, and providing users with better financial services. The number of updates to mobile applications can directly reflect the effectiveness of banks' use of fintech; once relevant technologies are adopted, banks will inevitably upgrade them promptly. In regression analysis, the natural logarithm of the number of updates to mobile application versions is used as the evaluation indicator.

IV. A. 3) Control variables

Bank efficiency is influenced by numerous factors. To more accurately assess the relationships between these factors and eliminate their interference, this paper requires variable management. This paper primarily selects appropriate control variables based on the research findings of past scholars and the broader context of China's economic and financial development.

(1) Macroeconomic Environment

For national economic development, GDP growth rate can serve as a standard for measuring the value added of the national economy. In this process, banking operations play a crucial role in the stability and development of the entire financial market, and their operational efficiency is often significantly influenced by changes in the economic environment. When the economic situation is favorable, banks can obtain more resources to expand their credit business, thereby enhancing their profit levels; however, if the economic situation deteriorates, banks may not only face a reduction in credit scale but also encounter greater difficulties in promoting their products and services, ultimately leading to a decline in their yield rates and a weakening of their overall operational efficiency. The CPI index, or current consumer price index, can be used to assess the degree of inflation. If price indices rise, banks' ability to attract deposits will be affected, thereby reducing their performance. At the current stage, the broad money growth rate reflects the circulation of money in the market. The higher a country's degree of monetization, the higher its level of financial development, and the performance of enterprises and other financial institutions is relatively more stable. Therefore, studying the monetary policy environment helps understand financial market activities and facilitates national macroeconomic regulation.

(2) Internal factors

The size of a company's total assets is an important basis for evaluating the scale of its assets. The capital adequacy ratio is used to assess the level of operational risk a company can bear. If the capital adequacy ratio is relatively stable, it indicates that the company has strong risk-bearing capacity at the current stage. Additionally, effective control and management of the capital adequacy ratio can significantly curb a company's blind expansion. For profit-seeking enterprises, the primary performance metric of interest is the average return on total assets, which is positively correlated with a commercial bank's profitability and is measured by calculating the average value obtained by subtracting the initial total assets from the total assets at the end of the calculation period. To achieve higher income, banks will improve their operational management quality, thereby driving efficiency growth, which constitutes a positive feedback mechanism.

IV. B. Construction of measurement models

This paper selects a static short panel model for regression analysis and sets the model as follows:

$$y = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \sum\nolimits_{j=3}^{8} \beta_i c_{ji} + \varepsilon_i \tag{6}$$

Among them, y represents the operational efficiency of banks, x_{1i} denotes the intensity of financial technology investment, x_{2i} denotes the application outcomes of financial technology, $c_3 \sim c_8$ are control variables, representing stock market activity, financial leverage ratio, market share, cost management capability, risk management capability, and business innovation capability, respectively. i denotes an individual bank, β denotes the regression coefficient of the individual variable, and ε_i denotes the regression residual.

IV. C. Analysis of empirical results

IV. C. 1) Descriptive Statistics and Multiple Linear Tests

The descriptive statistical results of the main variables in this paper are shown in Table 1. It can be seen that the changes in total factor productivity (TFP), which represents bank operational efficiency, and its decomposition indicators—the technological progress index and the technological efficiency change index—are consistent with the analysis discussed earlier. The mean value of TFP is 1.194, primarily influenced by the mean value of the TPI, which is 1.131 (the mean value of the TEVI is 1.049, with relatively weaker fluctuations), indicating that the overall operational efficiency of banks is showing a positive growth trend due to technological progress. The maximum values for the financial technology indicators—financial technology investment intensity and financial technology application outcomes—are 0.423 and 162, respectively, while the minimum values are 0.016 and 0, respectively. The mean values are 0.092 and 19.839, respectively. This indicates that the sample banks are developing financial technology at a relatively fast pace, with overall improvements in development levels.

Table 1: Descriptive statistical results of major variables

Variable	Mean	SD	Min	Max
Total factor productivity	1.194	0.405	1.040	1.411
Technological progress index	1.131	0.512	0.927	1.385
Technical efficiency index	1.049	0.419	0.923	1.206
Financial technology investment intensity	0.092	0.061	0.016	0.423
Financial technology application results	19.839	15.999	0.000	162.000
Economic added value of national economy	0.067	0.006	0.063	0.072
Inflation level	3.114	0.872	1.091	4.925
Market share	0.017	0.022	0.000	0.116
Monetization	1.036	0.431	0.033	2.785
Size of bank	0.955	0.165	0.572	1.818
Earning capacity	0.554	0.156	0.073	0.954

This section further uses the variance inflation factor (VIF) method to test for multicollinearity, with the results of the multiple linear regression analysis shown in Table 2. As can be seen from the data in the table, the VIF values for all variables are less than 5, indicating that there is no multicollinearity issue among the variables.

Table 2: Multiple linear test results

Variable	VIF	1/VIF
Financial technology investment intensity	1.807	0.553
Financial technology application results	2.217	0.451
Economic added value of national economy	2.07	0.483
Inflation level	1.181	0.847
Market share	2.908	0.344
Monetization	2.598	0.385
Size of bank	2.936	0.341
Earning capacity	2.842	0.352

IV. C. 2) Regression results

This section uses SPSS software to conduct regression analysis on the dependent variables—total factor productivity, technological progress index, and technological efficiency change index—yielding the regression results shown in Table 3. As indicated in the table, the regression coefficients for financial technology investment intensity and bank total factor productivity, technological progress index, and technological efficiency change index are 0.231, 0.134, and -0.022, respectively. Additionally, the regression coefficients for the application outcomes of financial technology on banks' TFP, the technological progress index, and the technological efficiency change index are 0.128, 0.093, and -0.016, respectively. Among these, the regression coefficients for financial technology investment intensity and financial technology application outcomes on banks' TFP and the technological progress index are significantly positive, while the regression coefficient for the technological efficiency change index is negative but not significant. This result indicates that the development of fintech has a significant positive impact on technological progress but a negative impact on technological efficiency, though the latter is not significant.

The reason for this is that the development of fintech promotes technological innovation in banks, enhances their profitability and customer base, and increases their market share, but it also intensifies industry competition. Banks continuously seek further technological breakthroughs to maintain their competitive advantage. However, the positive impact of fintech on banks' internal economies of scale, management capabilities, and quality control is not significant, and in some cases, it even has an inhibitory effect.

Table 3: Correlation analysis results

Variable	Total factor productivity	Technological progress index	Technical efficiency index
Financial technology investment intensity	0.231***(5.673)	0.134***(6.417)	-0.022(4.492)
Financial technology application results	0.128***(1.975)	0.093***(2.248)	-0.016(1.527)
Economic added value of national economy	-3.817***(-3.692)	-2.173***(-4.435)	-2.285***(-4.198)
Inflation level	0.065***(1.643)	0.038***(1.174)	0.057***(1.442)
Market share	10.271***(9.773)	8.632***(8.165)	7.296***(8.541)
Monetization	0.009(0.885)	0.001(0.627)	0.003(0.836)
Size of bank	-0.003(0.221)	-0.006(0.142)	-0.002(0.105)
Earning capacity	0.219***(3.614)	0.273***(2.243)	0.195***(2.317)
_cons	1.367***(8.764)	1.253(9.462)	1.085(13.976)

Note: ***p<0.01, **p<0.05, *p<0.10.

IV. C. 3) Heterogeneity test

This section categorizes banks into three types—state-owned large banks, national joint-stock banks, and city banks—as in the preceding text, and examines the impact of financial technology investment intensity and financial technology outcomes on the operational efficiency of banks of different types. The results of the heterogeneity test are shown in Table 4.

As shown in the table, the intensity of financial technology investment has varying degrees of impact on the three key indicators of the aforementioned three types of banks. The impact on state-owned large banks is the most significant, with coefficients ranging from 0.587 to 0.769, and passing the 0.01 level of significance test. The impact on national joint-stock banks is the next most significant, while the impact on city banks is the least significant. The impact of fintech achievements on state-owned large banks is the only one that passes the significance test, with coefficients of 0.171, 0.164, and 0.147 for total factor productivity, technological progress index, and technological efficiency change index, respectively. The impact on national joint-stock banks and city banks is not significant.

In summary, financial technology has a significant positive effect on the overall efficiency, technological progress index, and technological efficiency index of state-owned large banks, a result consistent with the previous analysis of banks as a whole. This phenomenon may be because state-owned large banks are directly regulated by the central government, and national policies supporting the development of financial technology are implemented first and most effectively in such banks. Additionally, these banks have strong policy implementation capabilities, robust financial strength, and adequate R&D investments, which further explain the aforementioned positive correlations. Compared to state-owned large banks, national joint-stock banks and city banks demonstrate greater flexibility and local advantages. However, their overall capital base is insufficient to fully support the implementation of flexible solutions such as technological transformation and updates, thereby slowing their ability to adopt emerging technologies to explore new operational models. As a result, the impact of fintech development on operational efficiency is less pronounced in these two categories of banks, leading to the relatively lower significance and smaller coefficients observed in the results.

Table 4: Heterogeneity test results

Variable		Financial technology investment intensity	Financial technology application results
Large state Banks	Total factor productivity	0.769***	0.171***
		(6.238)	(0.121)
	Technological progress index	0.587***	0.164***
		(6.479)	(0.113)
	Technical efficiency index	0.602***	0.147***
		(5.713)	(0.124)
National shareholding bank	Total factor productivity	0.357***	0.012
		(7.142)	(-2.375)
	Technological progress index	0.269***	0.015
		(5.573)	(1.245)
	Technical efficiency index	0.314***	0.018
		(4.671)	(1.325)
City bank	Total factor productivity	0.143*	0.022
		(3.251)	(3.275)
	Technological progress index	0.115*	0.039
		(2.243)	(3.746)
	Technical efficiency index	0.127*	0.027
		(1.985)	(3.084)

Note: ***p<0.01, **p<0.05, *p<0.10.

IV. C. 4) Robustness testing

To confirm the reliability of the conclusions, a robustness test of bank operational efficiency was conducted on two indicators of financial technology: financial technology investment intensity and financial technology outcomes. The results of the robustness test are shown in Table 5. Based on the results of the robustness test, it can be seen that the signs of the coefficients of the explanatory variables and control variables are consistent with the original regression results, and the significance of some variables' coefficients has changed slightly. However, overall, the analysis coefficients and significance of the regression results remain largely consistent. Therefore, the conclusions drawn are reliable.

Table 5: Robustness test results

Variable	Total factor productivity	Technological progress index	Technical efficiency index
Financial technology investment intensity	0.209***(5.341)	0.121***(6.286)	-0.020(4.517)
Financial technology application results	0.135***(1.693)	0.087***(2.135)	-0.013(1.212)
Economic added value of national economy	-2.931***(-3.315)	-1.986***(-3.918)	-2.157***(-4.283)
Inflation level	0.052***(1.451)	0.030***(1.102)	0.043***(1.256)
Market share	9.635***(9.812)	8.418***(8.203)	7.182***(8.315)
Monetization	0.006(0.672)	0.002(0.591)	0.001(0.768)
Size of bank	-0.003(0.212)	-0.004(0.118)	-0.001(0.093)
Earning capacity	0.204***(2.147)	0.183***(1.955)	0.189***(2.245)
_cons	1.243***(8.516)	1.079(9.113)	0.973(12.684)

Note: ***p<0.01, **p<0.05, *p<0.10.

V. Conclusion

The article is based on panel data from 35 typical listed banks from 2015 to 2024. It uses the DEA-Malmquist method to calculate the operational efficiency of the 35 sample banks and conducts static and dynamic analyses. To examine the impact of fintech development on bank operational efficiency, multiple control variables are selected, and a static short panel model is used to empirically study the impact of fintech development on bank operational efficiency and conduct robustness tests. Through empirical verification, the study confirms the existence of a mediating effect of fintech development in this process, leading to the following conclusions:

The results of the DEA model indicate that the operational efficiency of the sample banks fluctuated between 2015 and 2024, with an average annual improvement of 19.4%, a technical efficiency increase of 13.1% annually, and relatively limited progress in technological advancement. Static analysis indicates that the development of fintech has the greatest impact on the growth of operational efficiency in state-owned large banks, with a growth rate of 31.2%.

In the multicollinearity test, the VIF values of all variables ranged from 1.181 to 2.936, far below 5, indicating that there is no multicollinearity issue among the variables. The intensity of fintech investment significantly improves banks' total factor productivity, while it has a negative effect on technological progress, though not significantly.

The intensity of financial technology investment has a significant positive impact on the three key indicators of state-owned large banks, national joint-stock banks, and city banks, while the application outcomes of financial technology only have a significant positive impact on the three indicators of state-owned large banks.

References

[1] Vives, X. (2017). The impact of FinTech on banking. European Economy, (2), 97-105.

[2] Komandla, V., & PERUMALLA, S. (2017). Transforming traditional banking: Strategies, challenges, and the impact of fintech innovations. Educational Research (IJMCER), 1(6), 01-09.

[3] Dasilas, A., & Karanović, G. (2025). The impact of FinTech firms on bank performance: evidence from the UK. EuroMed Journal of Business, 20(1), 244-258.

[4] Chen, K. C. (2020). Implications of Fintech developments for traditional banks. International journal of economics and financial issues, 10(5), 227.

[5] Lee, C. C., Ni, W., & Zhang, X. (2023). FinTech development and commercial bank efficiency in China. Global Finance Journal, 57, 100850.

[6] Khan, H. H., Kutan, A. M., & Qureshi, F. (2024). Fintech integration: Driving efficiency in banking institutions across the developing nations. Finance Research Letters, 67, 105772.

[7] Chen, X., You, X., & Chang, V. (2021). FinTech and commercial banks' performance in China: A leap forward or survival of the fittest?. Technological Forecasting and Social Change, 166, 120645.

[8] Singh, R., Malik, G., & Jain, V. (2021). FinTech effect: measuring impact of FinTech adoption on banks' profitability. International Journal of Management Practice, 14(4), 411-427.

[9] Bueno, L. A., Sigahi, T. F., Rampasso, I. S., Leal Filho, W., & Anholon, R. (2024). Impacts of digitization on operational efficiency in the banking sector: Thematic analysis and research agenda proposal. International Journal of Information Management Data Insights, 4(1), 100230.

[10] Lee, S., Chang, T. H., & Chiu, Y. H. (2024). Exploring the influence of fintech patents on operation efficiency and market efficiency in Taiwan's commercial banking sector-meta entropy dynamic two-stage DDF model. Managerial and Decision Economics, 45(6), 4276-4291.

[11] Al-Shari, H. A., & Lokhande, M. A. (2023). The relationship between the risks of adopting FinTech in banks and their impact on the performance. Cogent Business & Management, 10(1), 2174242.

[12] Le, T. D., Ho, T. H., Nguyen, D. T., & Ngo, T. (2021). Fintech credit and bank efficiency: International evidence. International Journal of Financial Studies, 9(3), 44.

[13] Ahmad, Z., Khan, A. A., & Burki, A. K. (2024). Financial Sustainability in Emerging Markets: The Role of Fintech, Risk Management, and Operational Efficiency. Contemporary Journal of Social Science Review, 2(04), 339-353.

[14] Rahman, M. M. (2023). The effect of business intelligence on bank operational efficiency and perceptions of profitability. FinTech, 2(1), 99-119.

[15] Onorato, G., Pampurini, F., & Quaranta, A. G. (2024). Lending activity efficiency. A comparison between fintech firms and the banking sector. Research in International Business and Finance, 68, 102185.

[16] 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, 101338.

[17] Lee, C. C., Li, X., Yu, C. H., & Zhao, J. (2021). Does fintech innovation improve bank efficiency? Evidence from China's banking industry. International Review of Economics & Finance, 74, 468-483.

[18] Rehman, T. U., ul Hassan, M. N., Imran, Z., & Khan, R. M. N. (2022). FinTech implementation: a way forward to expedite bank operations. Journal of Financial Technologies (Fintech), Inclusion and Sustainability (JFTIS), 1(1), 27-38.

[19] Kayed, S., Alta'any, M., Meqbel, R., Khatatbeh, I. N., & Mahafzah, A. (2025). Bank FinTech and bank performance: evidence from an emerging market. Journal of Financial Reporting and Accounting, 23(2), 518-535.

[20] Goel, R., & Kashiramka, S. (2025). FinTech Advancement in the Banking Industry: Is It Driving Efficiency?. International Journal of Finance & Economics.

[21] Suhaib Al-Khazaleh,Nemer Badwan,Qais Saleh,Mohammad Almashaqbeh & Ihab Qubbaj. (2025). Corporate financial trends, dynamics of FinTech impact and financial regulation: joint evidence from Jordan and Palestine. Digital Policy Regulation and Governance,27(5),553-570.

[22] Hafizullah Radmand,Farshid Eshraghi,Ali Keramatzadeh & Habibullah Rezaei. (2025). Efficiency analysis of wheat production in Baghlan Province: a data envelopment analysis (DEA) based approach. Discover Food,5(1),153-153.

[23] Yongqin Xie & Yuejiao Song. (2020). Spatiotemporal Analysis of Urban Water Use Efficiency of the Yangtze River Economic Zone in China: Based on Undesirable Super-efficiency EBM-DEA Model. Journal of Coastal Research,103(sp1),458-463.