sustainability

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An Empirical Analysis of the Impact of Digital Finance on the Efficiency of Commercial Banks

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Abstract: Based on the background of the digital transformation of commercial banks, the advantages and benefits of this study are to study the promotion effect of digital finance on the production efficiency of commercial banks from four aspects: technological innovation, financial innovation, deep integration of technology and finance, and industry advantages. This study verifies that digital finance has a positive impact on the total factor productivity of commercial banks. In order to study the impact of the development of digital finance on the efficiency of commercial banks, this paper puts forward two assumptions. Using the "text mining method" and taking the total factor productivity of commercial banks as the explanatory variable and the digital finance index as the core explanatory variable, this paper empirically studies the impact of digital finance on bank efficiency. Through empirical research, it is believed that through the analysis of total factor productivity, digital finance has strongly promoted the improvement of the total factor productivity of commercial banks through the technology spillover effect. The impact of digital finance on banks is therefore heterogeneous.

Keywords: digital finance; commercial banks; total factor productivity; DEA Malmquist

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Citation: Zuo, L.; Li, H.; Xia, X. An Empirical Analysis of the Impact of Digital Finance on the Efficiency of Commercial Banks. *Sustainability* **2023**, *15*, 4667. https://doi.org/10.3390/su15054667

Academic Editor: Antonio Boggia

Received: 29 December 2022
Revised: 13 February 2023
Accepted: 22 February 2023
Published: 6 March 2023

1. Introduction

Digital finance promotes the integration of commercial banks and digital technology and promotes the degree of digitalization of commercial banks. At the same time, the application of digital technology has generated a new type of financial service business with the help of the Internet, competing with the traditional commercial banking business and products. As an important financial intermediary, commercial banks continue to develop disintermediation. In the process of economic operation and development, the efficiency of commercial banks has a decisive impact on the development of the entire financial system and the application of funds. Therefore, further analysis and study of the real impact of digital finance on the efficiency of commercial banks and the important role of digital finance in the context of the digital transformation of the financial industry is of great and practical significance. This has an important reference value for the development of the digital finance of commercial banks. At the same time, the analysis of different commercial banks can compare the heterogeneity of different equity commercial banks in the development of digital finance which is helpful for the development of the digital finance of commercial banks with different scales and different equity attributes.

Digital financial innovation affects commercial banks and their total factor productivity through disruptive technologies. For example, consumer credit has been growing in recent years. However, due to the lack of an accurate personal information database, consumer credit is greatly limited. The application of machine learning technology can meet and expand this personal credit demand. Digital finance can also contribute to the local economy. The digitalization of commercial banks realized by digital finance through technology investment can have a secondary impact on the improvement of sustainable productivity. Commercial banks began to invest in financial technology and digital activities to achieve business transformation and efficiency improvement, and then triggered factor productivity improvement through three main channels. The first is the production channel, through which more efficient production technology can save costs and improve production efficiency. Second, through the use of financial technology and digital toolkits, the transaction channels reduce the transaction costs of commercial banks (such as customer search, transaction negotiation, and contract execution). The third is the management channel which improves the internal management efficiency. The improvement of TFP will optimize the technical efficiency and scale efficiency of commercial banks. Therefore, the improvement of total factor productivity has an incentive effect for commercial banks to increase investment in science and technology and has formed a positive feedback mechanism.

Zhu Nan et al. studied the efficiency of China's commercial banks from the perspective of legal compliance and they believed that commercial banks and all companies share the same features, namely, the pursuit of profits. They ranked and analyzed the efficiency of 14 commercial banks with a data envelopment analysis method and believed that the efficiency of state-owned commercial banks was lower than that of joint-stock commercial banks [1]. Zheng Lujun and others used the DEA method to analyze the efficiency of commercial banks. They believed that the equity differences of state-owned, joint-stock, and urban commercial banks were not the main reason for affecting the efficiency of commercial banks. As the equity changes and tends to be concentrated, the efficiency of commercial banks is in an inverted U shape [2]. Zhang Jianhua analyzed the efficiency of commercial banks from 1997 to 2001, measured the distribution of resources, ranked the efficiency, proposed a comprehensive evaluation method for the banking industry, measured the scale efficiency, and used the Malmquist efficiency index to perform the calculations [3]. Wang Cong used the SFA method to measure the efficiency index of X profit of commercial banks from 1990 to 2003. He believed that GDP growth rate had a significant role in promoting X profit efficiency [4]. Liu Zhixin and others used DFA to study the efficiency of commercial banks; analyzed the efficiency of China Construction Bank, Agricultural Bank of China, Bank of China, and the Industrial and Commercial Bank of China with the free distribution method; and believed that the Bank of China has the highest efficiency [5]. Wang Jian and others used the DEA Malmquist index to analyze the relationship between efficiency and risk in the post-crisis era and made a comparative analysis of the efficiency changes of commercial banks before and after the crisis. They believed that the improvements of technical efficiency and technological progress were the key to the improvement of the overall efficiency of commercial banks [6]. Paradi analyzed the financial industry as the center of modern economic development and proposed that the efficiency improvement and operating efficiency of commercial banks have important impacts on the national macroeconomic lifeline [7].

There is much research on the efficiency of foreign commercial banks, mainly including research on technical efficiency, technical progress efficiency, scale efficiency, frontier efficiency, X-efficiency, cost efficiency, and profit efficiency. Simon used the stochastic frontier method to study the cost efficiency of Hong Kong commercial banks and found that the average X-efficiency of Hong Kong banks was about 16–30% of the total cost observed. In addition, they also found that the efficiency of the average large bank is lower than that of the average small bank, but the scale effect seemed to be related to the differences in portfolio characteristics between the banks of different sizes [8]. H Kiyota used the stochastic frontier method to conduct a comparative analysis of the profit efficiency and cost efficiency of commercial banks operating in 29 sub-Saharan African (SSA) countries from 2000 to 2007, including bank ownership (domestic banks, SSA foreign banks, or non-SSA foreign banks), and bank size. A Tobit regression was used to assess the impact of environmental factors on the efficiency of commercial banks. The main findings of this empirical analysis show that foreign banks are often better than domestic banks in terms of profit efficiency. As far as the scale efficiency of banks is concerned, the smaller the bank size is, the higher the profit efficiency of banks is. Medium or relatively large banks are often the most cost-effective [9]. WK Wang used the DEA analysis model to evaluate the relative efficiency of the Bank of China. The DEA analysis model includes CCR, BCC, bilateral, relaxation-based measurement, and the FDH model. We also used a bilateral model to measure and compare the efficiency of state-owned banks and private banks, and studied the most productive scale of commercial banks [10]. RM Odunga studied the impact of liquidity and capital adequacy ratios on the operating efficiency of commercial banks in Kenya to try to determine the impact of bank-specific liquidity ratios and capital adequacy ratios (core capital ratio, risk). The research showed that the operating efficiency ratio, the current assets to short-term liabilities ratio, and the total capital ratio of the previous year had a positive and significant impact on the operating efficiency of the banks. This means that the company's historical performance affects the company's progress in streamlining its operational strategy. Therefore, banks should seek mechanisms to improve the ratio of current assets to deposits and the ratio of total capital to improve operational efficiency and maintain market competitiveness [11]. CN Simiyu determined the impact of financial liberalization on the X-efficiency of Kenyan commercial banks, assuming that there is a positive relationship between liberalization and the X-efficiency of Kenyan commercial banks [12]. RA Ajisafe investigated the relationship between the competition and efficiency of Nigerian commercial banks between 1990 and 2009. The collected data were analyzed using the combined least squares and dynamic panel generalized methods of moment estimation techniques with fixed effects. The analysis results showed that there is a positive and significant relationship between the competitiveness and efficiency of Nigerian commercial banks. It was concluded that the reform introduced in the banking industry in the late 1980s improved the competitiveness and efficiency of Nigerian commercial banks [13]. Klein believes that joint-stock commercial banks with diversified equity distributions usually have more branches. This strategic pattern is conducive to the accumulation of internal funds in the financial market, and the overall efficiency of commercial banks are improved through the continuous increase in branches [14–17].

Nguyen, Q. K. used the relevant data of ASEAN countries to analyze the relationship and impact between the efficiency of the audit committees of financial institutions, the efficiency of banks, and risk taking. It is believed that efficiency and risk taking have a reverse effect. Using the data from ASEAN countries, this paper studies the effectiveness of bank risk management from the perspective of risk governance structures. Using the quantile regression method, this paper studies the relationship between the ownership results of commercial banks in ASEAN countries and the risk taking of commercial banks. Starting from the role of market discipline, this paper studies the important role of financial technology development in the financial stability of emerging markets [18–21].

Phan, D. H. B, and others put forward the hypothesis that the growth of financial technology will have a negative impact on bank performance. They used the data of 41 commercial banks to study the development of the Indonesian market and financial technology, and they believed that financial technology had a negative impact on bank performance [22]. Other scholars have compared foreign banks with China, using DEA two-stage network model to link interest-bearing business and non-interest-bearing business through the number of referrals. Based on the DEA two-stage model, this paper analyzes the impact on commercial banks [23–25].

Based on the availability of data and the public disclosure information of banks that have laid out the market in financial technology and digital financial development in recent years, this paper selects the panel data of 41 commercial banks from 2011 to 2021 as research samples, according to the asset scale, income, profit, and digital financial development of commercial banks This study also compiled quarterly reports, annual reports, research reports, internal journals, company announcements, enterprise news, and other materials of city commercial banks, as well as analyses of the sample commercial bank data in the wind database and the CSMAR database and research and analysis on the impact of digital finance on bank efficiency and system risk and on the development and digital transformation of digital finance.

The article has four parts. The first part is the introduction, which mainly introduces the background, significance, the literature, structure, and other contents of the article. The second part is the theoretical analysis and hypothesis proposal. First, the relevant theories are analyzed, and then two hypotheses are proposed and verified. The third part is the definition of variables and model setting, which mainly defines each variable, designs the measurement model, and designs the data analysis methods and steps. The fourth part is an empirical analysis, which analyzes the data used in the article. The fifth part is the conclusion, which summarizes and prospects of the article.

2. Theoretical Analysis and Hypothesis Presentation

Starting from the asset-liability structure of commercial banks, the first hypothesis is put forward: digital finance has changed the asset-liability structure of commercial banks and the production efficiency has been significantly affected. Based on the analysis of banks' assets, the second hypothesis is put forward: the application of technology leads to the intensification of competition, which makes the business increase the investment in technology to obtain higher profit returns.

(1) Digital finance has changed the asset liability structure of commercial banks and the production efficiency has been significantly affected.

The development of digital finance has changed the financial ecological environment and product factors, changed the asset liability structure of commercial banks, and significantly affected the production efficiency of commercial banks. From the perspective of commercial banks' liabilities, from 2011 to 2021 the deposits of Chinese commercial banks declined and the financing ratio declined year by year. The rapid development of digital finance has created a technology-oriented financial service system which has a great impact on traditional financial services. Compared with traditional financial models, digital finance can quickly and accurately capture market information with the help of big data, artificial intelligence, and other technical means, with the advantage of more convenient and accurate access to customers. It uses network information matching and artificial intelligence technology to quickly realize the connection between financing and investment and between accurate mining and the rapid transmission of information; divert the traditional business of commercial banks, namely deposit business; and increase the cost of capital utilization of commercial banks. As a result, the main profit mode of commercial banks has changed and the deposit loan interest margin is no longer the main source of profit. Commercial banks gradually integrate technology into services and products, discarding the business model that does not adapt to the development of competition, expanding the business scope, improving efficiency, and obtaining more effective customers. From the perspective of macroeconomic operation trends, the digital economy has penetrated into the financial industry. Compared with the development of other industries, the integration speed and transformation requirements of the digital economy in the financial industry, especially the banking industry, are more rapid, and the capital and human costs of investment are higher. Since the outbreak of COVID-19, most commercial banks at home and abroad, especially large commercial banks, have been exploring strategies and paths for digital transformation, putting the development of digital finance on the agenda. Internationally, emerging direct selling banks and open banks have developed for nearly five years in Europe, the United States, Southeast Asia, and other countries and regions, and have accumulated relatively successful experiences. On the domestic side, some joint-stock commercial banks and large state-owned commercial banks are also actively exploring the business model of direct selling banks.

(2) From the perspective of the bank's asset accounts, the application of technology has led to intensified competition, making the business increase its investment in technology to obtain higher profit returns.

The intensification of competition caused by application of technology makes commercial banks invest further in technology resources to obtain higher profit returns. Farmll put forward a new research and analysis framework for technical efficiency which makes the concept of technical progress separate from the average production function and connects with the boundary production function. When the economic subject reaches the optimal production state, the behavior point is on the production boundary, highlighting the optimal state. The fierce competition in the deposit market is directly related to the rights and interests of commercial banks. In order to broaden profit channels and increase commercial profits, commercial banks expand the introduction of technical personnel and invest more R and D capital. In order to improve the competitiveness of the industry, the rapid development of digital finance increases the debt cost of banks, leading to the increase in bank loan interest rates, making lenders more willing to apply for high-risk, high-return assets, and leading to the increase in the proportion of risky assets of banks. Digital finance brings new challenges to the risk governance of commercial banks. First, it increases the possibility of commercial banks facing risk shocks, increases risk factors at the data level, breaks through the composition of traditional commercial banks' risk data, leads to more diversified data, refines data granularity, expands data extension, and enhances the accuracy of data and the precision of customer information screening. Secondly, the risk control governance system of commercial banks has been rebuilt, the traditional risk control means have been abandoned, and the emerging risk control model and other technologies have been used to optimize and improve the credit rating of commercial banks, which has diversified the dimensions of data monitoring, broadened the setting of data variables, and improved the accuracy of the model. Third, a new digital financial model and system have been established to achieve clear risk control management under financial data governance, sharing, classification and integration, machine learning, and other technologies. Fourthly, the process system of the internal control management of commercial banks was built again, which abandoned the situation of isolated information and unclear responsibilities of traditional commercial banks. Digital technology has been used to open up all links of the front, middle, and back office, which has made the risk management process more standardized, optimized the management efficiency, achieved the goal of information resource sharing by means of blockchain and other technologies, and made transactions in the financial industry more orderly. This cannot be tampered with to achieve effective records on the decentralized chain, avoiding information forgery, protecting important secret information, reducing the bank's operational risk, and significantly reducing the systemic risk.

(3) According to the technology spillover theory, digital finance has had a huge impact on the traditional commercial banking system and has promoted the improvement of total factor productivity through various ways.

The development of digital finance has had a huge impact on the traditional commercial banking system and has played an important role in the total factor productivity of commercial banks. According to the theory of technology spillover, the technology services, technology transfers, and technology cooperation provided by advanced scientific and technological innovation enterprises have a positive impact on the technology of financial enterprises, which can promote the total factor productivity of commercial banks in a variety of ways. The first aspect is the leading and demonstration effect; the advanced technology created by digital finance has a demonstration effect on commercial banks. Because Internet enterprises and emerging financial businesses in the field of digital finance are more advanced in technology, traditional commercial banks can learn from their advanced service models and product designs, absorb digital thinking, and apply it to services and products to improve operating efficiency. The second aspect is that the development of digital has caused a competitive effect on commercial banks. The development of digital finance has eliminated the monopoly operation pattern of commercial banks and improved the production efficiency of commercial banks. The service scope of digital finance has penetrated into the business field of commercial banks, which has had an impact on the payment settlement and deposit and loan business of commercial banks. The long-term development further affects the core loan business of banks. The emergence of digital finance finally forced the monopoly commercial banks to change their input-output mix and upgrade their technology. The third aspect is the mobility of technical personnel. As the carrier of technology, the flow of technical personnel from some Internet enterprises in the industry to financial enterprises has enhanced the business ability of technical personnel in commercial banks. The fourth aspect is the relevance relationship. Internet enterprises and commercial banks continuously cooperate and develop; commercial banks absorb and integrate the advanced technologies of Internet financial enterprises. Financial enterprises provide Internet enterprises with traditional financial services such as fund management and settlement. Internet financial enterprises bring customer information to traditional financial enterprises based on big data technology. Through the cooperative development of traditional commercial banks and Internet financial enterprises, technology penetration and resource integration can be achieved, and the production efficiency of commercial banks can be improved in an innovative way.

Through the theoretical analysis of (1), (2), and (3) above, hypothesis one is proposed.

Hypothesis 1. *Digital finance deeply affects the balance sheet structure of commercial banks and improves the production efficiency of commercial banks in terms of technological innovation, financial innovation, deep integration of technology and finance, and industrial advantages.*

(4) The differentiated assets and operations of commercial banks lead to the heterogeneity of the absorptive capacity of digital finance.

In the development driven by digital finance, large state-owned banks, joint-stock banks, urban commercial banks, and rural commercial banks have implemented digital transformations. Due to their different assets and business scopes, their strategies and structures are heterogeneous in the process of digital transformation. In terms of asset scale, banks that occupy the advantage of asset scale and asset light banks adopt different digital paths. Various commercial banks in China are quite different in asset allocation, ownership, resource constraints, product attributes, business philosophy, etc. This study distinguishes the ownership structure and economic location of banks; deeply analyzes the integration of banks and digital finance and the characteristics of innovation level, management levels of education and the extension level of business networks; and discusses the factors that influence the development of digital finance of heterogeneous commercial banks on the change of efficiency.

First, from the perspective of equity attributes, digital finance has brought great opportunities. Large, state-owned commercial banks have significant advantages in asset scale and business scope, have stable customer resources, and have strong strengths in product innovation and technology upgrading. The goodwill and macro strategy of enterprises provide congenital advantages for innovation. They cooperate with high-tech enterprises to fully absorb the technology spillover factors of digital finance. At the same time, the advantages of scale and capital also limit the speed of digital development of large commercial banks, which have a certain lag. The historical problems of their monopolistic operations make digital finance ineffective in promoting digital transformation and market competition. Their huge size and complex institutional settings also lead to slow responses to the impact of digital finance. At the same time, large, state-owned banks have more cross-regional businesses and longer business chains, leading to their inability to quickly and effectively absorb the dividends brought by digital finance in the digital transformation; therefore, the iteration of digital technology in the risk management level is slow. However, due to the favorable restrictions of corporate systems and equity structures on budget constraints and the business philosophy of joint-stock banks maximizing profits, their profit model of self-financing makes them better at corporate governance and ownership. In contrast, large, state-owned commercial banks are more conducive to the rapid integration of digital finance and traditional financial business and the use of joint-stock banks' agile organizational forms and talent echelons to promote scientific and technological innovation integration, with the help of the technology spillover effect, to achieve continuous breakthroughs.

Second, in terms of capital scale and network opening, urban commercial banks and rural commercial banks are at a disadvantage. They are more sensitive to interest rate marketization and external competitors and have higher digital transformation costs than large commercial banks. However, most of their customer relationships and business contacts are mainly concentrated in small- and medium-sized enterprises, private enterprises, and technology enterprises, which complement the small and micro businesses and inclusive financial businesses involved in financial technology enterprises. Digital finance and technology spillover effects have more obvious advantages for urban commercial banks and rural commercial banks. According to the above analysis, due to the heterogeneity of the share structure and ownership, the sensitivities of banks' operating efficiency to financial innovation integration, technology spillovers, and competitive effects brought by digital finance are differentiated.

(5) This paper analyzes the heterogeneity of the impact of digital finance on the efficiency of commercial banks from the integration of commercial banks and digital finance, product and service innovation, and corporate governance.

This paper explores the path and characteristics of the development and changes of digital finance, that is, the integration of commercial banks and digital finance, the innovation ability of products and services, and the level of corporate governance, and analyzes the heterogeneous impact of digital access to banks on their efficiency.

First, the integration process of digital finance and commercial banks has been accelerated, and direct selling banks have emerged as the times require. For the traditional bank's private data and face-to-face closed business model, the non-contact digital financial products and services with the Internet as the carrier have expanded the business coverage of commercial banks, becoming the main way for commercial banks to integrate technological achievements and improve efficiency. At present, driven by market competition, commercial banks have invested in digital R and D and transformation, and a new generation of digital direct banks has emerged in some domestic cities. Therefore, assuming that traditional commercial banks conform to the trend of economic and social development and establish direct selling banks and open banks, digital finance has a more significant impact on the efficiency of commercial banks that have developed direct selling banking business. Second, importance has been attached to the business innovation capability. Banks with strong internal drives in technology upgrading and R and D capital investment are more suitable for the macro environment of digital economy development, comply with the development trend of the digital economy, carry out technology iterations and efficiency improvements, develop new products and services, expand service scopes, attract more customer groups, and optimize the technical efficiency and total factor productivity. Third, according to the high-level echelon theory, the knowledge level, competition awareness, value cognition, and other characteristics of the senior management of an enterprise have an impact on the strategic planning and performance level of the organization. These characteristics reflect their impact through age, gender, education, and other statistical information as mapping indicators. Among them, the management personnel's age represents their experience and risk tolerance. Technology changes, knowledge updates are fast, and young company managers have new knowledge and technology reserves. Therefore, the analysis shows that the age level and knowledge structure of managers are more relevant to the digital financial transformation of commercial banks and that they can more easily capture favorable market information and improve their profitability through digital financial innovation integration and technology spillover. Fourth, commercial banks with large business coverages in multiple regions have capital and geographical advantages in attracting high-tech talents, building digital financial talent gradients, and cooperating with technologically leading enterprises for win-win results, which are more conducive to upgrading products, improving services, and realizing digital financial transformation using emerging technologies. According to the above analysis, the integrated development of digital technology and finance has a heterogeneous impact on the efficiency of commercial banks due to bank assets, scale, and other factors.

On the basis of Hypothesis 1 and the above theoretical analysis (4) and (5), Hypothesis 2 is proposed.

Hypothesis 2. *Based on the analysis of the extension of the scale, assets, and business network of banks, the positive advantage effect of digital financial development on large, state-owned commercial banks and joint-stock commercial banks is significantly higher than that of urban commercial banks and rural commercial banks.*

3. Variable Definition and Model Setting

3.1. Interpreted Variable

Taking the total factor productivity of commercial banks as the explanatory variable, in order to obtain a robust measurement result, this paper uses the data envelopment analysis method because it does not require sample dimensions and production functions. In terms of measuring the efficiency of commercial banks, the DEA model has many shortcomings. Based on the method of "merging optimization model" proposed by Wood and Lewis, we designed an unguided DEA model to avoid the problems that cannot be solved by the efficiency of collective targets. The Malmquist index and non-oriented DEA model are introduced to jointly build a dynamic model to measure the change process of the total factor productivity of commercial banks within the timeline.

The following hypothetical period is t, the input of commercial banks is s, and the output is expressed as I_s^t and J_s^t. The deposit is expressed as K_s^t. Here, we separately consider the Malmquist productivity index of the input and the output of the decision-making unit; its formula is as follows:

$$\mathrm{M}(\mathrm{J}_{t+1},\mathrm{I}_{t+1},\mathrm{J}_1,\mathrm{I}_1) = \left[\mathrm{L}^{t}\left(I_s^{t+1},J_s^{t+1}\right) * \mathrm{L}^{t+1}\left(I_s^{t+1},J_s^{t+1}\right)/\mathrm{L}^{t}\left(I_s^{t},J_s^{t}\right) * \mathrm{L}^{t+1}\left(I_s^{t},J_s^{t}\right)\right]^{1/2} \quad (1)$$

In the above formula, L^{t} represents the distance function from the technological frontier in the t period and L^{t+1} represents the distance function between the observation point and the technological frontier in the t + 1 period. $L(I,J)$ refers to the independent evaluation unit. $\mathrm{M}(\mathrm{J}_{t+1},\mathrm{I}_{t+1},\mathrm{J}_1,\mathrm{I}_1)$ represents the Malmquist model index, which refers to the evolution trend of the total factor productivity (TFP) of the research unit from the first stage (t h) to the second stage (t + 1 h). If the calculated M index is greater than one, this indicates that the total production productivity of the research unit is on the rise from the first stage (t h) to the second stage (t + 1 h). If the M index is equal to one, this means that the production efficiency remains unchanged. When the M index measurement result is less than one, this means that the technical efficiency has declined during this period. $\mathrm{L}^{t}\left(I_s^{t+1},J_s^{t+1}\right)$ represents the technical efficiency status of the second stage (t + 1) under the technical index status of the first stage (t h) and $\mathrm{L}^{t}\left(I_s^{t},J_s^{t}\right)$ represents the current production efficiency status value under the technical index status of the first stage (t h). $\mathrm{L}^{t+1}\left(I_s^{t},J_s^{t}\right)$ represents the technical efficiency state at time t under the production efficiency status at the second stage (t + 1).

The DEA Malmquist model is used to calculate the four index values in different periods and different states, and finally the index is calculated. According to the calculation results, $\mathrm{L}^{t+1}\left(I_s^{t+1},J_s^{t+1}\right)$ and $\mathrm{L}^{t}\left(I_s^{t},J_s^{t}\right)$ belong to ordinary linear programming. The formula is as follows:

$$\begin{aligned}\mathrm{M}(\mathrm{J}_{t+1},\mathrm{I}_{t+1},\mathrm{J}_1,\mathrm{I}_1) &= \left[\mathrm{L}^{t}\left(I_s^{t+1},J_s^{t+1},K_s^{t+1}\right) * \mathrm{L}^{t+1}\left(I_s^{t+1},J_s^{t+1},K_s^{t+1}\right)/\right.\\ &\left.\mathrm{L}^{t}\left(I_s^{t},J_s^{t},K_s^{t}\right) * \mathrm{L}^{t+1}\left(I_s^{t},J_s^{t},K_s^{t}\right)\right]^{1/2}\end{aligned} \quad (2)$$

Drawing on lessons from Holod and Lewis (2011) [26] we designed an unguided DEA model to solve $\mathrm{L}^{\mathrm{t}}\left(I_s^t, J_s^t, K_s^t\right)$.

$$\left[\mathrm{L}^{\mathrm{t}}\left(I_s^t, J_s^t, K_s^t\right)\right]^{-1} = Max\theta_s^t \text{ s.t} \begin{cases} \sum_{n=1}^{N} I_n^t w_n^t \leq I_s^t\left(2-\theta_s^t\right) \\ \sum_{n=1}^{N} K_s^t w_n^t = K_s^t \\ \sum_{n=1}^{N} J_n^t w_n^t \geq J_s^t \\ w_n^t \geq 0, \ \theta_s^t \geq 1 \end{cases} \tag{3}$$

In the above formula, w_n^t represents the weight of bank s over bank n (n = 1, 2,... n). Next, we replaced all t in (3) with t + 1 to obtain $\mathrm{L}^{\mathrm{t+1}}\left(I_s^{t+1}, J_s^t, K_s^{t+1}\right)$ and continued to solve $\mathrm{L}^{\mathrm{t}}\left(I_s^{t+1}, J_s^t, K_s^{t+1}\right)$. The linear programming is expressed as:

$$\begin{gathered} \left[\mathrm{L}^{\mathrm{t}}\left(I_s^{t+1}, J_s^{t+1}, K_s^{t+1}\right)\right]^{-1} = Max\theta_s^{t+1} \\ \text{s.t} \begin{cases} \sum_{n=1}^{N} I_n^t w_n^t \leq I_s^{t+1}\left(2-\theta_s^{t+1}\right) \\ \sum_{n=1}^{N} K_n^t w_n^t = K_s^{t+1} \\ \sum_{n=1}^{N} J_n^t w_n^t \geq J_s^{t+1}\varepsilon_s^{t+1} \\ w_n^t \geq 0, \ \varepsilon_s^t \geq 1 \end{cases} \end{gathered} \tag{4}$$

We exchanged t and t + 1 of the above equation to obtain $\mathrm{L}^{\mathrm{t+1}}\left(I_s^t, J_s^t, K_s^t\right)$. Taking the above distance function in (2) in turn, we obtained the non-oriented DEA Malmquist index. Referring to Li Xinghua's variable design method, based on the availability of data, we use the following three indicators to express the input factors of commercial banks: the number of scientific and technological employees (R1), the fixed net asset value (R2), and the financial technology investment (R3). In terms of output indicators, the following two indicators were used to express the output variables of commercial banks: operating income (C1) and profit (C2). The total deposit (R3) was selected as the intermediate variable and the total factor productivity of commercial banks from 2011 to 2021 was calculated using Deap2.1 software.

The Malmquist index of DEA model was used to measure the total factor productivity of commercial banks, which do not depend on the production function and sample dimensions and can obtain a more stable result. Using the panel data from 2011 to 2021 and referring to the existing research, the net value of fixed assets and deposits and the number of scientific and technological employees of commercial banks were designed as input indicators, and the total loans and pre-tax profits were used as output indicators. The calculation results are shown in Table 1.

Table 1. Total factor productivity indicators of commercial banks.

Type	Name	Symbol	Minimum Value	Maximum	Average Value	Standard Deviation	Median
Input variable	Number of scientific and technological staff (personnel)	R_1	25,074	35,017	26,489	24,297	28,031
	Net value of fixed assets (CNY 10,000,000)	R_2	114.10	17,143.50	4201.91	5501.87	1110.45
	Financial technology investment (CNY 10,000,000)	R_3	807.44	1763.37	921.87	889.43	951.46
Output variable	Operating income (CNY 10,000,000)	C_1	500.22	65,889.27	16,113.59	17,909.44	8259.72
	Profit before tax (CNY 10,000,000)	C_2	260.91	36,171.30	8701.72	9927.65	4017.13
Intermediate variable	Total deposits (CNY 10,000,000)	Z_0	397.95	1972,868.96	113,264.76	229,871.66	11,209.17

Note: The number of scientific and technological workers and financial technology investment data are from the company's information disclosure; other data are from CSMAR database and WIND database.

According to the calculation results in Table 2, the following basic judgments were made. On the whole, based on the sample data of commercial banks, the average total factor productivity was 1.088 from 2011 to 2021, which indicates that the technical level of China's commercial bank improved year by year during this period. From the perspective of time dynamics, the total factor productivity of commercial banks in all sample ranges from 2016 to 2017 had just reached one. Combined with the analysis of the macroeconomic environment in this period, it was found that the profitability of the banking industry during this period was weak, with low growth and low interest rate environments.

Table 2. Measurement results of commercial banks' non-oriented DEA-Malmquist. Index from 2011 to 2021.

Particular Year	Total Factor Productivity	Digital Efficiency Changes	Digital Progress and Change	Pure Number Conversion Efficiency Change	Change in Scale Efficiency
2011	1.075	1.031	1.043	1.004	1.027
2012	1.124	0.979	1.148	1.007	0.972
2013	1.104	1.021	1.081	0.997	1.024
2014	1.123	1.017	1.104	1.021	0.996
2015	1.057	1.021	1.035	1.014	1.007
2016	1.000	0.987	1.013	0.967	1.021
2017	1.006	1.018	0.988	1.013	1.005
2018	1.181	1.005	1.175	1.014	0.991
2019	1.216	1.103	1.102	1.052	1.048
2020	1.042	1.024	1.018	1.036	0.988
2021	1.041	1.015	1.026	1.029	0.986
Mean Value	1.088	1.020	1.067	1.014	1.006

Remarks: Relative market share is the weighted averages; table displays the weighted averages by the number of banks.

From the four dimensions of total factor productivity, the digital progress change index is the highest, reaching 1.067, and the scale efficiency change index is the lowest, reaching only 1.006. The scale efficiency index changed from 2011 to 2021. In 2011, the scale efficiency index was 1.027. Based on the analysis of the capital scale of commercial banks in 2011, the banking industry at that time took scale operations as the main mode. With the development of digital finance, the scale efficiency index of commercial banks gradually declined, reaching 0.988 in 2020 and 0.986 in 2011, which shows that digital financial business has gradually become the main source of bank operating income. The above calculation results are closely related to the development of the digital finance of commercial banks from 2011 to 2021 and the achievements of digital transformation, which can effectively explain the driving factors of the development of financial technology and digital finance to the efficiency change. From the perspective of the change trend, the change of digital efficiency, digital progress, and pure numeralization efficiency has an obvious "catching up effect". The difference between the three indicators is not large and the operation boundary tends to converge.

In addition, we used the two-stage network DEA model to calculate the above data. The model design is shown in Figure 1. The calculation results are consistent with the above results, which will not be repeated here.

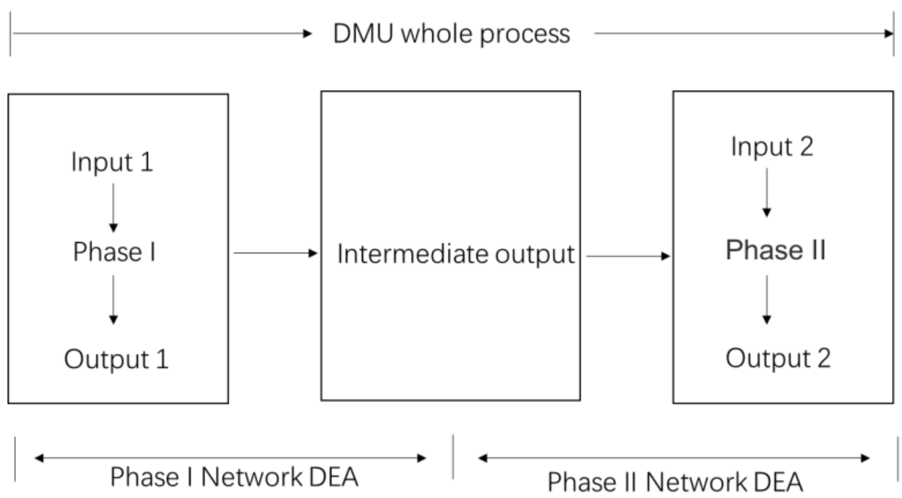

Figure 1. Two-stage network DEA model.

3.2. Core Explanatory Variables

The core explanatory variable is the digital financial index. The construction of the digital financial index requires scientific and technical means, which are important methods for testing the results of the empirical research and can further reasonably explain and clarify the technology spillover effect. The existing research focuses less on the digital financial development index and uses text mining method to establish the digital financial index. The specific design is as follows:

First, the concept of financial function is the theoretical starting point. Combined with the practical cases of digital finance application, this paper divides digital finance into six categories: digital clearing and payment mode, digital equity financing mode, digital risk prevention and control mode, digital financial bank mode, financial and technology coupling mode, and digital trader incentive mode, corresponding to the clearing and payment function, equity financing function, risk management function, and digital banking function. The technology goes deep into the financial function and the incentive function of the trading partner, and the initial lexicon is established on the basis of this theory. We coupled the functions of digital finance with emerging technologies which play a major role into six aspects: clearing and payment, financing and equity refinement, risk management, digital financial system, digital technology integration, and incentives for trading parties. Therefore, from the perspective of financial function, this paper has designed the initial thesaurus of the six dimensions shown in Table 3.

Table 3. Initial thesaurus of digital financial index.

Dimension Index		Specific Description				
1st dimension	Payment and liquidation	Online payment	Mobile payment	Third-party payment	Online payment	Mobile payment
		0.225	0.329	0.349	(0.5601) ***	0.520
2nd dimension	Details of financing and equity	Online loan	Unsecured loan	Crowd-funding	Risk investment	Microfinance
		0.522	(0.183) *	0.094	0.413	(0.413) *
3rd dimension	Digital risk management	Financial risk	Bank risk	Credit risk	Policy risk	Credit risk
		0.194	(0.350) *	0.187	(0.017) *	0.417
4th dimension	Bank digitalization	Direct selling bank	Digital currency	Internet banking	Online banking	Virtual currency
		0.234	(0.549) *	0.412	0.3011	0.493
5th dimension	Integration of finance and technology	Data mining	Big data	Artificial intelligence	Cloud computing	Blockchain
		0.501	(0.413) *	0.3904	0.324	0.541
6th dimension	Trader incentives	Information asymmetry	Information disclosure	Property right transaction	Incentive compatibility	Incentive and restraint mechanism
		0.237	(0.302)*	0.233	0.178	0.224

Note: The figures in brackets represent Pearson correlation coefficient between the annual word frequency of the keyword and the annual mean value of the unguided DEA Malmquist index. * represents $p < 0.05$, *** represents $p < 0.01$, and the following conditions are the same.

Second, this paper used the Baidu Index to find the keyword search frequency of digital finance. The first step was to use the big data of the Baidu Index to search the number of online searches of the initial keyword "digital finance" from 2011 to 2021. The second step was to count the total number of keywords searched on the Internet every year and the frequency of keywords searched on the Internet every year. The third step was to sort out and summarize the annual word frequency of keywords, and use the word frequency after sorting out and summarizing as the basic data for building the digital financial index.

Third, we used the linear correlation to measure the relationship between keyword variables, eliminate invalid words, and retain valid keywords. We standardized the word frequency of initial keywords and then used Pearson correlation coefficient analysis to calculate the word frequency of initial keywords. When the variables were normal continuous variables and had a linear relationship with each other, they were expressed by Pearson's simple correlation coefficient. The specific formula is as follows:

$$\mathrm{r} = N\sum x_i y_i - \sum x_i \sum y_i / \left[N\sum x_i^2 - \left(\sum x_i\right)^2\right]^{1/2}\left[N\sum y_i^2 - \left(\sum y_i\right)^2\right]^{1/2} \tag{5}$$

We used this formula to represent the correlation coefficient between variables x and y. If the absolute value of the correlation coefficient between variables is larger, the correlation between them is stronger. That is, when the value of the correlation coefficient is close to 1 or −1, the correlation is stronger. When the absolute value of correlation coefficient is close to zero, the correlation between the variables gradually weakens. When r = 0, this means that there is no correlation between x and y and there is no linear relationship. For range classification, a correlation coefficient of 0.8–1.0 indicates an extremely strong correlation, 0.6–0.8 indicates a strong correlation, 0.4–0.6 indicates a moderate correlation, 0.2–0.4 indicates a weak correlation, and 0–0.2 indicates an extremely weak correlation or no correlation. According to the rules for the value of the correlation coefficients, we explored the degrees of correlation between the word frequency of keywords and the annual mean value of the DEA Malmquist index. The analysis results are shown in Table 3. With reference to Larson and Farber's methods, the correlation coefficient 0.3 is used as the weak correlation critical point. The keywords with a correlation coefficient less than 0.3 were removed and the remaining 11 keywords were retained.

Fourth, we used factor analysis to synthesize the digital financial index. Based on the remaining 11 keywords, a comprehensive factor analysis was carried out to calculate the digital financial index, which was used as the benchmark index for quantitative analysis. Based on multi-dimensional keywords, a hierarchical factor analysis was conducted to calculate the clearing and payment index, financing and equity refinement index, digital risk management index, digital banking index, financial and technology integration index, and trader incentive index, in turn. These six indices are used as alternative indicators for the robustness test to analyze and build a digital financial index, as shown in Figure 2.

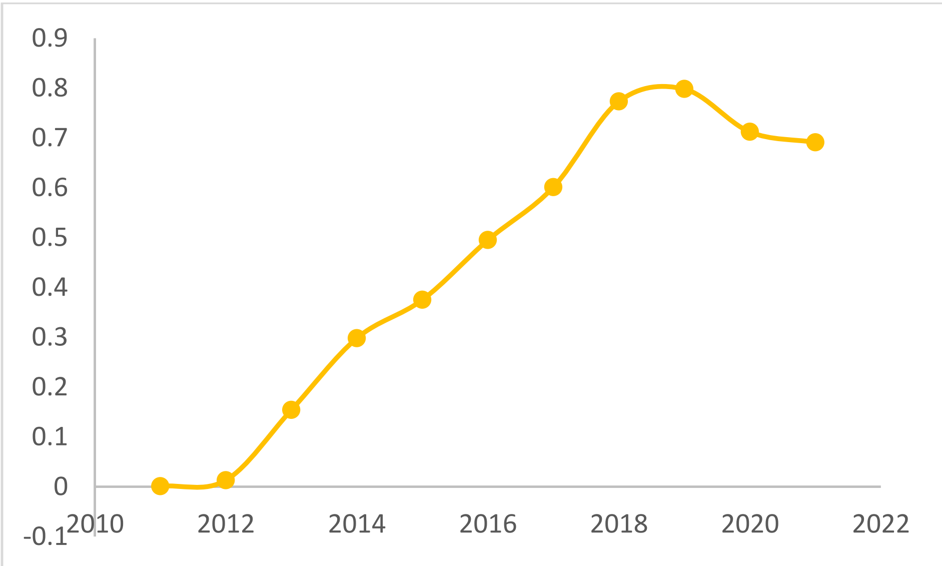

Figure 2. Digital financial index from 2011 to 2021.

3.3. Control Variable

Klumpes found that the total factor productivity of commercial banks was affected by many factors, including changes in the macro environment, financial regulatory policies, the competitive pattern of the capital market, the asset liability structure, etc. Therefore, the empirical model included the following four levels of control variables. At the macro level, the nominal GDP growth rate (GDP) and the ratio of total stock market value to GDP (GP) were selected to control the impact of the economic aggregate and capital market development. At the policy level, the year dummy variable (JG) was used to measure the impact of credit scale management policies. At the end of 2007, the credit scale management tool was re-enabled. Therefore, the JG of 2011 and 2012 was set to one and the JG of other years was set to zero. At the industry level, banking concentration (JZ4) and banking openness (KF) are used to control the impact of the market structure. At the bank level, the ratio of capital assets (CD), the ratio of current assets (LD), and the dummy variable of bank listing financing (RZ) were selected to measure the impact of bank risk bearing, liquidity level, and listing financing. We made RZ = 0 before the bank goes public for financing and RZ = 1 in the year after the bank goes public for financing. Variable definitions and descriptive statistical analyses are shown in Table 4.

Table 4. Variable setting and analysis description.

Variable Classification	Variable Name	Symbol	Variable Interpretation	Mean Value	Standard Deviation	Minimum Value	Maximum
Interpreted variable	Total factor productivity	M	Unguided DEA Malmquist index	1.036	0.023	0.997	1.053
Core explanatory variables	Digital finance	S0	Digital financial index	0.341	0.347	0.000	1.000
	Payment and liquidation	S1	Payment and settlement index	0.492	0.359	0.000	1.000
	Details of financing and equity	S2	Refining index of financing and equity	0.231	0.369	0.000	1.000
	Digital risk management	S3	Digital risk management index	0.258	0.318	0.000	1.000
	Bank digitalization	S4	Bank digital ondex	0.458	0.301	0.000	1.000
	Integration of finance and technology	S5	Financial and technological integration index	0.436	0.320	0.000	1.000
	Trader incentives	S6	Trader incentive index	0.421	0.341	0.000	1.000
control variable	Macroeconomic level	GDP	Nominal GDP growth rate × 100	15.798	4.387	7.597	23.289
	Stock market quotation	GP	Ratio of total stock market value to GPD × 100	50.309	29.210	17.498	123.196
	Regulatory policies	JG	"Credit scale management" dummy variable	0.190	0.405	0.000	1.000
	Banking concentration	JZ4	Proportion growth rate of assets of four major commercial banks × 100	−1.849	0.771	−3.102	−0.518
	Banking openness	KF	Growth rate of domestic and foreign banks × 100	8.458	5.895	0.528	22.298
	Bank risk-bearing	CD	Ratio of bank assets to capital	5.186	1.968	0.120	14.201
	Bank liquidity	LD	Ratio of bank current assets to assets × 100	26.102	12.691	2.116	79.402
	Public financing of banks	RZ	Listed financing dummy variable	0.279	0.448	0.000	1.000

4. Empirical Analysis

4.1. Model Setting and Method Selection

To test the spillover effect of digital financial technology from the aspects of existence and heterogeneity, the following basic models were constructed:

$$M_{pt} = \alpha_0 + \alpha_1 M_{p,t-1} + \alpha_2 S_t + \sum_{q=3}^{10} \alpha_q K_{qpt} + u_p + \varepsilon_{pt} \quad (6)$$

In the above formula, p is the bank and t is the year; α_2 represents the application of the technology spillover effect of digital finance to commercial banks; u_p is the fixed effect of commercial banks. The explanatory variable is the total factor productivity M of commercial banks; S represents the core explanatory variable of the digital financial index. The control variable is K; ε_{pt} represents a random error term. As the viscous dynamic characteristics of the productivity of commercial banks have been supported by the literature, this paper uses the previous value of total factor productivity as the explanatory variable in the model.

We expect α_2 to be significantly positive. When testing hypothesis two, we did not introduce dummy variables representing the type of commercial banks and their cross terms with the digital financial index, but adopted the identification strategy of group regression, which is expected to be based on the α_2, which has obvious differences. This approach is mainly based on the following three considerations. First, in small sample regression, cross terms tend to lead to multicollinearity, reducing the effectiveness of statistical inference. Secondly, in the dynamic panel estimation regression, it is easy to have extreme cases, such as cross terms, where the sample data is less than the number of tool variables, leading to the inability to obtain the estimated results. Thirdly, the virtual variable of commercial bank type is a dichotomous variable, and its volatility over time is very small, so it may cause serial correlation.

The heterogeneity, dynamics, and endogeneity of the econometric model should be comprehensively considered when selecting the estimation method. First, the data structure of this paper has the characteristics of large N and small T; a mixed-effect regression (POOL) that ignores the characteristics of the sample leads to errors in the empirical results, while the fixed effect regression (FE) and random effect regression (RE) that control individual characteristics help to solve the problem of heterogeneity. Therefore, POOL, FE, and RE methods are used to regress Equation (6). Secondly, the lag term of the explained variable is set as the explanatory variable and introduced into the model. In addition, the total factor productivity of commercial banks, capital risk-bearing and the liquidity ratio have causal relationships, so the empirical model may have endogenous problems. Therefore, this paper needs to further use the generalized moment estimation Equation (6) of the system.

In order to avoid the problem of multicollinearity, each explanatory variable was tested for correlation before regression analysis. According to the test results, there was no correlation between the explanatory variables, indicating that there was no serious multicollinearity between the variables. In order to prevent the "pseudo regression" problem, the proxy robustness test was conducted by replacing different proxy variables. The changes in digital efficiency (M1), digital progress (M2), pure number efficiency (M3), and scale efficiency (M4) were, respectively, replaced with the explanatory variable, Total Factor Productivity (M), for regression analysis and a stability test was conducted. The final results showed that these variables had no unit root. The regression results did not have the problem of "pseudo regression".

4.2. Correlation Test

Table 5 shows that correlation analysis was used to study the correlation between digital financial index and payment and clearing index, financing and equity refinement index, digital risk management index, bank digital index, financial and technology integration index, and traders' word frequency incentive index; the Pearson correlation coefficient was used to express the strength of the correlation. The specific analysis shows that there is no significant difference between the digital financial index and the payment and clearing index, the financing and equity refining index, the digital risk management index, the bank digital index, the financial and technology integration index, and the traders' word frequency incentive index. The correlation coefficient values are 0.527, −0.281, 0.230, 0.164, −0.123, and 0.306, all close to 0; the *p*-values are all greater than 0.05. This means that there is no correlation between the digital financial index and payment and clearing index, financing and equity refining index, digital risk management index, bank digital index, financial and technology integration index, and traders' word frequency incentive index, indicating that there is no serious multiple collinearity between the variables.

Table 5. Correlation test of technology spillover effect.

	SO	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
SO	1						
S1	0.527 0.095	1					
S2	−0.281 0.403	0.269 0.424	1				
S3	0.230 0.497	0.117 0.731	−0.427 0.190	1			
S4	0.164 0.630	0.206 0.543	0.115 0.736	−0.459 0.155	1		
S5	−0.123 0.719	−0.328 0.325	−0.134 0.694	−0.505 0.113	−0.015 0.965	1	
S6	0.306 0.360	−0.063 0.854	−0.101 0.767	−0.221 0.513	−0.336 0.313	0.428 0.189	1

4.3. Endogenetic Test

The GMM estimation model aimed to solve the endogenous problem, and the interpretation of the analysis results was basically consistent with that of the ordinary linear regression. First, a Wald chi-square test was used to test whether the GMM model is meaningful. If the model passed the Wald chi-square test ($p < 0.05$), this indicated that the model was meaningful, otherwise, it indicated that the model construction was meaningless. Second, the R-squared value of the model was used to analyze the fitting of the model. For example, 0.5 means that the model has a fitting degree of 50%.

Overidentifying restrictions were used to check the exogeneity of the tool variables. First, the overidentification test is only effective when the number of tool variables is greater than the number of endogenous variables (overidentification). Second, the original assumption of the overidentification test is that "all instrumental variables are exogenous". Third, if the p-value is greater than or equal to 0.05, this means that all tool variables are exogenous. Fourth, if the p-value is less than 0.05, this means that not all tool variables are exogenous; that is, at least one tool variable is not exogenous. Here, the p-value of the Hansen J test is greater than 0.05, so all tool variables are exogenous, as shown in Tables 6 and 7.

Table 6. Overidentifying restrictions.

Original Hypothesis	Inspection Results	Inspection Conclusion
All tool variables are exogenous	$\chi^2(1) = 1.995$, $p = 0.158$	Accept the original assumption

Table 7. Analysis results of GMM estimation model.

p	95% CI
0.014 *	0.528~4.775
0.456	−2.255~1.012
0.642	−0.588~0.954
0.059	−5.111~0.095
0.079	−6.154~0.332
0.956	−0.538~0.569
0.999	−1.019~1.020
0.488	−2.552~1.218

Explanatory variable: total factor productivity (M), C = constant. * $p < 0.05$.

Table 7 above shows that the R-squared value of the model is 0.893, which means that the digital financial index, payment and clearing index, financing and equity refining index, digital risk management index, traders' word frequency incentive index, bank digital index, and financial and technology integration index can explain the change of TFP. When conducting the Wald chi-square test on the model, we found that the model passed the Wald chi-square test (chi = 16.584, $p = 0.020 < 0.05$), which means that at least one of the digital financial index, payment and settlement index, financing and equity refinement index, digital risk management index, traders' word frequency incentive index, bank digitization index, and financial and technology integration index has an impact on TFP. The Wald chi-square test is used to test whether the GMM model is meaningful. If the model passes the Wald chi-square test ($p < 0.05$), this indicates that the model is meaningful and that there is no endogenous problem.

4.4. Regression Analysis

As shown in Table 8. In the regression of column (1) of the estimation results, it is found that there is a significant negative correlation between digital finance (S0) and the explanatory variable total factor productivity (M); this negative correlation still exists after controlling other variables and it passes the significance test, as shown in column (2) of the regression results. This shows that the better the development of the digital finance of commercial banks, the higher the total factor productivity. The development of digital finance helps promote the improvement of the total factor productivity of commercial banks and can effectively improve the "financial discrimination" and "financial mismatch" problems in traditional commercial banks. Digital finance promotes the total factor productivity of commercial banks by easing the financing constraints of enterprises. The vigorous development of artificial intelligence, big data, and cloud computing technology provide an opportunity for the deep integration and development of finance and emerging technologies. Digital finance integrates financial business and cutting-edge technologies; improves data processing capabilities in terms of scale, speed, and accuracy; and provides an opportunity to solve the difficulties faced by traditional financial development by reducing the costs and improving the risk management capabilities, thus verifying research hypothesis one.

Table 8. OLS estimation results.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
S0	−0.014 ***	−0.089 ***	−0.087 ***			−0.077 ***
	−(0.015)	(0.014)	(0.014)			(0.014)
S1	−0.029 ***	−0.072 ***	−0.080 ***			−0.071 ***
	(0.017)	(0.023)	(0.025)			(0.023)
S2				−5.807 ***	−3.737 ***	−2.887 ***
				−(0.629)	−(0.684)	−(0.674)
S3			−0.554	−0.629 ***	−0.281 ***	−0.229 ***
			(0.041)	(0.045)	(0.064)	(0.061)
S4				5.699 ***	3.299 ***	2.471 ***
				(0.640)	(0.675)	(0.645)
S5		0.067 ***	0.065 ***		0.088 ***	−0.089 ***
		(0.030)	(0.029)		(0.034)	(0.049)
S6		−0.649 ***	0.543 ***		0.569 ***	0.628 ***
		(0.221)	(0.228)		(0.158)	(0.149)
GDP		−0.051	−0.051		0.069	0.058 *
		(0.049)	(0.049)		(0.050)	(0.029)
GP		1.449 ***	1.359 ***		1.101 ***	1.213 ***
		(0.201)	(0.213)		(0.219)	(0.211)
JG		0.039	0.032		0.039	0.011
		(0.030)	(0.029)		(0.030)	(0.029)
JZ4		−4.227	−2.411		−1.911	0.569
		(3.689)	(3.889)		(4.101)	(3.829)
KF		−4.227	−2.320		−1.829	0.320
		(3.689)	(3.949)		(4.141)	(3.949)
CD		−0.039	−0.039		−0.019	−0.011
		(0.058)	(0.058)		(0.058)	(0.057)
LD	3.024 ***	0.129	0.149	1.221 ***	0.726	1.275
	(0.309)	(0.838)	(0.836)	(0.039)	(0.637)	(0.837)
RZ		0.037	0.031		0.036	0.012
		(0.029)	(0.027)		(0.028)	(0.030)
N	41	41	41	41	41	41
adj.R^2	0.204	0.712	0.713	0.409	0.684	0.724

Note: *** and * indicate passing the test at the levels of 1% and 10%, respectively. The standard error values are in brackets, with the same below.

Further analysis shows the impact of digital risk management (S3) and financing and equity refinement (S2) on the total factor productivity of commercial banks. First, from the regression results (4)–(6), we find that the variable coefficients of financing and equity refinement (S2) are significantly negative, indicating that financing and equity refinement has a negative effect on the improvement of the total factor productivity of commercial banks in the long run. The coefficient of digital risk management (S3) is significantly negative in the regression results, indicating that the impact of digital risk management on the total factor productivity of commercial banks is relatively weak. Digital risk management is an important part of the digital transformation of commercial banks; it uses new technologies to reconstruct the traditional risk management architecture and process of banks, promoting the development of the digital economy and digital finance. The rapid development of cutting-edge technologies such as big data, blockchain, cloud computing, and artificial intelligence have promoted the digital industrialization, industrial digitalization, and the digital transformation of commercial banks. Since COVID-19, "contactless" digital services have gradually emerged, accelerating the pace of the digital transformation of commercial banks and improving the total factor productivity of commercial banks through intermediary effects.

The coefficient of bank digitalization (S4) is significantly positive in the regression results (5) and (6), indicating that bank digitalization has a boosting effect on the development of digital finance and the boosting effect is relative. In the era of digital economy, digital transformation has become an important path for the high-quality development of all industries. Digital transformation can promote the improvement of the overall factor ratio by improving innovation ability, optimizing the human capital structure, promoting the integrated development of advanced manufacturing and modern service industries, and reducing the cost mechanisms. The ownership nature, enterprise size, factor intensity, and other relevant micro characteristics of commercial banks and intellectual property protection, as well as the external macro environment, such as the openness of the service industry, have different impacts on the efficiency improvement of digital transformation. The regression coefficient of financial and technological integration (S5) in all regression results is significantly positive, which also confirms that financial and technological integration contributes to the development of the total factor productivity of commercial banks. As a product of the deep integration of finance and science and technology, the application of the concept of financial technology in the financial field cannot be ignored in both breadth and depth. It has brought challenges and opportunities to traditional large commercial banks. Financial technology has an impact mechanism on the total factor productivity of commercial banks through demonstration, competition, talent flow, and connection effects, and has heterogeneity on the technology spillover effects of different commercial banks. At the same time, the higher the level of economic development, the more sufficient the factor liquidity, which can provide more support for the development of digital financial technology and promote the improvement of the total factor productivity of commercial banks.

The regression coefficient of trader incentive is S6, which has enriched the capital composition of commercial banks' relevant markets and further guaranteed the efficient operation of the market. On the other hand, the cycle of capital flow within and between industries becomes shorter and shorter with the optimization and upgrading of the industrial structure. Therefore, in the process of industrial structure adjustment, the demand for reducing transaction costs, reducing information asymmetry, and improving the efficiency of industrial collaboration will also increase, thus driving the improvement of the total factor productivity of commercial banks. The regression coefficient of the variable stock market quotation (GP) is significantly positive in all regression results, indicating that the improvement of the stock market quotation is conducive to promoting the development of digital finance and promoting the development of total factor productivity through intermediary effects. The stock market reflects the trend of capital accumulation. The trend and application of capital towards cutting-edge technology has a crucial impact on the production and development of enterprises. It also reflects the level of input and output in technology application to improve production efficiency. The improvement of capital investment has expanded the coverage of digital finance, which can serve all levels and regions; constantly promote the innovation of financial products, financial businesses, and business models; reduce the cost of financial transactions and services; improve the quality and efficiency of financial services; and thus enhance the development level of digital finance.

4.5. Stability Test

The proxy variable robustness test is conducted by replacing different proxy variables. The change of digital efficiency (M1), digital progress (M2), pure number efficiency (M3), and scale efficiency (M4) are, respectively, replaced by the explanatory variable total factor productivity (M) for regression analysis. The test results are shown in the following table. From the regression results (1)–(4), there is still a significant negative correlation between the explanatory variable digital financial index (S0) and the explanatory variables of each agent, which further supports research hypothesis one. The regression results (5)–(8) show that bank digitalization (S4) is significantly positive, indicating that the development of bank digitalization transformation has a certain boosting effect on the improvement of total factor productivity, which further supports research hypothesis one. The direction and significance of regression coefficients of other control variables still maintained good consistency, indicating that all business development followed the same logical framework. As shown in Table 9.

Table 9. Regression results based on robustness test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	M1	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
S0	−0.146 ***	0.202 ***	−0.331 ***	−0.171 ***	−0.126 ***	−0.173 ***	−0.306 ***	−0.149 ***
	(0.031)	(0.031)	(0.042)	(0.037)	(0.033)	(0.033)	(0.042)	(0.037)
S1	0.129 ***	0.071	−0.185 ***	−0.176 ***	0.132 ***	0.060	0.155 *	0.167 ***
	(0.058)	(0.058)	(0.079)	(0.069)	(0.060)	(0.061)	(0.080)	(0.071)
S2					−2.614 *	−3.396 **	−5.531 ***	−3.563 ***
					(1.540)	(1.566)	(2.027)	(1.762)
S3					−0.332 ***	−0.346 ***	−0.415 ***	−0.379 ***
					(0.134)	(0.135)	(0.176)	(0.153)
S4					2.695 ***	3.565 ***	5.764 ***	3.995 ***
					(1.520)	(1.537)	(1.989)	(1.731)
S5	0.320 ***	0.267 ***	0.265 ***	0.339 ***	0.202 **	0.247 **	0.237 *	0.035 ***
	(0.089)	(0.091)	(0.119)	(0.103)	(0.097)	(0.100)	(0.127)	(0.108)
S6	1.789 ***	1.869 ***	2.523 ***	1.953 ***	1.379 ***	1.407 ***	2.003 ***	1.320 ***
	(0.413)	(0.417)	(0.543)	(0.473)	(0.452)	(0.451)	(0.591)	(0.515)
GDP	0.058	0.104	0.083	0.070	0.119	0.157 *	0.142	0.132
	(0.093)	(0.093)	(0.124)	(0.185)	(0.096)	(0.089)	(0.127)	(0.107)
GP	2.114 ***	1.645 ***	3.251 ***	3.176 ***	1.828 ***	1.363 ***	2.863 ***	2.863 ***
	(0.401)	(0.403)	(0.512)	(0.459)	(0.419)	(0.419)	(0.549)	(0.479)
JG	0.035	0.015	−0.006	0.016	0.027	0.015	0.001	0.035
	(0.021)	(0.023)	(0.030)	(0.025)	(0.028)	(0.028)	(0.037)	(0.032)
JZ4	−0.291	0.438	0.138	−0.352	−0.193	0.542	0.261	−0.248
	(0.541)	(0.550)	(0.715)	(0.621)	(0.541)	(0.547)	(0.709)	(0.617)
KF	−0.001	−0.001	−0.001	−0.003	−0.002	−0.001	0.001	−0.002
	(0.011)	(0.012)	(0.014)	(0.012)	(0.012)	(0.011)	(0.014)	(0.013)
CD	0.231 **	−1.411	0.523	−1.987	−1.134	−1.001	−0.982	−2.035
	(0.090)	(1.103)	(1.432)	(1.248)	(1.193)	(1.205)	(1.561)	(1.354)
LD	0.073	0.127	0.095	0.086	0.139	0.173 *	0.186	0.172
	(0.098)	(0.097)	(0.144)	(0.194)	(0.099)	(0.112)	(0.177)	(0.142)
RZ	0.033	0.016	−0.006	0.014	0.031	0.013	0.001	0.031
	(0.019)	(0.027)	(0.027)	(0.023)	(0.026)	(0.027)	(0.035)	(0.028)
N	41	41	41	41	41	41	41	41
adj.R^2	0.502	0.520	0.574	0.581	0.511	0.531	0.587	0.596

Note: ***, ** and * indicate that they have passed the test at the level of 1%, 5% and 10% respectively, and the standard error values are in brackets.

4.6. Existence Test

In order to verify the impact of digital technology on the total factor productivity of banks and explore its technology spillover effect, we first used the mixed effect (PooL), fixed effect (FE) and random effect (RE) of static panels to estimate the impact, and the results are listed in Table 10. According to the rules set by the above model, when the F test is at the 5% significance level, the mixed estimate will be rejected and LM test will accept the original hypothesis that there is no individual random effect. Moreover, the Hausman test also strongly rejected the original assumption that the random disturbance term was not related to the explanatory variable. Therefore, it is preliminarily believed that the measurement equation should adopt the fixed effect model. However, the coefficient significance of the FE regression is poor, which indicates that the explanatory variable is not independent of the error term and Equation (6) is endogenous. The dynamic panel GMM estimation will continue to be used as follows. The AR (2) test results of Diff GMM and SYSGMM support that there is no second-order sequence correlation between the difference of the perturbation terms. Wald test is used to explain again that there is a strong correlation between the endogenous variables and instrumental variables. The Sargan test results show that all tool variables are exogenous. The above tests verify that the dynamic model and tool variables constructed by empirical analysis are effective and can reasonably explain the empirical process.

Table 10. Existence test of digital financial spillover effect.

Variable	POOL	FE	RE	DiffGMM	SYSGMM
L.M				0.1969 ***	0.1879 ***
				(0.0311)	(0.0447)
S0	0.0169	0.0148	0.0169	0.0109 *	0.0171 ***
	(0.0159)	(0.0158)	(0.0159)	(0.0061)	(0.0049)
GDP	0.0014	0.0013	0.0014	0.0013 **	0.0016 ***
	(0.0014)	(0.0014)	(0.0014)	(0.0008)	(0.0005)
GP	0.0004	0.0004	0.0040 **	0.0030 **	0.0040 ***
	(0.0030)	(0.0030)	(0.0030)	(0.0020)	(0.0020)
JG	0.0127	0.0129	0.0127 ***	0.0076 ***	0.0114 ***
	(0.0167)	(0.0168)	(0.0167)	(0.0039)	(0.0037)
JZ4	0.0126	0.0107	0.0126	0.0079 *	0.0101 ***
	(0.0073)	(0.0076)	(0.0073)	(0.0028)	(0.0028)
KF	−0.0007	−0.0006	−0.0007	−0.0005	0.0010 *
	(0.0010)	(0.0010)	(0.0010)	(0.0004)	(0.0006)
CD	−0.0001	−0.0012	−0.0001	0.0024 *	−0.0027 ***
	(0.0013)	(0.0017)	(0.0013)	(0.0010)	(0.0009)
LD	0.0006	0.0006	0.0006 *	0.0005 **	0.0006 ***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
RZ	0.0034	0.0116	0.0034	0.0145	0.0139 **
	(0.0055)	(0.0120)	(0.0054)	(0.0091)	(0.0065)
	0.0504	0.0770	0.0672		
F Inspection		2.11 **			
		(0.0211)			
LM inspection			0.00		
R^2			(1.0001)		
Hausman test			25.89 ***		
			(0.0000)		
AR (2)				1.56	1.49
				(0.1150)	(0.1347)
Wald test				745.77 ***	2657.06 ***
				(0.0000)	(0.0000)
Sargan test				29.07	21.27
				(0.7848)	(1.0000)

Note: The constant term is omitted from the regression results. The standard error is indicated in the brackets below the regression coefficient. The right square bracket of the model setting test represents the corresponding *p*-value. ***, ** and * indicate that they have passed the test at the level of 1%, 5% and 10% respectively, and the standard error values are in brackets.

According to the regression results of SYSGMM, it is found that there is consistency with hypothesis one and the estimated coefficient of the digital financial index is significantly positive. This test result verifies the existence of digital technology spillover effects and illustrates the positive impact relationship between digital finance and total factor productivity, which has a huge role in promoting development. Under China's strong regulatory policy and stable financial situation, digital finance has generated technology spillovers to commercial banks through demonstration, competition, personnel mobility, and business contacts. Commercial banks quickly receive technology research and development achievements to help their transformation and efficiency. The support of digital finance provides technical support and strategic direction, points out the path for commercial banks to get out of difficulties, injects vitality into the transformation and upgrading of banks, and creates good opportunities for the genetic transformation of the financial system.

The regression coefficient of the macroeconomic level is positive (significant at the level of 1%), indicating that the rapid development of the macro-economy has driven the production efficiency of the banking industry, which is consistent with the research conclusions of Zhang Jinqing and Wu Youhong. Commercial banks have a procyclical feature and their operating efficiency fluctuates with the level of macroeconomic development, which are closely related to each other. In particular, with the market financing structure dominated by indirect financing in China and the deposit loan interest margin as the main revenue of banks, under the unified supervision of the Central Bank and the economic operation environment, commercial banks are doomed to have a close relationship between the productivity index of commercial banks and the macro-economy.

The development of the stock market shows that the coefficient is positive and highly significant in statistics, indicating that the production efficiency of commercial banks can take advantage of the capital market. Due to various influences, financial market has its inherent defects. The money market and capital market are always competing for credit resources. Due to the continuous development of the capital market, the competition in various industries is increasingly fierce; the customer resources are limited and the profit space is limited. Therefore, China's commercial banks want to further seek development, adapt to the transformation of digital finance, and constantly enhance their customer acquisition ability and market competitiveness. According to the empirical analysis results, there is a positive relationship between the stock market and production efficiency.

With the regulatory policy as the variable, the coefficient is significantly positive after regression. It shows that one of the indicators used in this paper, namely, the central bank's credit management strategy which reflects the regulatory policy, has a positive impact on production efficiency. The control of loan scale is one of the tools of monetary policy macro-control. It can effectively control financial market risks, avoid the risk diffusion of commercial banks, improve the scale efficiency of banks, encourage banks to change the profit model relying on interest margin, and promote the further improvement of all-important productivity.

The measurement result of the banking industry concentration degree is highly positive, which proves that the banking industry market concentration degree is positively related to its production efficiency and concentration degree has a direct impact on efficiency changes. The market structure measured by JZ4 growth rate shows a positive change relationship with the operating performance of commercial banks. According to the "hypothesis of relative market dominance", the improvement of banking industry concentration can help enterprises realize their independent pricing power on the one hand, and, on the other hand, concentration can indirectly increase the size of enterprises, both of which can have a positive spillover effect on the production efficiency of enterprises.

The coefficient of the regression of banking openness is significantly negative. This shows that foreign banks entering the domestic market and forming a competitive relationship with domestic banks will weaken the production efficiency of domestic banks. Through comparative analysis, domestic commercial banks are in a backward position in terms of technical personality, talent introduction, innovation ability, etc. In addition, due to the negative impact of the "picking effect", the disadvantages of domestic banks are more prominent. Therefore, according to this analysis, the higher the degree of openness of the banking industry, the more restrained the efficiency level of Chinese commercial banks.

The risk-bearing level measured by the capital asset ratio of bank liquidity has a significant negative relationship with the operating efficiency of commercial banks. According to the research of John et al., the willingness to take risks is directly related to the sales growth and innovation project investment of enterprises. Reasonable risk taking is conducive to increasing profit opportunities, forming a good relationship of mutual benefit and competition, and improving the operating efficiency of enterprises. On the contrary, excessive risk taking leads to unstable operations and reduces the market performance of enterprises. In the process of economic development, under the financial system and mechanism with the government leading and macro policy regulation as the main line, the national credit guarantee has caused the bank operating leverage to remain high. The existing risk level of commercial banks has broken through the risk tolerance level and exceeded a reasonable threshold, so there is a negative relationship between risk taking and the total factor productivity of banks.

The liquidity level is measured by the proportion of current assets and shows a dynamic positive correlation with the production efficiency of commercial banks. Li Ximei believes that liquidity level is an important link in measuring bank performance indicators. Too high a liquidity reduces the profitability of commercial banks. When liquidity is too low, it will hinder the normal operation of commercial banks and affect the business operations. Therefore, the management must comprehensively weigh the liquidity and profitability of banks. The empirical results of this paper show that the total factor productivity of commercial banks with a high proportion of liquid assets also grows rapidly, which objectively shows that the liquidity level and profitability of Chinese commercial banks have a positive relationship and are closely linked and mutually reinforcing.

The listing of commercial banks in this paper is measured by dummy variables. According to the verification results, it is highly positively correlated with the efficiency of commercial banks, which is consistent with the research findings of Cai Yuezhou, Guo Meijun, Zhang Jianhua, and Wang Peng. Listing not only helps banks to enrich capital, increase the source of credit funds, and improve scale efficiency, it also reduces the principal-agent cost, strengthens market constraints, standardizes internal management, and thus improves the productivity of commercial banks.

4.7. Heterogeneity Test

Based on the estimation results of grouped samples, this paper discusses the heterogeneous impact of digital finance on the total factor productivity of commercial banks. For the regression analysis of the variable degrees of freedom, the following three sample sets are first designed for dynamic regression. Among them, sample set 1 (Y1) excludes large commercial banks from all samples, sample set 2 (Y2) excludes joint-stock commercial banks, and sample set 3 (Y3) excludes urban commercial banks. Second, we compare the regression results of the sub sample set and full sample. If the coefficient of the core explanatory variable in the regression of the sub sample set is increased, this means that the index items (technical absorptive capacity of commercial banks) excluded from the sub sample set are less than the average value of the sample banks, and the greater the increase in the regression coefficient, the weaker the absorptive capacity of the commercial banks excluded, and vice versa. The last step is to test whether the coefficient of grouping regression has a significant difference.

Based on this idea, hypothesis two is tested by SYSGMM estimation, and the regression results are listed in Table 11. The results of the AR (2) test and the Sargan test show that the choice of model and the choice of tool variables are effective and reasonable. The coefficient of the core explanatory variable H in Y1, Y2, and Y3 is 0.0259, 0.0071, and 0.0160, respectively. Compared with the full sample regression results, the change degrees of the core explanatory variable in the three sub samples are 48.28%, −58.97%, and −8.41%, respectively. This regression result is consistent with the theoretical expectation, which verifies the idea of hypothesis two. This clarifies that commercial banks with different capital scale and ownership structures have certain differences in the degree of reflection and technology absorption of digital financial spillover effects. The absorptive capacity of technology spillovers of joint-stock commercial banks ranks first, followed by urban commercial banks and large commercial banks, with relatively weak absorptive capacities.

Table 11. Heterogeneity test of digital financial technology spillover effect.

Variable	Y1	Y2	Y3	Variable	Y1	Y2	Y3
L.M	0.2699 ***	0.1731 ***	0.5097 **	FR	−0.0009 *	−0.0007 *	−0.0001 **
	(0.0419)	(0.0604)	(0.2526)		(0.0005)	(0.0003)	(0.0001)
	46.36%	−60.89%	170.99%		22.18%	−11.09%	−77.67%
H	0.2259 ***	0.0071 **	0.0160 *	AE	−0.0029 **	−0.0030 *	−0.0009 **
	(0.0089)	(0.0034)	(0.0091)		(0.0011)	(0.0016)	(0.0004)
	48.28%	−58.97%	−8.41%		10.68%	14.26%	64.26%
GDP	0.0019 ***	0.0021 ***	0.0011 ***	LI	0.0005 ***	0.0006 ***	0.0002 ***
	(0.0004)	(0.0005)	(0.0006)		(0.0002)	(0.0002)	(0.0001)
	31.23%	47.57%	20.03%		20.14%	60.13%	−40.01%
GS	0.0003 **	0.0002 **	0.0006 ***	SS	0.0216 ***	0.0081 *	0.0092 ***
	(0.0001)	(0.0000)	(0.0001)		(0.0057)	(0.0046)	(0.0042)
	−33.29%	−66.64%	66.65%		59.94%	−37.48%	−19.77%
XD	0.0039 *	0.0040 *	0.0278 ***	AR(1)	−2.9875 ***	−5.2941 ***	−0.8694
	(0.0021)	(0.0023)	(0.0109)		(0.0026)	(0.0000)	(0.3796)
	−65.49%	−62.90%	148.99%	AR(2)	0.7098	1.4509	−0.1248
CR4	0.0113 ***	0.0169 ***	0.0059 *		(0.4783)	(0.1629)	(0.9011)
	(0.0029)	(0.0049)	(0.0032)	Sargan test	17.1401	14.0597	6.2297
	9.76%	70.48%	−35.28%		(1.0000)	(1.0000)	(1.0000)

Note: The constant term is omitted from the regression results. "Standard error" is indicated in brackets below the regression coefficient. The figures below the "standard error" are: the regression ratio of each sub sample and the overall sample, the change direction, and range of each coefficient. The corresponding p-value is in the brackets below the model inspection. ***, ** and * indicate that they have passed the test at the level of 1%, 5% and 10% respectively, and the standard error values are in brackets.

The sign of the control variable coefficients of each sub sample Y1, Y2, and Y3 is consistent with the estimation result of the full sample. Among them, the regression coefficient of the policy variable "credit scale management" has the largest decline in Y1, indicating that the credit scale control policy has the greatest impact on large, state-owned commercial banks, which is conducive to improving their total factor productivity. The decline in the estimated results of stock market conditions and public financing is very prominent in sub Y2, which indicates that joint-stock banks are most affected by the fluctuation of the capital market and public financing listing because, for joint-stock banks, the public financing channel, namely listing and trading, is a favorable capital supplement and broadens the situation of narrow capital source channels. For large, state-owned commercial banks, there are no similar obstacles. The coefficients of variable macroeconomic level, banking concentration, banking openness, bank risk-bearing, and bank liquidity have dropped significantly in Y3, indicating that urban commercial banks with small capital scales have a high degree of reflection on external risk shocks, which are closely related to their own capital ratio and other bank characteristics.

To ensure the accuracy of the results, we continued to test hypothesis two and used Acquaah (2012)'s T-test method for inter group comparison to compare the estimated results of the digital financial index in the regression of each group (sub sample) [27]. The results showed that the difference coefficients of the digital financial indexes in Y1 and Y2 and Y1 and Y3 are 0.0190 and 0.0110, respectively. The rejection of the original assumption that "the estimated coefficients have no bias" (at the level of 1% significance) further verifies that joint-stock commercial banks and city commercial banks are significantly better than large commercial banks in terms of digital financial technology spillover effects. The T-test results of the inter group comparison confirm the conclusion that the spillover effect of digital financial technology has greater heterogeneity among commercial banks with different characteristics. Through the analysis of total factor productivity, it is believed that digital finance has strongly promoted the improvement of the total factor productivity of China's commercial banks through technology spillover effects. The absorptive capacity of commercial banks with different attributes to digital financial technology spillovers is different; joint-stock commercial banks have the most obvious positive response and reception to digital finance, followed by urban commercial banks, and large commercial banks are weak.

5. Conclusions

With the rapid development of digital economy, digital technology has been integrated into the financial industry, overturning the traditional financial model and providing opportunities and challenges for industry transformation. Based on the total factor productivity theory and technology spillover theory, this paper analyzes the impact mechanisms of digital finance on the total factor productivity of commercial banks from the perspective of balance sheet structures and discusses the heterogeneity of digital finance technology spillovers in differentiated banks. The research takes the data of 41 commercial banks as samples, takes the total factor productivity of the commercial banks measured by DEA Malmquist model as the explanatory variable, and takes the digital financial index constructed by "text mining method" as the core explanatory variable for empirical testing. By using panel data and empirical analysis, it is found that the development of digital finance has promoted the rapid strategic transformation of commercial banks to the digital mode and improved the production efficiency of commercial banks. In addition, through mechanism analysis, it is found that the use of emerging technology to innovate product service modes has made a great contribution to efficiency improvement. By comparing the data of various commercial banks, it is found that, due to the characteristics of the historical evolution of commercial banks, commercial banks of different sizes and capital structures have heterogeneity in their sensitivity and influence to the transformation of digital finance; digital finance has a more significant impact on the productivity of joint-stock commercial banks. Its integration with digital finance technology is broader and deeper, its digital finance product and service innovation ability is more adaptable to market demand, and its decision-makers pay more attention to the future benefits of the digital finance transformation and invest more in the development of digital finance. The business scope of joint-stock commercial banks is relatively broad; they have carried out business in many provinces and cities and have the traditional characteristics of focusing on scientific research investment. These characteristics make them more sensitive to the impact of digital finance, which is more conducive to improving productivity.

The empirical research of this paper mainly analyzes the following aspects. First, from the perspective of economic and financial theories, there are few references to study the efficiency contribution of digital finance to China's commercial banks. Many previous studies focused on the impact of financial technology on banking systems in different regions, focusing on the main reasons for the increase in the total factor productivity. Based on the theory of total factor productivity, combined with technology spillover theory and digital financial index mining, this paper explores the contribution value of digital finance to the improvement of total factor productivity and the decomposition efficiency of commercial banks, and analyzes its internal mechanism. This paper analyzes the similarities and differences of the multiple heterogeneity of commercial banks in the digital financial competition. Based on the research on the factors that affect the efficiency of digital technology, it broadens new research ideas and further enriches the research on the theory and mechanism of total factor productivity. Second, in view of the availability of data and the urgency of digital transformation of commercial banks in reality, the academic community mainly adopts case study methods or empirical research using commercial bank samples to study the impact of digital finance on commercial banks. On the one hand, this study uses the actual data of the annual report of commercial banks and uses the DEA Malmquist index model efficiency evaluation method to enrich the ideas and methods of commercial bank efficiency research from an empirical perspective. Thirdly, on the analysis of the impact path of digital finance on the transformation and development of commercial banks, the technology spillover theory is applied to identify the transmission mechanism of the impact of digital finance on commercial banks. Fourthly, it analyzes and explores the multiple heterogeneity of commercial banks, verifies the positive relationship between digital finance and bank efficiency, further distinguishes the impact of digital financial heterogeneity on commercial banks, enlightens banks to adjust strategies and transformation paths according to their own characteristics, more effectively obtains competitive advantages and core competitiveness, promotes the transformation of commercial banks' business strategies, and conforms to the practice of digital economic transformation. It has practical and theoretical significance.

The research draws multiple conclusions. First, through the analysis of total factor productivity, it is believed that digital finance has strongly promoted the improvement of the total factor productivity of Chinese commercial banks through technology spillover effects. Second, commercial banks with different attributes have different absorptive capacities for digital financial technology spillovers; joint-stock commercial banks have the most obvious positive reflection and reception of digital finance, followed by urban commercial banks, while large commercial banks are weak. According to the conclusions of this paper, the following policy recommendations are put forward: commercial banks should adhere to technological innovation, continue to actively respond to the impact of the development of the digital economy, vigorously improve digital financial products and services, and continue to promote the process of financial digitalization in China.

When constructing the digital financial index, six dimensions are considered: clearing and payment, financing and equity refinement, digital risk management, digital banking, financial and technology integration, and trader incentive. However, the impact of the six dimensions of the development of digital finance on bank systemic risk has not been analyzed. In the future, we can continue to analyze the impact of the six dimensions of digital finance on bank systemic risk.

Author Contributions: Conceptualization, L.Z. and H.L.; Methodology, L.Z.; Software, L.Z.; Validation, L.Z., H.L. and X.X.; Formal Analysis, X.X.; Investigation, L.Z.; Writing—Original Draft Preparation, L.Z. and H.L.; Writing—Review and Editing, X.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: We are very grateful to the editors and anonymous reviewers for their comments on the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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