mathematics

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Assessing the Impact of Digital Finance on the Total Factor Productivity of Commercial Banks: An Empirical Analysis of China

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Abstract: With the development of technologies such as big data and artificial intelligence, digital technology and finance are becoming increasingly intertwined. At present, digital finance has altered the competitive environment of commercial banks, and the traditional competitive edges in service scenarios and channels, customer information, and capital have been challenged. Based on perfect competition and technology spillover effects, this study attempted to measure the impact of digital finance on commercial banks' total factor productivity (TFP) and its mediating and moderating mechanisms. We have used the data envelopment analysis-based Malmquist productivity index to measure the total factor productivity of 132 commercial banks in China between 2011 and 2019. The results show that (a) digital finance significantly enhances the TFP of commercial banks; (b) risk taking partially mediates the relationship between digital finance and TFP. The study further tests the effect of the nature of property rights and the moderating effect of diversification. The findings suggest that digital finance significantly improves the TFP of non-state-owned commercial banks but has no significant effect on the TFP of state-owned commercial banks. Additionally, the implementation of diversification can strengthen the effect of digital finance on TFP.

Keywords: digital finance; total factor productivity; commercial banks; risk taking

MSC: 03C98

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Citation: Wu, C.; Liu, T.; Yang, X. Assessing the Impact of Digital Finance on the Total Factor Productivity of Commercial Banks: An Empirical Analysis of China. *Mathematics* **2023**, *11*, 665. https://doi.org/10.3390/math11030665

Academic Editor: Zongwei Luo

Received: 5 January 2023
Revised: 24 January 2023
Accepted: 26 January 2023
Published: 28 January 2023

1. Introduction

A new round of technological revolution and industrial change is in the ascendant. Core digital technologies, such as cloud computing, artificial intelligence, blockchain, and big data, are deeply integrated within the finance industry [1], and digital finance has emerged. Digital finance is similar to internet finance and fintech in connotation, emphasizing that traditional financial institutions as well as internet enterprises employ digital technologies to create new business models, such as financing, payment, and investment [2], and its competitive edge vis-à-vis cloud data, low cost, information flow integration, and convenient high efficiency will undoubtedly engender consequential challenges to old business models. Over the past few years, the impact of digital finance on traditional banking business has led to the intensification of "financial disintermediation." As financial transactions become increasingly closely related to customers' consumption or work and life scenarios, fintech companies, with their customer networks and data advantages, have impacted the banking system with innovative financial products in payment and clearing, as well as off- and on-balance-sheet businesses [3]. Thus, commercial banks' single-business, profit-driven model by scale has been significantly challenged. In this context, commercial banks have successively increased their investment in digital finance, using digital finance technology to reshape various links, such as strategies, operations, product services, channels, and risk control, and taken steps to differentiate their services. According to disclosure by the China Banking and Insurance Regulatory Commission, total investment in technology by commercial banks reached 207.8 billion CNY in 2020, with a year-on-year growth rate of over 25%. Commercial banks have integrated digital finance from a strategic level to technology investment and are shifting toward mastering the initiative of the digital finance market. Therefore, against the backdrop of full competition triggered by the rise of digital finance, can commercial banks successfully turn "pressure" into "power"? What will be the impact of digital finance on the total factor productivity (TFP) of commercial banks after changing the competition pattern?

Notably, TFP, which refers to the input–output ratio of business activities, is used to measure whether the allocation of resources is effective. In the existing research, there are many studies on TFP, but only a few studies have focused on the impact of digital finance on the TFP of commercial banks, and the findings are inconsistent. One view is that digital finance improves the efficiency of commercial banks by increasing their rate of technical progress. Based on the technology spillover theory, Shen and Guo [4] explored the relationship between internet finance and commercial bank efficiency and introduced external internet technologies through demonstration, competition, employee mobility, and business linkages to improve TFP. Liu and Yang [5] further confirmed this view after replacing the sample and measurement methods of relevant variables; that is, internet finance could enhance TFP by improving banks' technical levels. The implementation of merger and acquisition (M&A) strategies strengthens technology spillover effects. However, another view is that digital finance cuts the monopoly rents of commercial banks and impacts traditional business operations, thus significantly reducing their efficiency. Zhang and Liu [6] believe that the substitution effect of internet finance on banks is greater than the technology spillover effect, thus ultimately reducing the efficiency of capital allocation; that is, the deepening of internet finance will impact the scale of traditional business to a certain extent. Feng and Guo [7] argue that digital finance decreases bank returns through the substitution effect and perfect competition. Liu [8] analyzed four aspects of bank assets, liabilities, payment and settlement, and off-balance-sheet business and reported that internet finance reduces bank returns by decreasing both interest and non-interest income. There is a divergence of views between empirical evidence and theoretical analysis. Thus, further research is warranted.

In addition, digital finance is flourishing, which will reduce the share of traditional deposit and loan businesses, hence squeezing the profit space and forcing commercial banks to adjust their strategies and resource allocation practices to enrich their sources of income and compete for customer resources to seek new growth points [9]. Digital finance will inevitably have an important impact on the competitive environment, risk taking, innovation capacity, economies of scope, and the scale of commercial banks, which will subsequently affect TFP. However, there is a lack of research on transmission channels and the moderating effects of digital finance on bank efficiency. The banking system is the main channel for the distribution of savings and credit, and it plays an essential financial intermediation role in the economy [10,11]. The efficiency of financial intermediation directly affects the speed of a country's economic growth, while its bankruptcy may lead to systemic crises and thus negatively affect the economy. Hence, an in-depth exploration of these issues is not only beneficial for commercial banks to improve their efficiency, accelerate transformation, and stabilize their market position in an increasingly fierce competition, but it is also crucial for regulators to formulate policies to maintain a stable market. Based on existing studies, this study measured the TFP of 132 commercial banks in China between 2011 and 2019 via data envelopment analysis (DEA) and empirically tested the relationship between digital finance and commercial banks' efficiency, as well as the mediating effect of risk taking.

2. Theoretical Background and Research Hypothesis

2.1. Digital Finance and the TFP of Commercial Banks

Digital finance can improve the efficiency of commercial banks by breaking the monopoly of the banking industry to generate perfect competition and optimize the management model [12]. Guo and Shen [13] argue that digital finance has accelerated the process of interest rate marketization, causing deposit liabilities to be diverted, costs to be raised, and profit space to be squeezed. Financial intermediaries are gradually being transferred from banks to non-bank institutions in the context of digital finance; thus, the traditional finance industry is facing increasingly fierce external competition. Moreover, there is a "line" between emerging fintech companies and traditional commercial banks, which means that they compete with each other but find it difficult to replace one another. The financial efficiency of commercial banks will continuously improve in mutually reinforcing competition [14]. Lee et al. [3] also showed that fintech innovation improves the cost efficiency and technology gap of commercial banks overall. Because increased competition is likely to reduce banks' risk-taking level and enhance financial stability [15,16]. Navaretti [17] also suggests that fintech companies do not replace commercial banks, which supports the view of competition stability. In other words, commercial banks can obtain more monopoly rents with less competition; thus, their management is extensive and less efficient [18], while increased competition will create a "catfish effect." To avoid being completely replaced by fintech companies, commercial banks will definitely reform and innovate business models to further optimize the efficiency of resource allocation and improve the input–output ratio [19].

Furthermore, digital finance can also enhance the technical level by generating a technology spillover effect, hence providing commercial banks with risk management, customer acquisition, and lower-cost financial services, thereby improving efficiency. At present, previous studies have shown that commercial banks can enjoy the benefits of the technology spillover effect through fintech innovation, such as optimizing business performance and improving risk control capabilities [20,21]. The specific steps are presented as follows: first, to improve the quality of assets. Traditional commercial banks are gradually employing emerging technologies, such as cloud computing, artificial intelligence, blockchain, and big data [22], to reduce information asymmetry in credit approval and strengthen credit risk management while improving fund utilization rates [23,24]. The second step is to reduce service costs. Traditional banking businesses are highly dependent on their employees. For example, small and micro loans rely heavily on the experience and personal judgment of employees. However, with the aid of digital fintech, commercial banks can leverage relevant technologies to provide convenient business and standardized processes, thereby reducing costs and improving efficiency [25]. The third step is to broaden business channels. Digital technologies can assist commercial banks in gaining access to previously unreachable customers and expanding the coverage of financial services [26].

Hypothesis 1. *Digital finance improves the TFP of commercial banks by generating perfect competition and technology spillover effects.*

2.2. The Mediating Effect of Risk Taking between Digital Finance and TFP

Digital finance can decrease the level of risk taking displayed by commercial banks by intensifying risk transfer motivation and improving risk management. From a risk transfer perspective, digital finance intensifies competition in the banking industry [7]; this has been especially true since the transition of China's commercial banking system to a fully liberalized banking system (Lee et al., 2015). Increased competition leads to higher interest rate elasticity for loans, thereby raising the cost of debt financing. The risk transfer motivation of commercial banks increases accordingly; thus, the level of risk taking decreases [27–29]. From a risk management perspective, the "mismanagement" hypothesis states that banks in poor management are not adept at credit scoring and tend to select a relatively high proportion of investments with low or negative net present values; collateral is improperly valued, and customers are not sufficiently monitored in order to ensure compliance with the loan contract. As a result, the risk level increases accordingly [18,30]. Mishkin and Strahan [31] held that the use of information technology could reduce information asymmetry in credit behavior, more accurately identify the profitability and solvency of the lender, improve loan quality, and reduce the risk of default, thereby lessening the risk-taking behavior of banks when approving and granting loans [32]. From a sample of 143 commercial banks in China, Liu [33] found that commercial banks relied on big data technology to improve risk management and reduce bankruptcy risk via four paths: expanding risk data sources, reforming risk models, building IT governance frameworks, and simplifying and standardizing risk management processes.

Both the "out of luck" and "mismanagement" hypotheses proposed by Berger and De Young [34] support a negative correlation between the level of risk taking and efficiency of commercial banks, and the "offsetting costs" hypothesis suggests that the cost of commercial banks and the risk level offset each other. If the risk-taking level is too high, the possibility of non-performing loans will be higher. Banks must expend extra effort to deal with problematic loans, which leads to a reduction in efficiency. Andrew [35] measured efficiency based on the stochastic frontier approach and studied the non-performing loan ratio as a proxy variable for risk taking, which showed that there was a negative relationship between risk taking and efficiency. The higher the non-performing loan ratio, the lower the asset quality and efficiency. Zhao [36] conducted a study based on the Chinese banking industry, and the results showed that improving asset quality and reducing risk levels had positive implications for bank efficiency. Hsiao [37] investigated the impact of the first financial reorganization on the efficiency of 40 Taiwanese commercial banks during the 2000–2005 period, which showed that the improvement in efficiency after the reform was attributed to the strengthening of bank risk management. Zhang [38] used a sample of BRIC commercial banks between 2003 and 2010 and suggested that banks could improve their performance by reducing credit, market, and overall risks, thus enhancing the stability of the banking industry. In summary, as efficiency is a concentrated expression of competitiveness, digital finance can lead commercial banks to adjust and optimize the structure of risk, improve asset quality, enhance competitiveness, and thus raise efficiency by increasing the competitiveness of the banking industry and promoting the introduction of advanced risk management technology.

Hypothesis 2. *Risk taking mediates the relationship between digital finance and the TFP of commercial banks.*

Based on the literature review and hypothesis development, the conceptual model of digital finance, risk taking, and TFP is shown in Figure 1.

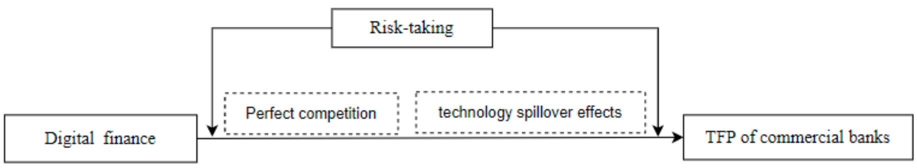

Figure 1. Theoretical model.

3. Research Design

3.1. Sample and Data

In this study, the data were obtained from the China Stock Market & Accounting Research (CSMAR) and Wind databases. This study selected banks that were operational between 2011 and 2019 as samples, excluding policy banks and foreign-funded banks, and deleting banks whose data (required to calculate TFP) were missing during data collection. Finally, we obtained the unbalanced panel data of 132 commercial banks (including five state-owned commercial banks). Furthermore, the data on digital finance in the banks' regions were obtained from the dataset of the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) [25], which is based on the underlying data of Ant Financial transaction accounts and constructed based on three dimensions: the coverage of digital finance, depth of digital finance, and degree of digitalization of inclusive finance. The coverage mainly reflects the degree of financial supply based on the number of users. Depth is measured using six financial parameters: payment, money fund, credit, insurance, investment, and credibility. The degree of digitalization mainly reflects the low-cost and low-threshold characteristics of digital finance. In addition, this study obtained the gross domestic product (GDP) for each province from the CSMAR database and manually collected the listed year for the listed banks in the sample.

The initial data were used for a descriptive analysis. Correlation and regression analyses were carried out with the data after centralized processing (including scaling the value of Df by 100 times). To unify the dimension, the data of all the variables were processed centrally.

3.2. Variables

3.2.1. Dependent Variable

The TFP of commercial banks (Be), as the main indicator used to measure the effectiveness of resource allocation, refers to the input–output ratio or cost–income ratio of business activities, which is a centralized reflection of the competitiveness and sustainable development of the banking industry. The measurement of TFP can be divided into parametric and nonparametric methods. The essence of both methods is to construct a production frontier, and the TFP of commercial banks is the gap between the actual productivity and this frontier. Compared with the parametric method, the nonparametric method does not need to assume the functional form of the model in advance, which can avoid errors. This study adopted the DEA-Malmquist index to measure the TFP of commercial banks, drawing on Cai [39] and Li [40] to select total deposits, interest expenses, and operating expenses as input variables, and loans, interest income, and net non-interest income as output variables (Table 1 shows the specific descriptions of these variables).

Table 1. Input and output variables of TFP.

Variable Type	Variable Name	Definition and Measurement
Output variables	Loans	Loans = Total loans − total loans × non-performing loan ratio
	Interest income	The value in banks' profit statement
	Net non-interest income	Fee and commission income − fee and commission expense + exchange net income + return on investment + incomes from change in fair value + other operating revenue
Input variables	Total deposits	Total deposits
	Interest expenses	The value in banks' profit statement
	Operating expenses	Tax and extra + operating and administration expense + credit impairment losses + other asset impairment losses + other business expense

3.2.2. Independent Variable

Digital finance (Df). Referring to Zhang [26] and Guo [25], the PKU-DFIIC was used as a proxy variable for digital finance. We matched the provincial-level data to the sample according to the location of commercial banks' headquarters. Moreover, with reference to Ma [41], the index was scaled 100 times to facilitate the presentation of the results, which did not affect the data structure or the results of the analysis.

3.2.3. Mediator

Risk taking (Risk). The indicators used to measure risk taking were primarily the expected default frequency, non-performing loan ratio, Z-value, and risk-weighted asset ratio. Previous analysis indicates that digital finance is passive in taking risks by changing the risk transfer motivation and risk management. Hence, to match the model, the non-performing loan ratio was employed to measure the level of risk taking according to Gu [32], which reflects the proportion of loans with default risk.

3.2.4. Control variables

Based on existing studies, the natural logarithm of total assets (LnSize) [42], asset allocation (Ltd) [9,27], capital structure (Eta) [27], management capacity (Cta) [43], capital adequacy ratio (Car) [7,33,37], and listing of banks (Ipo) [8,42] were selected as control variables for internal factors, while the stock market development (Gs) [5,7] and GDP growth (Gdp) [41,44] in each province were chosen as control variables for macroeconomic factors.

In sum, Table 2 shows the variables and definitions used.

Table 2. Definition of variables.

Variable Type	Variable Name	Variable Symbol	Definition and Measurement
Dependent variable	TFP of commercial banks	Be	DEA-Malmquist index
Independent variable	Digital finance	Df	Digital Financial Inclusion Index of China (DFIIC)
Mediator	Risk taking	Risk	Non-performing loan ratio
Control variables	Asset allocation	Ltd	Total loans/Total deposits
	Capital structure	Eta	Equity asset/Total asset
	Management capacity	Cta	Operating expenses/Total asset
	Capital adequacy ratio	Car	Capital adequacy ratio
	Bank size	LnSize	The natural logarithm of total assets
	Listing of banks	Ipo	Dummy variable
	GDP	Gdp	Growth of GDP in each province
	Stock market development	Gs	Total market value of shares/GDP

3.3. Models

To verify the impact of digital finance on the TFP of commercial banks, Model (1) was constructed, where Be is the TFP of commercial banks, μ denotes controlling for individual effects, λ denotes controlling for time effects, ε represents the random error, i represents different banks, k represents different provinces, j represents different control variables, and t represents time.

$$\mathrm{Be}_{i,t} = \beta_0 + \beta_1 \mathrm{Df}_{k,t} + \Sigma_{j=1}^{n} \beta_j \mathrm{Control}_{j,i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

With reference to Wen [45], we constructed models to verify the mediating effect of risk taking between digital finance and TFP.

$$\mathrm{Risk}_{i,t} = \theta_0 + \theta_1 \mathrm{Df}_{k,t} + \Sigma_{j=1}^{n} \theta_j \mathrm{Control}_{j,i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

$$\mathrm{Be}_{i,t} = \beta_0 + \beta_1 \mathrm{Df}_{k,t} + \beta_2 \mathrm{Risk}_{i,t} + \Sigma_{j=1}^{n} \beta_j \mathrm{Control}_{j,i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

4. Results

4.1. Descriptive Statistics

Table 3 presents the descriptive statistical results of the variables. Among them, the average value of TFP (Be) is 0.995, and the standard deviation is 0.081, indicating that the difference between samples is small, and the distribution is relatively uniform. The average value of digital finance (Df) is 217.736, the standard deviation is 93.430, and the gap between the maximum (399.003) and minimum values (29.740) is large, which is helpful to explore the impact of digital finance (Df) on TFP (Be). Table 3 provides the other descriptive statistics.

Table 3. Descriptive statistics of variables.

Variable	N	Mean	SD	Min	Max
Be	1167	0.995	0.081	0.739	1.271
Df	1167	217.736	93.430	29.740	399.003
Risk	1149	1.420	0.726	0.120	4.310
Ltd	1166	0.667	0.123	0.334	0.989
Eta	1166	0.074	0.016	0.043	0.122
Cta	1159	0.009	0.003	0.004	0.021
Car	1133	0.133	0.019	0.098	0.206
lnSize	1166	16.760	1.589	13.870	21.480
Ipo	1167	0.160	0.367	0	1
Gdp	1167	0.094	0.062	−0.250	0.299
Gs	1167	0.569	0.122	0.420	0.785

Please see Table 2 for the descriptions of the variables.

4.2. Correlations of Variables

Before the regression analysis of the model, Pearson's correlation analysis was performed on the variables to test whether multicollinearity exists between them. Table 4 shows that the absolute value of the correlation coefficient between most explanatory variables is less than 0.5, which indicates that there is no serious multicollinearity between the variables, and the model is well constructed.

Table 4. Correlations of variables.

	Be	Df	Risk	Ltd	Eta
Be	1.000				
Df	0.119 ***	1.000			
Risk	−0.002	0.421 ***	1.000		
Ltd	0.168 ***	0.441 ***	0.305 ***	1.000	
Eta	−0.044	0.097 ***	0.162 ***	0.265 ***	1.000
Car	−0.018	−0.005	−0.107 ***	0.005	0.614 ***
Cta	−0.131 ***	−0.283 ***	0.029	0.114 ***	0.281 ***
InSize	0.143 ***	0.360 ***	−0.058 **	0.268 ***	−0.303 ***
Ipo	0.046	0.233 ***	−0.039	0.229 ***	−0.107 ***
Gdp	−0.114 ***	−0.386 ***	−0.297 ***	−0.061 **	−0.036
Gs	0.064 **	0.458	0.319 ***	0.075 **	−0.011
	Car	Cta	InSize	Gdp	Gs
Car	1.000				
Cta	0.108 ***	1.000			
InSize	−0.218 ***	−0.424 ***	1.000		
Ipo	−0.077 ***	−0.214 ***	0.646 ***		
Gdp	0.160 ***	0.104 ***	−0.070 **	1.000	
Gs	−0.109 ***	−0.164 ***	0.138 ***	−0.344 ***	1.000

Statistical significance at: ** $p < 0.05$, *** $p < 0.01$.

Table 4 shows that the correlation coefficient between digital finance (Df) and TFP (Be) is 0.119, which is significant at the 1% level; that is, it shows a significant positive correlation, which provides preliminary data support for Hypothesis 1, indicating that the development of digital finance improves the TFP of commercial banks. The correlation coefficient between risk taking (Risk) and digital finance (Df) is 0.421, which is statistically significant at the 1% level; that is, it shows a significantly positive correlation, suggesting that digital finance reduces the risk taking level of commercial banks.

4.3. Regression Results

We adopted a panel data model with individual and time-fixed effects for the regression analysis to test our hypotheses. The results are presented in Table 5.

Table 5. Regression analysis.

Variable	**Model 1**
	Be
Df	0.1362 ***
	(2.79)
Ltd	0.2619 ***
	(5.40)
Eta	−0.6274
	(−1.55)
Car	0.5395 **
	(2.09)
Cta	−7.4729 ***
	(−3.17)
lnSize	0.0142
	(0.70)
Ipo	−0.0071
	(−0.65)
Gdp	−0.2238 ***
	(−3.32)
Gs	−3.2434 ***
	(−3.01)
_cons	2.0207 ***
	(4.31)
Observations	1124
R-squared	0.2222
Individual/Time	Yes
Hausman test (p-value)	38.1100 (0.0009)

Statistical significance at: ** $p < 0.05$, *** $p < 0.01$. The t-values are in parentheses. The Hausman test is conducted to assess the appropriateness of random or fixed effects models. Rejecting Ho indicates that the fixed effect is valid.

In Model 1, there is a significantly positive correlation between digital finance (Df) and TFP (Be) at the 1% confidence level ($\beta = 0.1362$, $p < 0.01$), indicating that digital finance can improve the TFP of commercial banks. One possible reason is that, on the one hand, digital finance forces commercial banks to raise their management and efficiency by generating perfect competition; on the other hand, the technology spillover effect enhances the level of digital technology, which alleviates the information asymmetry between banks and companies and optimizes the efficiency of credit resource allocation. Thus, H1 is supported. The relationship between the control variables and TFP (Be) is also largely consistent with theoretical expectations: the coefficient of asset allocation (Ltd) is positive at a 1% confidence level ($\beta = 0.2619$, $p < 0.01$), indicating that banks with better asset allocation are more efficient; the coefficient of capital adequacy ratio (Car) is positive at a 5% confidence level ($\beta = 0.5395$, $p < 0.05$), indicating that increasing the capital adequacy ratio is conducive to improving efficiency; the coefficient of management capacity (Cta) is negative at a 1% confidence level ($\beta = -7.4729$, $p < 0.01$), showing that better management can elevate efficiency; and the coefficient of GDP (Gdp) and stock market development (Gs) is significant, meaning that when economic development is considerable and market demand is prosperous, banks may be slack in management, which reduces efficiency.

As shown in Tables 5 and 6, the effects that digital finance (Df) has on the TFP (Be) of commercial banks are significant, which satisfies the conditions for testing the mediating effect.

Table 6. Test of the mediating effect.

Variable	Model 2	Model 3
	Risk	**Be**
Risk		−0.0137 **
		(−2.10)
Df	−1.7139 ***	0.1167 **
	(−5.89)	(2.31)
Ltd	1.3345 ***	0.2746 ***
	(5.38)	(5.58)
Eta	1.8661	−0.6285
	(0.90)	(−1.54)
Car	−6.8403 ***	0.4577 *
	(−4.53)	(1.76)
Cta	2.6433	−6.0207 **
	(0.17)	(−2.57)
lnSize	−0.1695	0.0060
	(−1.50)	(0.30)
Ipo	−0.0000	−0.0060
	(−0.00)	(−0.55)
Gdp	−0.3531	−0.2366 ***
	(−0.93)	(−3.49)
Gs	40.8962 ***	−2.7074 **
	(6.57)	(−2.42)
_cons	−13.2134 ***	1.9385 ***
	(−4.63)	(4.01)
Observations	1110	1110
R-squared	0.6691	0.2270
Individual/Time	Yes	Yes
Sobel		Z = 2.372

Statistical significance at: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-values are in parentheses.

In Models 2 and 3, there is a significantly negative correlation between digital finance (Df) and risk taking (Risk) at the 1% confidence level ($\beta = -1.7139$, $p < 0.01$). Additionally, digital finance (Df) and risk taking (Risk) have a significant impact on TFP (Be) ($\beta_{Df} = 0.1167$, $p < 0.05$, $\beta_{Risk} = -0.0137$, $p < 0.05$). The regression results show that digital finance can directly affect TFP, and can have an indirect effect through risk taking. According to Maxwell's [46] research, risk taking partially mediates the relationship between digital finance and TFP. One possible reason is that digital technology has improved information transparency and thus enhanced the credit quality of banks, which reduces the level of risk taking and ameliorates asset management to improve efficiency. Thus, H2 is supported.

4.4. Robustness Test

4.4.1. Replace the Variable

We used the coverage of digital finance (Cov), depth of digital finance (Use), and degree of digitalization of inclusive finance (Level) in each province as proxy variables for digital finance to replace the DFIIC. Moreover, the Z-value (Z) was selected to measure risk taking, where Z is the standard deviation of return on assets/(return on assets + capital-assets ratio). The larger the Z-value, the higher the level of risk taking, and the greater the bankruptcy risk. The results after reconducting the regression are shown in Table 7, which is consistent with the results in Tables 5 and 6.

Table 7. The regression of replacing the variable.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
	Be	**Be**	**Be**	**Z**	**Be**
Cov	0.1368 **				
	(2.10)				
Use		0.0461 **			
		(1.98)			
Level			0.0458 ***		
			(2.96)		
Df				−0.0359 ***	0.1218 **
				(−5.37)	(2.44)
Z					−0.5441 **
					(−2.12)
Ltd	0.2556 ***	0.2476 ***	0.2648 ***	0.0376 ***	0.2900 ***
	(6.47)	(5.14)	(5.41)	(5.58)	(5.80)
Eta	−0.7309 **	−0.6587	−0.6078	0.0578	−0.4794
	(−2.18)	(−1.62)	(−1.50)	(1.08)	(−1.15)
Car	0.6522 ***	0.5889 **	0.5662 **	−0.1659 ***	0.3535
	(2.89)	(2.29)	(2.19)	(−4.30)	(1.33)
Cta	−7.3105 ***	−7.0998 ***	−7.4670 ***	−0.3409	−6.9721 ***
	(−3.70)	(−2.98)	(−3.16)	(−1.02)	(−2.99)
lnSize	0.0058	0.0128	0.0148	−0.0019	0.0053
	(0.35)	(0.63)	(0.73)	(−0.81)	(0.25)
Ipo	−0.0065	−0.0070	−0.0088	−0.0035 **	−0.0094
	(−0.48)	(−0.64)	(−0.80)	(−2.18)	(−0.85)
Gdp	−0.2143 ***	−0.2001 ***	−0.2009 ***	−0.0073	−0.2553 ***
	(−3.78)	(−3.02)	(−3.05)	(−0.82)	(−3.79)
Gs	−2.9890 **	−1.3438 **	−1.6658 ***	0.8392 ***	−2.8532 **
	(−2.39)	(−2.42)	(−3.38)	(5.84)	(−2.57)
_cons	2.0340 ***	1.2515 ***	1.3969 ***	−0.2828 ***	2.0265 ***
	(3.52)	(3.91)	(4.22)	(−4.55)	(4.21)
Observations	1124	1124	1124	1089	1089
R-squared	0.2176	0.2172	0.2221	0.6341	0.2290
Individual/Time	Yes	Yes	Yes	Yes	Yes

Statistical significance at: ** $p < 0.05$, *** $p < 0.01$. The t-values are in parentheses.

4.4.2. Test for Heterogeneity

In 2013, the rise of financial products on the internet marked the integration of the internet and finance. Therefore, referring to Wang's [42] approach, the value is 0 when referring to any time between 2011 and 2013; otherwise, it is 1, which will generate a binary variable of "Year." The results after re-conducting the regression are shown in Table 8, where the interaction term between digital finance (Df) and year (Year) is significantly positive ($\beta = 0.0623$, $p < 0.05$), indicating that digital finance has significantly improved the efficiency of commercial banks since 2013. Thus, the results are consistent with the conclusions of this study.

4.4.3. Endogeneity Test

The TFP of commercial banks may affect digital finance, resulting in the endogeneity of reciprocal causation. Hence, this study adopted the SYS-GMM to estimate Model (1). Additionally, the Arellano-Bond test and Sargan test were performed for estimated results to examine the autocorrelation of residuals and the validity of instrumental variables (the lagged dependent variable, Be_{t-1}). The results are shown in Table 9, where AR (1) indicates that there is first-order autocorrelation of residuals, AR (2) indicates that there is no second-order autocorrelation, and the Sargan test indicates that there is no over-identification problem, meaning that the constructed model and selected variables are reasonably valid. Moreover, the results after re-conducting the regression are consistent with the abovementioned findings.

Table 8. The test for heterogeneity.

Variable	Be
Df	0.1011 *
	(1.96)
Year	−0.2953 *
	(−1.92)
Df × Year	0.0623 **
	(2.25)
Ltd	0.2608 ***
	(5.40)
Eta	−0.4845
	(−1.19)
Car	0.4239
	(1.63)
Cta	−7.2846 ***
	(−3.05)
lnSize	0.0230
	(1.10)
Ipo	−0.0082
	(−0.74)
Gdp	−0.2517 ***
	(−3.64)
Gs	−0.1600
	(−1.15)
_cons	0.4342
	(1.15)
Observations	1124
R-squared	0.2257
Individual/Time	Yes

Statistical significance at: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-values are in parentheses.

Table 9. Endogeneity test.

Variables	Be
Be_{t-1}	0.0772 ***
	(2.85)
Df	0.0551 **
	(1.99)
Gdp	−0.2014 ***
	(−5.16)
Ltd	0.6104 ***
	(12.80)
Eta	0.1403
	(0.42)
Cta	−11.3979 ***
	(−5.47)
Car	0.2536
	(1.29)
lnSize	−0.0067
	(−0.67)
Ipo	−0.0277 **
	(−2.45)
Constant	0.4658 ***
	(2.76)
Observations	658
N	88
AR(1)_P	0.0000
AR(2)_P	0.4314
Sargan_P	0.1039

Statistical significance at: ** $p < 0.05$, *** $p < 0.01$. The Z-values are in parentheses.

4.5. Further Discussion

4.5.1. The Moderating Effect of Diversification

Diversification refers to the business behavior of entering new fields to develop by utilizing internal growth or external M&A [47]. For commercial banks, diversification is essentially the innovative behavior of expanding businesses based on deposits and loans [48]. Both internal capital market theory and synergy effect theory support that diversification can improve firm performance. The former believes that through diversification, firms can generate an internal capital market that is superior to the external capital market by creating capital flows and capital allocation internally, thus improving firm performance [49]. The latter argues that diversification can increase firm performance by realizing economies of scope, economies of scale, and business process reengineering [50]. In addition, diversification can meet market diversity needs and gain higher market shares while spreading risks and cutting unit product and service costs [43,44], thereby offsetting the impact of digital finance on the profit space of deposit and loan businesses. The reduction in unit cost gives banks more low-cost channels to accumulate technological advantages, thus expanding the impact of digital finance on TFP [5].

The Herfindahl–Hirschman Index (HHI) of the income structure was chosen to measure diversification, according to Liu's [51] and Li's [52] approach. $HHI = 1 - (PNII^2 + PNET^2)$, where HHI represents the level of diversification, and the greater the value of HHI, the higher the level of diversification. In addition, PNII is equal to the ratio of net interest income to operating income, and PNET is equal to the ratio of net non-interest income to operating income.

Meanwhile, based on Model (1), we constructed Model (4) to verify the moderating effect of diversification, where Hhi is diversification.

$$\mathrm{Be}_{i,t} = \gamma_0 + \gamma_1 \mathrm{Df}_{k,t} + \gamma_2 \mathrm{Hhi}_{i,t} + \gamma_3 \mathrm{Hhi}_{i,t} * \mathrm{Df}_{k,t} + \Sigma_{j=1}^{n} \beta_j \mathrm{Control}_{j,i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

The regression results are presented in Table 10. In Model 4, we tested whether diversification moderates the relationship between digital finance (Df) and TFP (Be). The results show that the interaction term between digital finance (Df) and diversification (Hhi) is significantly positive ($\beta = 0.0682$, $p < 0.01$), suggesting that the positive effect of digital finance in enhancing efficiency intensifies with diversification. This is mainly because technology accumulation is accelerated, and the impact of competition is mitigated by adopting diversification in the context of digital finance, reducing the volatility of earnings and the non-performing loan ratio of banks, thus improving asset quality. In other words, diversification means the diversification of income and investments, which is reflected in performance improvement.

We also conducted an additional test to ensure that our results were robust. The net non-interest income was employed to measure diversification, and the regression results showed that our results are robust.

4.5.2. Effect of the Nature of Property Rights

To explore the impact of the nature of property rights, we divided commercial banks into two groups: state-owned and non-state-owned. The results are presented in Table 11. In Model 1 of state-owned commercial banks, the coefficient of digital finance (Df) is not significant ($\beta = -0.1280$, $p > 0.1$), demonstrating that digital finance does not promote efficiency. This may be because state-owned commercial banks primarily provide services to state-owned enterprises. Therefore, they are less affected by digital finance and have no incentive to develop a market to compete with other banks. In Models 1 and 2 for non-state-owned commercial banks, the coefficient of digital finance (Df) is significantly positive ($\beta = 0.1385$, $p < 0.01$), and the interaction term between digital finance (Df) and diversification (Hhi) is significantly positive ($\beta = 0.0713$, $p < 0.01$), which is consistent with the conclusions of this study.

Table 10. Test of the moderating effect.

Variable	Model 4
	Be
Df	0.1220 ** (2.47)
Hhi	−0.1049 *** (−4.06)
Df × Hhi	0.0682 *** (2.94)
Ltd	0.2441 *** (5.01)
Eta	−0.6171 (−1.53)
Car	0.5155 ** (1.99)
Cta	−7.5738 *** (−3.36)
lnSize	0.0081 (0.41)
Ipo	0.0009 (0.08)
Gdp	−0.2126 *** (−3.24)
Gs	−2.7980 ** (−2.56)
_cons	1.9654 *** (4.16)
Observations	1124
R-squared	0.2453
Individual/Time	Yes
Hausman test (p-value)	61.6500 (0.0000)

Statistical significance at: ** $p < 0.05$, *** $p < 0.01$. The t-values are in parentheses. The Hausman test is conducted to assess the appropriateness of random or fixed effects models. Rejecting Ho indicates that the fixed effect is valid.

Table 11. Effect of the nature of property rights.

	State-Owned Model 1	State-Owned Model 2	Non-State-Owned Model 1	Non-State-Owned Model 2
Variables	**Be**	**Be**	**Be**	**Be**
Df	−0.1280 (−0.49)	0.0830 (0.28)	0.1385 *** (3.10)	0.1323 *** (2.97)
Hhi		−0.5139 * (−1.91)		−0.1075 *** (−4.50)
Df × Hhi		0.2972 * (1.88)		0.0713 *** (3.24)
Ltd	0.9618 ** (2.65)	0.9996 *** (2.91)	0.2579 *** (6.40)	0.2387 *** (5.96)
Eta	5.4736 * (1.72)	4.9576 (1.68)	−0.6610 * (−1.93)	−0.6432 * (−1.91)
Car	−5.5335 ** (−2.57)	−4.1052 * (−1.97)	0.5601 ** (2.41)	0.5393 ** (2.35)
Cta	−2.8665 (−0.18)	−9.2201 (−0.47)	−7.5192 *** (−3.73)	−7.8127 *** (−3.93)
lnSize	0.0871 (0.91)	0.0909 (1.00)	0.0130 (0.74)	0.0022 (0.13)
Ipo	0.0113 (0.32)	0.0418 (1.14)	−0.0078 (−0.57)	0.0007 (0.05)
Gdp	−0.5912 (−0.80)	0.7579 (0.86)	−0.2308 *** (−4.03)	−0.2165 *** (−3.82)
Gs	2.1976 (0.38)	−3.6401 (−0.56)	−3.2780 *** (−3.48)	−2.9398 *** (−3.13)
_cons	−1.8142 (−0.60)	0.4610 (0.15)	2.0590 *** (4.60)	2.1249 *** (4.78)
Observations	45	45	1079	1079
R-squared	0.7984	0.8427	0.2215	0.2456
Individual/Time	Yes	Yes	Yes	Yes

Statistical significance at: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The t-values are in parentheses.

4.5.3. The Impact of Digital Finance on Different Types of Efficiency

We decomposed the TFP measured via the DEA-Malmquist index into technical progress (Tc) and technical efficiency (Ec) and re-examined Model (1). Technical progress (Tc) refers to the fact that more output can be obtained by improving the technical level with the same input. Technical efficiency (Ec) refers to efficiency that can be enhanced through institutional innovation and managing change at a given technical level. The results shows that the effects of digital finance on technical progress (Tc) (β = 0.1226, $p < 0.01$) and technical efficiency (Ec) (β = 0.0856, $p < 0.05$) are both significantly positive, which is consistent with the conclusions of this study. Digital finance affects the TFP of commercial banks by generating perfect competition and technology spillover effects, thereby improving technical progress and efficiency.

5. Conclusions

Taking 132 commercial banks operating between 2011 and 2019 as samples, this study examined the impact of digital finance on the TFP of commercial banks, the partial mediation of risk taking, and the moderation of diversification. The conclusions presented are as follows: (a) Digital finance positively affects TFP by generating the perfect competition and technology spillover effect, while there is heterogeneity in the nature of property rights; that is, the effect of digital finance on the efficiency of state-owned commercial banks is not significant, but that of non-state-owned commercial banks is significant. Furthermore, digital finance has a significantly positive correlation with technical progress and efficiency. (b) Risk taking partially mediates the relationship between digital finance and TFP; that is, digital finance can strengthen risk management by intensifying the competition in the banking industry and upgrading the technical level, thus reducing risk taking to improve efficiency. (c) Diversification has a positive moderating effect on the relationship between digital finance and TFP.

In the context of the accelerated development of digital finance, to boost bank efficiency more effectively, the following aspects should be considered:

First, while digital finance has a subversive impact on the traditional financial industry, it also provides transformational opportunities. The future competitive standing in the market depends on whether traditional commercial banks can seize this chance. Therefore, in the face of increasingly fierce competition, commercial banks should actively implement differentiation strategies, accelerate digital transformation, and innovate financial services.

Second, diversification is an effective way of avoiding risks. Commercial banks are bound to face great challenges in the process of transforming from traditional financial intermediaries to service intermediaries. At this point, commercial banks can take advantage of digital technology and new infrastructure to implement diversification, which can reduce the implementation risks and costs and mitigate the impact of digital finance on traditional businesses, thereby accelerating the pace of transformation and elevating efficiency.

Third, authorities should guide the transformation process. Simultaneously, they should gradually perfect the relevant laws and regulations to accelerate the development of digital technology; stimulate and guarantee digital transformation; and create a fair, efficient, and healthy developmental environment for the future development of the banking industry.

Limitations and Future Research

This study has several limitations, which provide opportunities for future research. From the perspective of control variables, the TFP of commercial banks is influenced not only by GDP and stock market development but also by other macro factors, such as the growth rate of money supply and the rate of unemployment, while further inquiry could add more control variables. In addition, limited to the availability of data, diversification was measured by interest and non-interest income, while subsequent studies can consider segmenting the revenue of commercial banks to investigate the moderating effect of different types of revenues on the relationship between digital finance and TFP.

Author Contributions: Conceptualization, C.W.; supervision, C.W.; writing—original draft, T.L. and X.Y.; writing—review and editing, T.L. and X.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Department of Economy and Information Technology Project: 2020 Enterprise Management Consulting and Diagnosis Activities in Anhui Province, grant number: QYJL2020003.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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

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