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THE INFLUENCE OF DIGITAL FINANCE DEVELOPMENT ON BANK EFFICIENCY: EVIDENCE FROM CHINA

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Abstract. Digital finance has enhanced financial service accessibility, reduced costs, and disrupted traditional business models. Based on the functional view of finance, a theoretical model including commercial banks, households, and enterprises is constructed to analyze the impact of digital finance on bank efficiency and explore its mechanisms through liabilities and assets. In this paper, a three-dimensional framework including digital financial foundation, digital banking business and new financial services is constructed and a digital finance index is calculated to represent the development of digital finance at the city level. Then, using the stochastic frontier analysis (SFA) method, the efficiency of commercial banks is measured with the data of Chinese banks between 2011 and 2020. This empirical study shows that digital finance significantly improved the efficiency of China's commercial banks. For every extra unit of digital finance, bank's cost efficiency will increase by 0.72% and its revenue efficiency will increase by 3.17%. This conclusion is still valid after multiple robustness checks, including substitution of explanatory variables, cutting samples and regression with instrumental variables. These findings also indicate that the influence of digital finance on the change in bank efficiency varies across different regions, scales, and types of ownership, among which high GDP regions, large-scale banks, and state-owned banks have a relatively strong effect on efficiency. A further analysis of the mechanism shows that digital finance affects liability structure of banks, i.e., banks are usually inclined to have a smaller proportion of interbank liabilities as digital finance advances. Concurrently, digital finance also alters banking risks, which in turn affects their asset side. The core process through which digital finance enhances banking efficiency is more closely connected to the strong optimization impact of digital finance on the liability side than to weakening effect on the asset side.

Keywords: digital finance, bank efficiency, asset side, liability side, mechanism analysis.

JEL Classification:G21, G14, D61.

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1. Introduction

Information technology has elevated digital economy to the core of national development strategies. Digital technology, including the internet, mobile communications, big data, cloud technology, machine learning, and blockchain, has spurred the swift growth of digital finance. Digital finance has improved the accessibility of financial services, reaching many groups that once had no access to financial markets, which has lowered financial service expenses and significantly advanced financial inclusion. Practically speaking, since Yu'E Bao's launch in June 2013, digital finance in China has rapidly advanced. New financial services companies such as

Ant Financial Group[1], *JD Finance*[2], and *Lufax*[3] dominate the global financial services sector.

Digital finance has impacted traditional financial institutions, which are represented by commercial banks, particularly in the following ways. First, the rise of mobile payment, online lending, and online investment has squeezed market share of commercial banks and broken monopoly of banks in this field, which has strained banks' supply and demand dynamics, tightening their deposit and lending capacities. Second, digital finance propels interest rate liberalization, which can increase bank costs and narrow the spread between borrowing and lending rates, therefore reducing the loan returns and increasing bank competition (Hou et al., 2016). Third, digital finance has broken time and place constraints, enabling consumers to access services on a 24-hour basis, thus radiating out to more financial demanders (Pierrakis & Collins, 2014). Facing the digital tide, traditional banks are also accelerating the construction of digital banks and competing for deposit and loan resources. On the one hand, banks are actively setting up electronic platforms to reduce their dependence on bank outlets and compete for financial resources in other regions. On the other hand, banks are adding more financial services to compete for consumers. In this context, examining digital finance's effect on commercial bank efficiency holds substantial theoretical and practical value.

This paper intends to discuss the effect of digital finance on bank efficiency through financial function. By constructing a three-dimensional digital finance index, we evaluate how digital finance affects bank efficiency and the process involved, offering a rationale for financial technology advancement and banking modernization. Digital finance has strongly promoted the efficiency of commercial banks, and this impact varies by geography, scope, and ownership models. We find that developed areas, large-scale banks, and state-owned banks have a relatively strong effect on bank efficiency. Because there are numerous banking businesses in developed areas, the problem of low efficiency can easily occur, which makes bank efficiency more sensitive to changes in digital finance. Large-scale banks and state-owned banks have less competitive pressure on funds than other financial institutions, and their management mode is relatively fixed, so the effect of digital finance on the efficiency of these banks is stronger. Mechanistic analysis reveals digital finance reshapes commercial banks' initial debt composition, affecting bank assets: on the one hand, pressured by digital finance, banks are compelled to pursue high-risk ventures for greater returns, leading to high risk-taking. On the other hand, the increasing effect of digital finance on the number of loans enhances the profitability of banks. The deep mechanism of increasing bank efficiency mainly lies in the fact that digital finance's positive impact on liabilities outweighs its negative impact on assets.

The contributions of this paper are as follows. First, based on the financial functional view, we construct a theoretical model including commercial banks, families, and enterprises to analyze the impact of digital finance on bank efficiency. Second, most of the literature has used *the Peking University Digital Financial Inclusion Index of China* as a proxy index. In contrast, we develop a digital finance index across three dimensions: digital finance foundation,

[1] *Ant Financial Group* is an Internet financial services company dedicated to providing financial services to consumers and small and micro enterprises.

[2] *JD Finance* is a personal financial business brand of Jingdong Technology Group, which is committed to providing users with personal financial services.

[3] *Lufax* is the world's leading internet wealth management platform.

digital banking and new financial services. This index gauges digital financial progress within China. Third, using stochastic frontier analysis (SFA), we assess the cost efficiency and revenue efficiency of banks and empirically examine the effect of digital finance on bank efficiency. Finally, we examine how digital finance impacts bank efficiency via bank assets and liabilities.

The remainder of this paper is organized as follows. Section 2 introduces the related literature. Section 3 builds a theoretical framework to examine how digital finance advancement affects bank efficiency. Section 4 proposes the empirical design, including the econometric models, variables and data. Section 5 is a discussion of the empirical results. Section 6 presents a heterogeneity analysis. Section 7 explores the influence mechanism between digital finance development and bank efficiency, and Section 8 concludes the paper and provides some suggestions.

2. Literature review

We study the influence of digital finance on bank efficiency and therefore, review the connotation and measurement of digital finance and its impact on banks.

2.1. Connotation and measurement of digital finance

In 1971, the *Nasdaq* system was established in the United States, and thus the concept of digital finance became a reality. The development of digital finance can be roughly divided into two stages: the first stage involved the digitalization process of the traditional financial industry. The second stage started in 2000 when the continuing role of the internet in the traditional financial industry led to the establishment of many new financial companies. The Chinese third-party payment platform *Alipay*[4] was released on October 15, 2003, marking the beginning of digital finance in China.

Information, network, and communication technologies have catalyzed the emergence of new financial practices, resulting in a series of terms related to digital finance, such as e-finance, internet finance, digital inclusive finance, and fintech. Xie et al. (2012) proposed internet finance in China, arguing that internet finance combines modern information technology represented by the internet and finance. Inclusive finance was proposed by a group at *the Digital Finance Research Center of Peking University* and mainly emphasized the inclusive nature of digital finance. Researchers have assessed the economic impacts of inclusive finance in recent times, and some important results have been achieved (Dupas & Robinson, 2013; Shan & Gu, 2024; Khalid et al., 2024). Fintech is a part of digital finance, with an emphasis on its technological attributes (Gomber et al., 2017; Kodongo, 2024; Rahadian et al., 2024). Digital finance comes from e-finance i.e., electronic finance. E-finance includes financial services and financial markets provided by electronic communication and computer technology (Allen et al., 2002). Huang and Huang (2018) noted that digital finance encompasses the integration of cutting-edge digital technologies by both conventional financial entities and tech-driven firms to streamline services such as funding, transactions, and investment opportunities, marking a shift toward innovative financial solutions. In contrast, digital finance has

[4] *Alipay* is an open third-party payment platform in China, and is one of the most popular online banking and online payment forms in the world.

a richer connotation, which covers all kinds of new financial business activities using digital technology, and it is more appropriate for describing the new trend of financial development supported by the new generation of information technology.

Digital finance has had an enormous influence on social production and life (Lee et al., 2025), and existing studies usually use the indexes of *the Peking University Digital Financial Inclusion Index of China*, third-party payment data or online banking transaction data as proxy variables of digital finance when examining the economic impact of digital finance (Beck et al., 2007). However, these proxy variables measure only part of digital finance. In fact, digital finance should include two parts: modernization of conventional financial systems and new financial services. Most of the proxy indicators used in current researches cover only one aspect and thus cannot completely describe digital finance. Moreover, the literature on digital finance measurement can be classified into two groups.

First, digital finance is measured at a macro level. Because of the relative completeness of data, numerous studies focus on assessing digital finance from a macroeconomic perspective. For example, Beck et al. (2007) measured financial inclusion progress across two key aspects: the service availability and service usage of financial institutions. Mialou et al. (2017) divided digital finance into three dimensions including availability, penetration, and usage, and used factor analysis to calculate the weights. In their view, accessibility refers to the extent to which financial institutions are accessible; penetration emphasizes the broad accessibility of financial services; and usage is concerned with the depth of use of financial services. In addition, some institutional organizations and government departments such as *the World Bank* (WB), the *Alliance for Financial Inclusion* (AFI), the *Global Partnership for Financial Inclusion* (GPFI), *the People's Bank of China*, and *the Digital Finance Research Center of Peking University* have also conducted relevant studies.

Second, digital finance is measured at a micro level. In the early literature, scholars mostly measured digital finance at the national, provincial, and city levels. In recent years, a few scholars have tried to measure digital financial indexes by using microdata. For example, based on the 2011 China Household Finance Survey database (CHFS), Zhang and Posso (2017) constructed a household financial inclusion index in the form of dummy variables using the multidimensional poverty index method. Based on the characteristics of the data, scholars usually use factor analysis (Mialou et al., 2017), principal component analysis (Camara & Tuesta, 2014), the geometric mean method (Gupte et al., 2012), exponential summation (Chakravarty & Pal, 2013), and average Euclidean distance (Sarma, 2012) to construct the digital financial index.

2.2. Impact of digital finance on banks

In fact, as an innovative financial model integrating internet technology with financial services, digital finance has a profound influence on residents, enterprises, and financial institutions (Berger & Gleisner, 2009). Grossman and Tarazi (2014) argue that, at the household level, digital finance boosts household spending through streamlined payments and access to savings and subsidies. In particular, the swift integration of digital finance into daily life (Chen, 2016) has made households more likely to use various financial services, such as mobile payments and online shopping. To some extent, this phenomenon can increase the level of household risk-taking (Hong et al., 2020) and influence their financial investment behavior. At the enterprise level, digital finance includes artificial intelligence, blockchain, and related innovations. The deep integration of digital technologies and enterprises reduces production costs, information exchange costs, and transaction costs. At the same time, digital technologies enable efficient resource distribution and increased transaction scales, which improve the productivity of enterprises (Anderson & Wincoop, 2004; Brynjolfsson et al., 2014; Hellmanzik & Schmitz, 2015). In addition, cloud computing and big data technologies can alleviate information asymmetry problems (Arjunwadkar, 2018) and remove information barriers between users, which helps digital finance break the "Pareto principle" in the traditional financial environment and ease the financing constraints of small and microenterprises.

Many researchers have studied the impact of digital finance on financial institutions. However, the early literature mainly focused on theoretical analysis and descriptive statistics because the data were limited. For example, Zeng and Reinartz (2003) argue that digital finance promotes the operational efficiency of banks and reduces the bankruptcy risk of commercial banks. Berger and Gleisner (2009) note that digital finance has competed for the deposit and loan resources of commercial banks, which has shaken the monopoly position of the commercial bank. Based on a summary of the literature, Jagtiani and Lemieux (2018) argue that digital finance faces challenges in replacing traditional finance, yet significant potential exists for their collaboration. Improved digital finance databases have spurred empirical research into its effects on banking institutions. These studies cover different topics, such as the effect of digital finance on bank behavior (Stoica et al., 2015), bank risk-taking (Hou et al., 2016), monetary transmission effects (Krueger, 2012), and bank efficiency (Beck et al., 2016).

In the literature, there are few studies on the effect of digital finance on bank efficiency, and the conclusions are not consistent. Digital finance, according to certain researchers, may boost commercial banks' total factor productivity by fostering competition, innovation, and imitation (Lyytinen et al., 2016). This positive effect is mainly reflected in three aspects. First, the centralized banking structure is not beneficial for sustaining economic growth (Guzman, 2000). Heightened rivalry among lenders facilitates enhanced corporate insight, mitigating informational imbalances. The competition between digital finance and commercial banks can encourage the latter to seek new ways of operating actively in the fields of cloud computing, blockchain, and artificial intelligence, which can improve financial efficiency (Dapp, 2015). Second, advances in information technology can promote banks' innovative behavior (Cui et al., 2015). Financial innovation activities can increase banks' risk-taking, increase their willingness to innovate, and broaden their business scope, which contributes to bank efficiency (Beck et al., 2016). Third, big data risk control technologies have information and model advantages, which can be beneficial to improving the bank efficiency (Frost et al., 2019). Especially, the credit scoring model calculated from this method is significantly superior to the traditional bank scoring method (Gambacorta et al., 2019). In this way, the deep integration of digital and traditional finance can promote the overall progress of the banking industry and enhance the catch-up effect, thus improving banking efficiency (Berger, 2003).

Conversely, certain researchers posit digital finance negatively impacts banking productivity, which is mainly embodied in the substitution effect of digital finance on traditional bank business. For example, Beck (2001) argues that digital finance undermines the existing position of traditional financial institutions by reducing transaction costs and barriers to market access for financial products. This impact mainly applies to standardized low-risk products. Dell'Ariccia (2001) notes that digital finance has changed the way financial services are obtained and provided and has an impact on the deposit, loan, and intermediary businesses of banks. Hou et al. (2016) argue that bank risk measures are positively correlated with deposit growth. Digital finance intensifies the deposit competition faced by banks and changes the sensitivity of deposit growth rates to bank risk indicators.

Most of the available literature confirms that digital finance has several impacts on banks (Stankevičienė & Kabulova, 2022), but there are some deficiencies. First, these studies mainly focus on macrolevel analysis and pay less attention to the impact of digital finance on the microfoundation of bank operations. In particular, most of the existing studies on bank efficiency lack comprehensive and systematic research. Second, prior studies of online finance centered on novel financial forms – *Alipay*, *AntHuabei*, etc. They did not address the impact of the digitization of the traditional financial industry and could not comprehensively evaluate the effect of digital finance on bank efficiency. In addition, the mechanism of the effect of digital finance on bank efficiency is rarely discussed in the literature, so suggestions for enhancing the effect of digital finance on bank efficiency cannot be provided. This research explores how digital finance impacts and shapes bank efficiency from a micro perspective by reconstructing the digital finance index, which offers salient insights into Chinese digital finance applications.

3. Theoretical analysis

In the book "*Financial Economics*", Bodie and Merton (2000) divided the functions of the financial system into six areas according to the modern view of financial functions: (1) resource allocation across periods, regions, and industries; (2) providing payment, clearing, and settlement; (3) providing methods and mechanisms for managing risks; (4) providing price information; (5) reserving resources and dividing ownership; and (6) creating incentives. Among these areas, the two basic functions of "resource allocation" and "payment and settlement" are usually carried out mainly by commercial banks, which is more obvious in China, while the latter four aspects are mainly undertaken by capital markets. Based on the view of the financial function, we construct a theoretical model of commercial banks, families, and enterprises from the perspective of "resource allocation". This model investigates how digital finance influences banking efficiency, which is the theoretical basis for the following empirical research.

3.1. Function analysis

The core of "resource allocation" is the process of transferring funds from the supplier to the demander through appropriate mechanisms. At the bank level, it is mainly a process of absorbing savings and making loans.

Absorbing savings is a liability-side behavior of banks. Bank liabilities mainly include customer deposits and interbank borrowing liabilities. In the past, like the capital market, money market, and foreign exchange market, traditional banks were also one of the channels for consumers to invest, especially as the main investment channel for idle funds. However, the rise of digital finance has provided consumers with more high-interest and low-cost financial management projects, such as *Yu Ebao*. Although they have been informed of the risks, consumers trust and approve of such products. Consumers have subjectively assimilated such products with high-interest demand deposits. Therefore, digital financial derivative products have a strong alternative effect on the liability side of commercial banks.

On the one hand, the current low deposit rate does not meet the requirements for investors' earnings. Deposit and loan interest rates are still depressed due to the existence of benchmark deposit and loan interest rates, window guidance, financial market segmentation, and macroprudential assessment of interest rate pricing indicators, which has led to some bank deposits in the internet financial market. On the other hand, due to the competition of digital financial derivatives for users, commercial banks have launched high-interest-rate wealth management products to seize the market share of funds. While this may ease the funding squeeze in bank deposits, it is also competing for banks' original share of deposits. Moreover, a reduction in deposit resources would force banks to borrow funds in other ways to avoid disrupting normal lending activities. For example, banks would have to increase their liabilities in the interbank market. The interbank market rate is set by the market and is higher than the deposit rate. Interbank debt is traded more freely because it is not subject to reserve requirement restrictions.

In the early stage of digital finance, some of the funds from internet wealth management products such as *Yu Ebao* will be invested in the interbank market. Funds raised by commercial banks through wealth management products are also channeled through peer channels (Huang & Ratnovski, 2011), which also raises costs for banks. With digital finance, this kind of negative impact will turn into a positive impact instead. On the one hand, while digital finance diverts bank deposits, the economic growth that is brought by digital finance can provide a steadily increasing flow of capital to banks, which can increase bank deposits without increasing financing costs. On the other hand, regulatory restrictions on internet wealth management products will reduce their unique high-interest rate advantage, which encourages some users to return to using bank deposits. In other words, the rise of digital finance may change the debt structure of banks. This is beneficial for bank efficiency in the long run.

The process of bank lending is an asset-side behavior. We mainly analyze the impact of digital finance on loan quality, that is, the recovery rate, of the loan. State-owned enterprises are guaranteed by the government, so commercial banks, which usually have lower interest rates than others but good repayment guarantees, prefer to lend to them. The competitive pressure on banks from digital financial-related products has driven down interest rates, squeezing profits and revenues (Saunders & Schumacher, 2000). In this case, the former loan business cannot meet the bank's profit needs, and to pursue higher returns, banks have to invest in high-risk products. In addition, fintech companies have created new capital needs for banks, but they have also posed problems (Wei & Lin, 2016). Fintech companies have grown rapidly in recent years. For example, Suning Financial's net profit was 1.11 billion yuan in 2019, up 217% year-on-year from 350 million yuan in 2018. Fintech companies are innovative but risk-averse. Their increasing size is often accompanied by an increase in financial risk (Lin et al., 2013). Therefore, digital finance may increase the risk-taking of banks and reduce the efficiency of capital use.

3.2. Theoretical model

Efficiency represents the gap between the actual output and the optimal output under a certain input. Using the intermediary method to calculate efficiency, it can be expressed as follow:

$$y = y\left(w, p, a, b\right), \tag{1}$$

where y is the bank efficiency, w is the price vector of the input, p is the price vector of the output, a is the input vector, and b is the output vector. The intermediary law defines a bank as an intermediary between depositors and lenders. It believes that banks invest capital, labor, and physical assets to provide services, obtain loanable funds by taking deposits, and convert them into profitable assets such as loans and investments. From the perspective of bank operation, bank efficiency can be understood from the asset side and the liability side respectively. The asset side reflects the bank's profit level. The higher the profit level, the higher the bank's output and efficiency will be. The liability side reflects the cost of the bank, and the higher the cost of the bank, the higher the input price and the lower the efficiency. Based on the above analysis, refer to Zhan et al. (2018), we build a theoretical model of commercial banks, families and enterprises and analyze the mechanism of the impact of digital finance on bank efficiency.

3.2.1. Banks

There are two main sources of funding for commercial banks: ordinary deposits (F_{1t}), which pay a monetary base of α%, and interbank lending liabilities (F_{2t}), which do not. The former rate r_{1t} is lower than the latter rate r_{2t}. Banks use the latter to supplement their loan needs when the current funds do not meet their loan needs. Banks lend to three types of enterprises: first, large state-owned enterprises (Enterprise 1); and second, digital finance-related enterprises (Enterprise 2), whose loan volume is positively correlated with the level of development of digital finance (df_t). We assume that for the first two enterprises, because they have better qualifications, bank loans have been able to meet al. needs. Third, banks lend to small and micro enterprises (Enterprise 3). Such enterprises can only borrow part of their funds from banks, and the remaining funds need to be obtained in the informal market and through internet lending. Because the qualifications of these enterprises do not meet the requirements of banks, their risk of loans is relatively large.

Banks' profits on loans to enterprises 1 can be expressed as profits from inter-bank borrowing liabilities and profits from ordinary deposits. The profit from inter-bank borrowing liabilities can be written as $\beta_1 F_{2t} R_{1t}\,(W_1, F_{2t}) - C_{11}(F_{2t})$, where β_1 is the proportion of inter-bank borrowing liabilities obtained by enterprise 1, R_{1t} is the lending rate of banks to enterprise 1, $C_{11}(F_{2t})$ is the cost of loans issued by banks, assuming that it is positively correlated with the amount of interbank borrowing liabilities, and W_1 is the collateral value that enterprise 1 can provide. The profit from ordinary deposits can be expressed as

$(1-\alpha)\left(\lambda_1 F_{1t} R_{1t}\left(W_1, F_{2t}\right)-C_{12}\left(W_1\right)\right)$, where α is the deposit reserve ratio, λ_1 is the proportion of enterprise 1 that obtain loans from ordinary loans, and C_{12} (W_1) is the cost of loans issued by banks.

Banks' profits on loans to enterprises 2 can be expressed as profits from inter-bank borrowing liabilities and profits from ordinary deposits. The profit from inter-bank borrowing liabilities can be expressed as $\beta_2 F_{2t} R_{2t}$ (W_2, F_{2t}) – C_{21}(F_{2t}), where β_2 is the proportion of inter-bank borrowing liabilities obtained by enterprise 2, R_{2t} is the lending rate of banks to enterprise 2, C_{21} (F_{2t}) is the cost of loans issued by banks, assuming that it is positively correlated with the amount of interbank borrowing liabilities, and W_2 is the collateral value that enterprise 2 can provide. The profit from ordinary deposits can be expressed as $(1-\alpha)\left(\lambda_2 F_{1t} R_{2t}\left(W_2, F_{2t}\right)-C_{22}\left(W_2\right)\right)$, where λ_2 is the proportion of enterprise 2 that obtain loans from ordinary loans and C_{22} (W_2) is the cost of loans issued by banks.

Banks' profits on loans to enterprises 3 can be expressed as profits from inter-bank borrowing liabilities and profits from ordinary deposits. The profit from inter-bank borrowing liabilities can be expressed as $\left(1-\beta_1-\beta_2\right) F_{2t} R_{3t}\left(W_3, F_{2t}\right)-C_{31}\left(F_{2t}\right)$, where R_{3t} is the lending rate of banks to enterprise 3, C_{31} (F_{2t}) is the cost of loans issued by banks, assuming that it is positively correlated with the amount of interbank borrowing liabilities, and W_3 is the collateral value that enterprise 3 can provide. The profit from ordinary deposits can be expressed as $(1-\alpha)\left(\lambda_3 F_{1t} R_{3t}\left(W_3, F_{2t}\right)-C_{32}\left(W_3\right)\right)$. λ_3 is the proportion of enterprises that obtain loans from ordinary loans, C_{32} (W_3) is the cost of loans issued by banks. In addition, the bank will also use the remaining ordinary deposits for risk-free investment, and the profit can be expressed as (1 – α) (1 – λ_1 – λ_2 – λ_3)$R_t F_{1t}$, where R_t is the risk-free interest rate bank. The overall profit of the bank can be expressed as the sum of the profits of the three types of enterprises and the risk-free investment income minus the loan cost of inter-bank borrowing liabilities and deposits. The cost of inter-bank borrowing liabilities is $r_{2t}F_{2t}$, where r_{2t} is the inter-bank borrowing rate deposit. The cost of the deposit is $r_{1t}F_{1t}$ and r_{1t} is the ordinary deposit rate. Considering the level of competition in the market, the profit maximization behavior of banks is as follows:

$$\max pr_1=\left[\beta_1 F_{2t} R_{1t}\left(W_1, F_{2t}\right)-C_{11}\left(F_{2t}\right)+\beta_2 F_{2t} R_{2t}\left(W_2, F_{2t}\right)-C_{21}\left(F_{2t}\right)+\left(1-\beta_1-\beta_2\right) F_{2t} R_{3t}\left(W_3, F_{2t}\right)-\right.$$
$$\left.C_{31}\left(F_{2t}\right)\right]+(1-\alpha)\left\{\left[\lambda_1 F_{1t} R_{1t}\left(W_1, F_{2t}\right)-C_{12}\left(W_1\right)\right]+\left[\lambda_2 F_{1t} R_{2t}\left(W_2, F_{2t}\right)-C_{22}\left(W_2\right)\right]+\left[\lambda_3 F_{1t} R_{3t}\left(W_3, F_{2t}\right)-\right.\right.$$
$$\left.C_{32}\left(W_3\right)+\left(1-\lambda_1-\lambda_2-\lambda_3\right) R_t F_{1t}\right\}-r_{1t} F_{1t}-r_{2t} F_{2t}+\varepsilon F V_i. \quad (2)$$

We use εFV_i to measure the effect of market competition on bank profits. ε is the discount factor. FV_i is the franchise value of the bank, which refers to the price of the bank's financial franchise license or the discounted value of the future excess cash flow obtained due to market access. When the degree of market competition is high, banks do not have monopoly ability, FV_i =0. With the increase of bank market competitiveness, franchise value FV_i > 0.

3.2.2. Households

We standardize household wealth to 1 and consider that households invest their wealth in general deposits, bank accounts, internet accounts, and internet loans (the informal market and internet lending are lumped together here). Because of competition, banks and internet wealth management products are regarded as having the same rate of interest. The return on general deposits can be expressed as $\varphi_1 r_{1t}$, where φ_1 is the proportion of general deposits in household investments. The income of banking and Internet banking can be expressed as $\varphi_2 r_{2t}$. φ_2 is the proportion of banking and Internet banking in household investment. The income of Internet loans can be expressed as $\left(1-\varphi_1-\varphi_2\right) r_{ln_t}\left(df_t\right)$. $r_{ln_t}\left(df_t\right)$ is the income of Internet loans, which is positively related to digital finance. Household wealth should be the sum of three types of investment income, family utility maximization behavior is as follows:

$$\max pr_2=\varphi_1 r_{1t}+\varphi_2 r_{2t}+\left(1-\varphi_1-\varphi_2\right) r_{ln_t}\left(df_t\right), \tag{3}$$

where pr_2 is the household wealth gain.

3.2.3. Enterprises

The profit maximization functions of the three types of firms should be the difference between the income and cost of borrowing. The loan income of enterprise 1 is $\left(L_{11t}+L_{12t}\right)(E\gamma_1-R_{1t}(W_1))$. L_{11t} and L_{12t} are the loans from general bank deposits and interbank lending liabilities to Enterprise 1. $E\gamma_1$ is expected rates of return per unit of capital for enterprise 1. R_{1t} is the loan interest rate of bank to Enterprise 1. The loan income of enterprise 2 is $\left(L_{21t}+L_{22t}\right)(E\gamma_2(df_t)-R_{2t}(W_2))$. L_{21t} and L_{22t} are the loans from general bank deposits and interbank lending liabilities to Enterprise 2. $E\gamma_2$ is expected rates of return per unit of capital for enterprise 2, assuming that the income of enterprise 2 is positively correlated with the digital finance. R_{2t} is the loan interest rate of bank to enterprise 2. The loan income of enterprise 3 is $\left(L_{31t}+L_{32t}+L_{33t}\right)\left(E\gamma_3\right)-\left(L_{31t}+L_{32t}\right)R_{3t}\left(W_3\right)-L_{33t}R_{I_{nt}}$. L_{31t}, L_{32t} and L_{33t} are loans from general bank deposits, interbank lending liabilities and internet lending to enterprise 3. $E\gamma_3$ is expected rates of return per unit of capital for enterprise 3. R_{3t} is the loan interest rate of bank to enterprise 3. $R_{I_{nt}}$ which is the Internet loan interest rate. Each firm maximizes profit function form are as follows:

$$\max PR_{D_{1t}}=\left(L_{11t}+L_{12t}\right)(E\gamma_1-R_{1t}(W_1))-D_{11}; \tag{4}$$

$$\max PR_{D_{2t}}=\left(L_{21t}+L_{22t}\right)(E\gamma_2(df_t)-R_{2t}(W_2))-D_{21}; \tag{5}$$

$$\max PR_{D_{3t}}=\left(L_{31t}+L_{32t}+L_{33t}\right)(E\gamma_3)-\left(L_{31t}+L_{32t}\right)R_{3t}(W_3)-L_{33t}R_{I_{nt}}-D_{31}, \tag{6}$$

where D_{11}, D_{21} and D_{31} are the operating costs of Enterprises 1, 2 and 3.

3.2.4. Equilibrium

From the perspective of a bank, there are two asset-liability-related markets in the current economy: one is the market for supply and demand of funds between households and firms; the other is the market for supply and demand of funds between banks and firms. To ensure a balance between supply and demand, it is necessary to ensure that both markets are in equilibrium, that is:

$$\varphi_1=F_{1t}; \tag{7}$$

$$\varphi_2=F_{2t}=L_{12t}+L_{22t}+L_{32t}; \tag{8}$$

$$L_{11t}=\left(1-\alpha\right)\lambda_1 F_{1t}; \tag{9}$$

$$L_{21t} = (1-\alpha)\lambda_2 F_{1t}; \tag{10}$$

$$L_{31t} = (1-\alpha)\lambda_3 F_{1t}; \tag{11}$$

$$L_{12t} = \beta_1 F_{2t}; \tag{12}$$

$$L_{22t} = \beta_2 F_{2t}; \tag{13}$$

$$L_{32t} = (1-\beta_1-\beta_2) F_{2t}. \tag{14}$$

(1) Impact on the liability side. From Equations (1)–(5), we have:

$$\frac{\partial pr_2}{\partial F_{1t}} = 0; \tag{15}$$

$$r_{1t} + r_{2t}\frac{\partial F_{2t}}{\partial F_{1t}} + \frac{\partial L_{33t}}{\partial F_{1t}} r_{In_t} = 0; \tag{16}$$

$$E\gamma_1 = \frac{\alpha_1 \frac{\partial F_{2t}}{\partial F_{1t}}\left[(1-\alpha)\lambda_1 F_{1t} + \beta_1 F_{2t}\right]}{(1-\alpha)\lambda_1 + \beta_1 \frac{\partial F_{2t}}{\partial F_{1t}}} + \alpha_1 F_{2t}; \tag{17}$$

$$E\gamma_2 = \frac{\alpha_2 \frac{\partial F_{2t}}{\partial F_{1t}}\left[(1-\alpha)\lambda_2 F_{1t} + \beta_2 F_{2t}\right]}{(1-\alpha)\lambda_2 + \beta_2 \frac{\partial F_{2t}}{\partial F_{1t}}} + \alpha_2 F_{2t}; \tag{18}$$

$$E\gamma_3 = \frac{\alpha_3 \frac{\partial F_{2t}}{\partial F_{1t}}\left[(1-\alpha)\lambda_3 F_{1t} + \beta_3 F_{2t}\right] + \frac{\partial L_{33t}}{\partial F_{1t}} R_{I_{nt}}}{(1-\alpha)\lambda_3 + (1-\beta_1-\beta_2)\frac{\partial F_{2t}}{\partial F_{1t}} + \frac{\partial L_{33t}}{\partial F_{1t}}} + \alpha_3 F_{2t}. \tag{19}$$

The partial derivative of the above four equations for d_{ft} is obtained as[5]: $\frac{\partial F_{1t}}{\partial df_t} = f_1 + f_2 + f_3$ >0. Although digital finance provides more choices for households' financial resource allocation, the amount of general bank savings input does not decrease. In other words, with sufficient amounts of various types of funds, banks will prefer lower-cost general savings deposits as a source of funds. Although digital finance has been adopted by some original users of banks, digital finance-related enterprises and economic development also provides banks with more sources of general savings. Moreover, this development increases the general deposit input of banks. The increase in the amount of general deposit input helps to reduce the cost of the bank and this improve the efficiency of the bank from the perspective of input. Thus, we propose the following Hypothesis:

H1: *Digital finance will increase general savings and change the debt structure of banks, which improves their efficiency from the input perspective.*

(2) Impact on the asset side. Based on the above analysis results, the partial derivative of d_{ft} can be obtained as follows[6]:

[5] Where f_1, f_2 and f_3 are all complex functions of df_t; only a simplified demonstration.

[6] Where $f_1^{'}, f_2^{'}$ and $f_3^{'}$ are all complex functions of df_t; only a simplified demonstration.

$$\frac{\partial R_{1t}}{\partial df_t} \approx \frac{\partial R_{2t}}{\partial df_t} \approx \frac{\partial R_{3t}}{\partial df_t} \approx f_1^{'} + f_2^{'} + f_3^{'} > 0, \tag{20}$$

$$\frac{\partial\left(1-\beta_1-\beta_2\right)}{\partial df_t} =$$

$$\frac{\alpha_3 \frac{\partial \frac{\partial F_{2t}}{\partial F_{1t}}}{\partial df_t}\left[\left(1-\alpha\right)\lambda_3 F_{1t} + \beta_3 F_{2t}\right] + \alpha_3 \frac{\partial F_{2t}}{\partial F_{1t}}\left[\left(1-\alpha\right)\lambda_3 \frac{\partial F_{1t}}{\partial df_t} + \beta_3 \frac{\partial F_{2t}}{\partial df_t}\right] + \frac{\partial L_{33t}}{\partial F_{1t}} \frac{\partial R_{lnt}}{\partial df_t}}{\frac{\partial F_{2t}}{\partial F_{1t}}\left(E\gamma_3 - \alpha_3 F_{2t}\right)} > 0. \tag{21}$$

Digital finance may have a positive effect on banks' lending rates and increase the loan proportion of enterprise 3. Such enterprises generally lack loan qualification and repayment ability cannot be fully guaranteed, which is often accompanied by greater repayment risk, thus increasing the probability of non-performing loans of banks and reducing the efficiency of banks from the perspective of output. Thus, we propose the following Hypothesis:

H2: *The competition brought by digital finance makes banks change their risk preference, which will change their loan structure and increase the rate of nonperforming loans. This situation reduces the efficiency of banks from an output perspective.*

According to the above theoretical analysis, on the one hand, digital finance contributes to bank efficiency from the liability side. On the other hand, digital finance contributes negatively to bank efficiency from the asset side. Therefore, under the joint action of assets and liabilities, net influence of digitized finance on banking efficacy remains unclear, contingent on the comparative strength of opposing effects.

4. Models and variables

4.1. Empirical model

To test the above hypotheses, we construct a panel data model, which is as follows:

$$Y_{it} = \beta_0 + \beta_1 DFI_{jt} + \gamma Control_{jit} + u_i + \tau_t + \varepsilon_{it}, \tag{22}$$

where i is the bank and t is the corresponding year; the dependent variable Y_{it} is the efficiency of commercial banks in year t, which mainly measures cost efficiency and revenue efficiency; the core explanatory variable is the digital finance index DF_{jt} in the region j where bank i is registered; $Control_{jit}$ represents the control variables, including the bank and the regional level; u_i is the fixed effect of commercial banks; τ_t is the year fixed effect; ε_{it} is the random error term; and β_1 characterizes the effect of digital finance on the efficiency of commercial banks.

4.2. Variable selection

According to the classification criteria of the *CBRC* and data availability, we select 406 banks as research samples. The sample interval is from 2011 to 2020. The data are obtained from the *WIND* database, the *CSMAR* database, and the annual reports of major banks. The reason for choosing China as a sample is that China's digital financial development is very special in the global development. Although China's digital finance started later than other countries, the speed of development is very impressive. The main reason is, first, the relative tolerance of regulation. Developed Western nations feature robust financial instruments and oversight, and in this case, the development of new financial models in existing markets is very limited. China's dual-track financial system is consistent. Both formal and informal financial markets coexist simultaneously, and it is in the reform stage of the financial system. The marketization of interest rates, the liberalization of exchange rates and relaxation of financial regulation provide a very broad space for digital finance. Second, there is a large gap in financial demand, and the digital finance growth model diverges from the Western approach. Given that financial markets in Western countries are already fairly well-established, digital finance there tends to concentrate on leveraging internet technology to boost the efficiency of existing financial institutions, rather than on creating entirely new financial products from scratch. However, China's financial system is still developing, and China's digital finance focuses more on the development of new financial products to meet the financing needs of long-tail users and micro, small and medium-sized enterprises. In other words, online portals directly link capital sources to users, and revitalizes the resources free from the traditional financial market. Third, Chinese consumers have a high acceptance of digital payments and Internet financial products. Cultural differences and privacy concerns have limited the speed at which digital finance can spread in other countries. With the swift evolution of digital finance in China, selection of this sample can more effectively study the characteristics of digital finance and its impact on banks. Although other countries are not developing as fast as China, digital finance is still in a state of constant development. In the process of development, it will also face similar problems as China. Thus, this research offers insights applicable to digital finance advancement globally.

4.2.1. Dependent variable

We choose the efficiency of commercial banks as the explanatory variable. Bank efficiency includes cost efficiency and revenue efficiency. There are three common methods for selecting input-output indicators: the production method, the income method, and the intermediation method. In most studies, input-output indicators are selected based on the intermediation approach or a blend of the intermediation strategy with alternative techniques (Ray & Das, 2009). Therefore, we chose to use this method. The intermediation method, which was proposed by Lindley (1977), emphasizes the intermediary role of banks between depositors and lenders, so the efficiency measured by this method also focuses on this aspect. Under the intermediation method, the inputs mainly include interest and noninterest costs. The outputs cover interest loans, other investments, and noninterest income. Accordingly, we select interest expenses and noninterest expenses as input indicators. We select total deposits, total loans, other earning assets, and noninterest income as output indicators.

We use the supra-logarithmic SFA method, which Sun et al. (2013) use to measure efficiency. The specific forms are as follows:

$$\ln\left(\frac{CO_{it}}{W_{2it}*z_{it}}\right)=B+C\ln\left(\frac{W_{1it}}{W_{2it}}\right)+\sum_{k=1}^{4}D_k\ln\left(\frac{X_{kit}}{z_{it}}\right)+E\ln\left(\frac{W_{1it}}{W_{2it}}\right)^2+\sum_{k=1}^{4}F_k\ln\left(\frac{X_{kit}}{z_{it}}\right)^2+$$

$$H\ln\left(\frac{X_{1it}}{z_{it}}\right)\ln\left(\frac{X_{2it}}{z_{it}}\right)+\sum_{k=1}^{4}J_k\ln\left(\frac{W_{1it}}{W_{2it}}\right)\ln\left(\frac{X_{kit}}{z_{it}}\right)+\varepsilon_{i,t}+\mu_{i,t}+year_t; \tag{23}$$

$$Y_{1it}=e^{-\mu_{i,t}}; \tag{24}$$

$$\ln\left(\frac{RE_{it}}{W_{2it}*z_{it}}\right)=B+C\ln\left(\frac{W_{1it}}{W_{2it}}\right)+\sum_{k=1}^{4}D_k\ln\left(\frac{X_{kit}}{z_{it}}\right)+E\ln\left(\frac{W_{1it}}{W_{2it}}\right)^2+\sum_{k=1}^{4}F_k\ln\left(\frac{X_{kit}}{z_{it}}\right)^2+$$

$$H\ln\left(\frac{X_{1it}}{z_{it}}\right)\ln\left(\frac{X_{2it}}{z_{it}}\right)+\sum_{k=1}^{4}J_k\ln\left(\frac{W_{1it}}{W_{2it}}\right)\ln\left(\frac{X_{kit}}{z_{it}}\right)+\varepsilon_{i,t}-\mu_{i,t}+year_t; \tag{25}$$

$$Y_{2it}=e^{-\mu_{i,t}}. \tag{26}$$

We measure efficiency using one-stage simultaneous estimation. Equation (23) and (24) are employed to calculate the cost efficiency Y_{1it}. Where CO_{it} is the sum of interest expenses and noninterest expenses when measuring cost efficiency; W_{1it} is the price of loanable funds = interest expenses/total deposits and W_{2it} is the price of operating inputs = noninterest expenses/total assets; X_{1it} = total loans, X_{2it} = total deposits, X_{3it} = other earning assets, X_{4it} = noninterest income, and $\varepsilon_{i,t}$ is a random disturbance term obeying $N(0, \rho^2)$; $\mu_{i,t}$ is a nonnegative inefficiency term obeying $N^+(0, \rho^2)$, $year_t$ is a time dummy variable, and z_{it} represents total assets. Descriptive statistics of each indicator are detailed in Appendix Table A2. Equation (25) and (26) are employed to calculate the revenue efficiency Y_{2it}. When measuring revenue efficiency, RE_{it} represents total operating income.

4.2.2. Core independent variable

(1) Index selection

Many existing studies have used *the Peking University Digital Financial Inclusion Index of China* to characterize the level of digital finance development. The index was jointly compiled by *the Peking University Financial Research Center* and *the Ant Financial Group*, to reflect the growth of digital finance at the provincial and city levels in China. However, this index mainly relies on data from *Ant Financial Group* and focuses on reflecting digital finance development through consumer behavior while neglecting the reflection of financial institution behavior. Given that the research object of this study is commercial banks, using this index to test the research topic may not provide sufficient accuracy (Allen et al.,2005).

Therefore, we aim to create a digital finance index that is more suitable for the research topic by taking into account the development context and main business models of digital finance. Digital finance is an emerging concept that has not yet been clearly defined. However, regardless of the "Internet Finance" defined by ten ministries and commissions, the "Fintech" defined by *the Financial Stability Council*, or the "Digital Finance" defined by Huang and Huang (2018), digital finance is a catch-all term for when traditional financial institutions and tech companies alike leverage digital technologies to create new financial business models, particularly in areas like financing, payments, and investments, that is, digital finance is divided into two parts. One is the digitization process of traditional financial services, such as electronic banking and mobile banking. The other is the financial platforms established by internet companies, such as *P2P* and *Alipay*. Therefore, we should build a digital financial index to cover these two parts. Additionally, some scholars have created digital finance indexes based on the financial function perspective, which also includes measuring the information processing capability of digital finance, reflecting its development foundation. The development foundation of digital finance is necessary because it determines its future development space. Therefore, we construct a three-dimensional index system to calculate the digital finance index at the city level from three dimensions: digital finance foundation, digital banking business, and new financial services. Table 1 shows the specific indicators underlying the digital finance index, and we measured the digital finance index for 141 cities.

Digital Financial Foundation. Although this dimension is not considered a financial service, it is crucial for its development. The extent to which digital finance penetrates enterprises depends on two factors. First, since digital finance relies on internet technology, the state of infrastructure development makes it closely linked to the communication facilities available in the region. Second, the level of digital awareness within businesses, as a practical use of digital finance to support the real economy, requires awareness of the benefits of digital services. To measure infrastructure development, internet penetration rates and optical cable

Table 1. Indicators underlying the digital finance index

Dimension	Definition	Primary indicator	Secondary indicator
Digital financial foundation	Not a financial service, but a foundation for digital finance	Regional digital infrastructure	Internet penetration rate
			Fiber optic cable density
		Enterprise digital concept	Share of enterprises with e-commerce transaction activities
			Number of computers owned by enterprises
Digital banking business	Traditional financial institutions achieve the financing of funds through electronic transactions	Digital banking transaction base	Percentage of digital investment in the financial industry
		The scale of digital banking transactions	The scale of mobile banking transactions
			Online banking transaction scale
New Financial Services	Providing online financial services through new financial platforms	Network investment business	Peking University Digital Inclusive Finance Usage Depth Sub Index
		Internet insurance business	
		Internet lending business	
		Internet wealth management	
		Three-party payment business	Number of non-financial institution Payment service business units
		Financial intermediary business	Number of financial information service business units

Note: This table reports the definition and composition of the digital finance sub-index.

density are used, while the proportion of companies engaged in e-commerce transactions and the number of computers owned by businesses are used to assess digital awareness.

Digital Banking Business. This dimension evaluates the offerings of conventional financial service providers through digital technology, such as mobile banking and online banking. Digital banks offer advantages such as lower operating costs, improved efficiency, and convenience, enabling them to effectively address the financial demands of businesses anytime and anywhere. To develop digital banks, investment in relevant resources is essential, which is why the level of digital investment by traditional financial institutions is also taken into account. This level is measured by the proportion of digital investment in the financial industry. The scale of digital banks is measured by the transaction volume of mobile banking and online banking.

New Financial Services. This dimension refers to financial services that are offered online by new financial companies. The emergence of *Yu Ebao* in 2013 spurred the rapid growth of internet-based financial management businesses. Related services such as online insurance, third-party payment, and *P2P* online lending have made financial services more convenient for the public. Obtaining data on internet finance at the city level can be challenging, but *Peking University's Digital Inclusive Finance Usage Depth Subindex* includes payment, monetary funds, credit, insurance, investment, and credit services. Therefore, we use this index as a representative measure. Additionally, the number of nonfinancial institution payment service providers and financial information service providers are used to evaluate third-party payment and financial intermediary businesses among the new services.

(2) Measurement method

We construct a digital finance index using the methodology developed by Sarma (2012) as follows:

Step 1: Determine the indicators to be used. We select the initial indicators listed above based on the observed trends in digital finance.

Step 2: Standardize the selected indicators. The standardization method is as follows: $x_i = \frac{A_i - m_i}{M_i - m_i}, i = 1,2,\ldots,10$, where A_i is the specific value of the i^{th} indicator; M_i is the maximum value of the ith indicator; and m_i is the minimum value of the ith indicator. x_i is the final standardized result, and the indicators are comparable after standardization.

Step 3: Determine the weights of each indicator. We use several methods, such as the analytic hierarchy process (AHP), covariance AHP, factor analysis, principal component analysis (PCA), and coefficient of variation, to calculate the weights of the digital finance indicators. After comparing the results, we select the principal component analysis method, which is commonly used by most scholars, to determine the weights (Mialou et al., 2017). The weight of the jth principal component is represented as:

$$w_j = \frac{CV_j}{\sum_{j=1}^{n} CV_j}, \quad (27)$$

where CV_j denotes the respective loadings of the j^{th} dimensional synthetic index, and n is the number of selected principal components.

Step 4: Synthesize the digital finance index. We use a cumulative loading of 85% as the standard and calculate the weights to synthesize the Digital Financial Index (*DF*I). We then use the same method to synthesize the subindices of the digital finance index, as follows:

$$DFI = \sum_{j=1}^{n} w_j F_j^*, \tag{28}$$

where F_j^* is the jth principal component used to construct the digital finance index. Based on the measurement results of principal component analysis, the digital financial foundation index ($DFI11_{it}$), digital banking business index ($DFI12_{it}$), and new financial services index ($DFI13_{it}$) measurement models are as follows:

$$DFI11_{it} = 0.508F_{11it}^* + 0.275F_{12it}^* + 0.217F_{13it}^*; \tag{29}$$

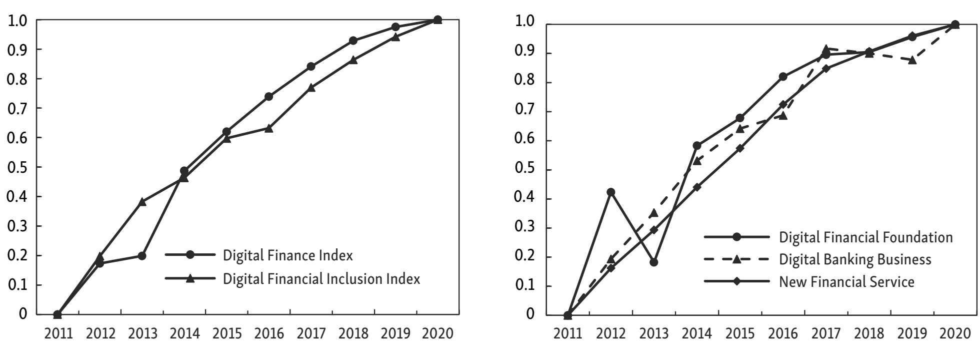
$$DFI12_{it} = 0.653F_{21it}^* + 0.347F_{22it}^*; \tag{30}$$

$$DFI13_{it} = 0.798F_{31it}^* + 0.202F_{32it}^*, \tag{31}$$

where F_{11it}^*, F_{12it}^*, F_{13it}^*, F_{21it}^*, F_{22it}^*, and F_{31it}^* and F_{32it}^* represent different main factors used to create the digital financial index (DFI_{it}). To test the reliability of the digital financial index, we compared it with four commonly used digital financial proxy variables: *the Peking University Digital Financial Inclusion Index of China*, the market size of third-party internet payments, the business scale of third-party mobile payments, and the scale of *Yu Ebao*. The results showed that the digital financial index that was constructed using different models had a significant positive correlation at the 1% level. The correlation coefficients between the digital financial index constructed in this study and the four comparison indexes were all greater than 0.92, indicating that the index is reliable.

(3) Result

Figure 1 shows the results. The development level of digital finance in China shows first an upward trend of an increasing margin and then a decreasing margin, which is in line with the general trend of *the Peking University Digital Financial Inclusion Index of China*, but the fluctuation characteristics are slightly different. Before 2013, the development of



Notes: The figure reports trends in the total and sub-indices of digital finance. The data in the figure represent the annual mean of the digital finance indices and have been standardized for ease of comparison.

Figure 1. Development trend of digital finance in China

digital finance was relatively slow. From 2013 to 2017, the development of digital finance entered an accelerated period. After 2018, the development of digital finance slowed again. In particular, before 2013, digital finance as a new thing was not trusted by the public. In June 2013, the establishment of *Yu Ebao* not only enriched the types of new financial services but also showed the public and traditional financial institutions that digitalization has brought convenience to life. Since then, *P2P* network lending, crowdfunding, and other forms of the digital finance industry have risen rapidly. After 2018, digital finance emerged as a key component of the financial system. New types of services are widely used by the public, but the pace of development has slowed down.

From the subindex point of view, the growth trend of each dimension and the total index tend to be the same, which shows that the three dimensions of digital finance develop in synergy, but there are also some differences among them. In comparison, in most years, the digital financial base index is at the bottom. The digital banking business index led before 2018, and the new financial services index took second place. After 2018, the new financial services index surpassed the digital banking business index. A possible reason for this is that the rapid development of new financial services has had a great deal of impact on the traditional banking industry, but the inadequacy of early supervision led to the occurrence of Ponzi schemes in the new financial markets. This reduced public confidence in new financial services. Simultaneously, legacy banks expanded digital offerings. Measures such as canceling the handling fees of mobile phone bank transfers have brought the same convenience to the public as new financial services have. The growth of *Alipay* users can also prove this point. From the establishment of *Alipay* in 2004 to 2017, the number of *Alipay* users was approximately 520 million. In 2020, the number of *Alipay* users exceeded 1 billion, and we can see that the new financial services have developed rapidly over those three years.

4.3. Control variables

Referring to the study by Klumpes (2004), we selected control variables at the bank and macroeconomic levels. The bank-level control variables included the loan-to-deposit ratio (*LDR*), which was measured as the ratio of total bank loans to total deposits; the level of

Table 2. Descriptive statistics

Variables	Symbol	N	Mean	SD	Min	Max
Cost efficiency	Y_1	3363	0.4866	0.1421	0.0082	0.9362
Revenue efficiency	Y_2	3363	0.5204	0.3074	0.1035	0.9257
Digital Finance Index	*DFI*	3363	0.7696	1.4821	–3.4084	5.183
Loan-to-deposit ratio	*LDR*	3363	0.6739	0.1845	0.2103	7.0553
Capital adequacy ratio	*CAR*	3363	14.8268	4.9357	–11.14	66.78
Bank size	*SIZE*	3363	25.4235	1.9414	19.0596	31.1379
Loan to asset ratio	*DAR*	3363	0.3755	0.2316	0.0001	0.9373
GDP per capita (log)	*GDP*	3363	11.0854	0.4038	9.5878	12.2807
GDP share of primary sector	*GDP*1	3363	0.4866	0.1421	0.0082	0.9362

Notes: This table tabulates the descriptive statistics for our variables of bank efficiency and control variables. Detailed definitions are available in Appendix Table A1.

bank capital adequacy ratio (*CAR*), which was measured as the ratio of total bank capital to risk-weighted assets; bank size (*SIZE*), which was measured as the logarithm of total bank assets at the end of the year; and the loan-to-asset ratio (*DAR*), which was measured as the ratio of outstanding loans to total bank assets at the end of the year. The macroeconomic control variables included the logarithm of per capita GDP (*GDP*) and the share of GDP from the primary industry (*GDP1*).

Table 2 presents summary statistics for all variables.

5. Empirical studies

5.1. Baseline regression results

A Tobit model was used for regression analysis, given that cost efficiency and revenue efficiency values were between 0 and 1. The results are presented in Table 3. The first two columns of Table 3 show the regression results without other control variables, while the last two columns show the results with controls. The estimated coefficients for the DFI are all positive and statistically significant at the 1% level, which confirms the positive impact of digital finance on bank efficiency. This result aligns with studies by other researchers.

Table 3. Impact of digital finance on bank efficiency

Variables	(1)	(2)	(3)	(4)
	Y_1	Y_2	Y_1	Y_2
DFI	0.0054**	0.0155***	0.0072***	0.0317***
	(0.0024)	(0.0049)	(0.0025)	(0.0064)
LDR			–0.0589***	–0.0525**
			(0.0105)	(0.0267)
CAR			–0.0029***	0.0030***
			(0.0004)	(0.0011)
SIZE			–0.0756***	–0.0283***
			(0.0027)	(0.0069)
DAR			–0.8113***	–0.2299***
			(0.0222)	(0.0565)
GDP			0.0055	–0.0070
			(0.0076)	(0.0193)
GDP1			0.0016	0.0042
			(0.0012)	(0.0030)
Control Variables	NO	NO	YES	YES
Fixed Effect	YES	YES	YES	YES
N	3,363	3,363	3,363	3,363
Pseudo R^2	–0.8492	2.1263	–1.2772	2.1653

Notes: This table presents the results from regression of bank efficiency on digital finance (DFI) and control variables. Columns (1) and (3) are the results of the cost efficiency, and columns (2) and (4) are the results of the revenue efficiency. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Although the rapid development of digital finance has increased the risk exposure of banks, its larger contribution to diminished bank expenditures significantly bolstered commercial bank efficiency.

The anticipated results of the control variables largely align with our expectations. The *SIZE* coefficient is negative and significant at the 1% level in all columns, indicating that as banks grow in size, their cost and income efficiency decrease. Although large banks have natural advantages, such as large asset and customer bases, their inefficiency and cumbersome personnel structure have also been criticized. The *GDP* coefficient is significantly positive, indicating that economic development improves bank efficiency. However, the impact of *DAR* and the share of *GDP1* have negative effects on bank efficiency.

5.2. Robustness tests

Based on robustness considerations, the following robustness tests are conducted in this paper.

5.2.1. Replace key variables

In the baseline model, we used principal component analysis to combine ten indicators and create the *DFI*. To ensure the robustness of our findings, we recalculated *DFI1* and *DFI2* using factor analysis and the information entropy weight method. The findings are presented in the first four columns of Table 4. The coefficients of the digital finance substitution index (*DFI1* and *DFI2*) are significantly positive. This indicates that digital finance greatly enhances efficiency in costs and revenues, aligning with our preliminary regression findings.

Moreover, considering that the SFA method has too many assumptions for the model, the calculation results may be biased. We used the Malmquist model in DEA method to re-calculate the bank efficiency. The input indicators are loanable funds price and operating input price. The output indicators are total loans, total deposits, other earning assets and non-interest income. The bank total factor productivity (Y_3) was calculated. The specific efficiency measurement method is as follows:

$$Y_3 = \left[\frac{D^t\left(X_i^{t+1}, Y_i^{t+1}\right)}{D^t\left(X_i^t, Y_i^t\right)} \frac{D^{t+1}\left(X_i^{t+1}, Y_i^{t+1}\right)}{D^{t+1}\left(X_i^t, Y_i^t\right)} \right]^{1/2}, \tag{32}$$

where, D^t and D^{t+1} respectively represent the distance function between the observation point and the technical front in t and t + 1 periods, X_i^t and Y_i^t are the input vector of bank i in t period and the output vector of bank i in t period. $D^t\left(X_i^t, Y_i^t\right)$ use the following method to solve:

$$\left[D^t\left(X_i^t, Y_i^t\right)\right]^{-1} = \mathrm{Max}\,\theta_i^t$$

$$\text{s.t} \begin{cases} \sum_{k=1}^{K} X_k^t \lambda_k^t \le X_i^t\left(2-\theta_i^t\right) \\ \sum_{k=1}^{K} Y_k^t \lambda_k^t \le Y_i^t \theta_i^t \\ \lambda_k^t \ge 0,\ \theta_i^t \ge 1 \end{cases}, \tag{33}$$

where, λ_k^t represents the weight of bank i on bank k, replace all t in the above Equation with t + 1, it can be obtained $D^{t+1}\left(X_i^{t+1}, Y_i^{t+1}\right)$. $D^t\left(X_i^{t+1}, Y_i^{t+1}\right)$ use the following methods to solve:

$$\left[D^t\left(X_i^{t+1}, Y_i^{t+1}\right)\right]^{-1} = \mathrm{Max}\, \varepsilon_i^{t+1}$$

$$\text{s.t}\begin{cases} \sum_{k=1}^{K} X_k^t \lambda_k^t \le X_i^{t+1}\left(2-\varepsilon_i^{t+1}\right) \\ \sum_{k=1}^{K} Y_k^t \lambda_k^t \le Y_i^{t+1}\varepsilon_i^{t+1} \\ \lambda_k^t \ge 0,\ \theta_i^{t+1} \ge 1 \end{cases}. \quad (34)$$

It can be obtained $D^{t+1}\left(X_i^t, Y_i^t\right)$ by interchanging t and $t+1$ in the above Equation. The regression results are shown in columns (5) of Table 4. The regression coefficient is significant at the 10% level, indicating that digital finance can promote the growth of bank cost and income efficiency.

In addition, considering that the efficiency measured by baseline regression does not take into account the influence of heterogeneity factors. We used the common frontier DEA method to measure the efficiency and performed the regression again. Specific practices are as follows: The east and west are divided into three group frontiers according to the criteria. The eastern region where the bank is registered is brought into the DEA-Malmquist model to measure the efficiency of the eastern region under the group frontier. The steps of the central and western regions are the same. The input index is loanable capital price and operating input price. The output indicators are total loans, total deposits, other earning assets and non-interest income. It is assumed that the efficiency of measurement is Y_4. In addition, we added the city dummy variable to Equation (23) and Equation (25) to re-measure the cost efficiency (Y_5) and revenue efficiency (Y_6), as shown below:

$$\ln\left(\frac{CO_{it}}{W_{2it} * z_{it}}\right) = B + C\ln\left(\frac{W_{1it}}{W_{2it}}\right) + \sum_{k=1}^{4} D_k \ln\left(\frac{X_{kit}}{z_{it}}\right) + E\ln\left(\frac{W_{1it}}{W_{2it}}\right)^2 + \sum_{k=1}^{4} F_k \ln\left(\frac{X_{kit}}{z_{it}}\right)^2 +$$
$$H\ln\left(\frac{X_{1it}}{z_{it}}\right)\ln\left(\frac{X_{2it}}{z_{it}}\right) + \sum_{k=1}^{4} J_k ln\left(\frac{W_{1it}}{W_{2it}}\right)\ln\left(\frac{X_{kit}}{z_{it}}\right) + \varepsilon_{i,t} + \mu_{i,t} + year_t + city_j, \quad (35)$$

$$\ln\left(\frac{RE_{it}}{W_{2it} * z_{it}}\right) = B + C\ln\left(\frac{W_{1it}}{W_{2it}}\right) + \sum_{k=1}^{4} D_k \ln\left(\frac{X_{kit}}{z_{it}}\right) + E\ln\left(\frac{W_{1it}}{W_{2it}}\right)^2 + \sum_{k=1}^{4} F_k \ln\left(\frac{X_{kit}}{z_{it}}\right)^2 +$$
$$H\ln\left(\frac{X_{1it}}{z_{it}}\right)\ln\left(\frac{X_{2it}}{z_{it}}\right) + \sum_{k=1}^{4} J_k ln\left(\frac{W_{1it}}{W_{2it}}\right)\ln\left(\frac{X_{kit}}{z_{it}}\right) + \varepsilon_{i,t} - \mu_{i,t} + year_t + city_j, \quad (36)$$

where, $city_j$ is a fixed urban effect. The regression results are shown in columns (6) –(8) of Table 4. The regression coefficients of digital finance are positive and pass the statistical significance test at the 5% level, suggesting that digital finance enhances bank efficiency growth.

Table 4. Regression results for alternative variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Y_1	Y_2	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6
DFI1	0.0034***	0.0099***						
	(0.0012)	(0.0031)						
DFI2			0.0072***	0.0477***				
			(0.0025)	(0.0106)				
DFI					0.0122***	0.0058***	0.0082***	0.0073**
					(0.0042)	(0.0022)	(0.0029)	(0.0030)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
N	3,363	3,363	3,363	3,363	3,363	3,363	3,363	3,363
Pseudo R^2	–1.2771	2.1566	–1.2772	2.1626	1.4411	–0.9003	–1.1035	–1.1902

Notes: This table presents the regression results for replacement variables. Columns (1)–(2) is the results of the *DFI1*, columns (3)–(4) is the results of the *DFI2*, column (5) –(8)is the result of the *DFI*. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

5.2.2. Split sample

We also conducted robustness tests using sample splitting, and the results are presented in Table 5. First, the metropolitan economy is developed, and the bank has more optional resources, which is different from other cities. This may affect the regression results of digital finance on bank efficiency. To address this, we removed the metropolitan samples and conducted the regression analysis again. The results are presented in the first two columns of Table 5. In addition, the outbreak of the *COVID-19* pandemic has had a huge impact on the real economy, leading to a sharp reduction in economic activity worldwide. This reduces

Table 5. Regression results for split samples

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Excluding data from municipalities		Excluding data from the epidemic period		Excluding data from systemic banks	
	Y_1	Y_2	Y_1	Y_2	Y_1	Y_2
DFI	0.0078***	0.0361***	0.0074**	0.0098*	0.0064**	0.0342***
	(0.0027)	(0.0069)	(0.0029)	(0.0058)	(0.0026)	(0.0066)
Control Variables	YES	YES	YES	YES	YES	YES
Fixed Effect	YES	YES	YES	YES	YES	YES
N	3,136	3,136	3,117	3,117	3,319	3,319
Pseudo R^2	–1.2083	2.1332	–1.3592	2.2503	–1.2583	2.1261

Notes: This table presents the results from regression of bank efficiency on digital finance (DFI) and control variables. Columns (1)–(2) is the results excluding data from municipalities, columns (3)–(4) is the results excluding data from the epidemic period, and columns (5)–(6) is the results excluding data from systemic banks. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

the financial resources of banks, which may affect the efficiency of banks and disrupt the regression results of digital finance. Thus, we removed the data from 2020 and reconducted the regression analysis. The results are presented in Columns (3) and (4) of Table 5. Furthermore, systemically important banks generally have larger scale, fixed customers, and business transactions. They may have slower reactions to new things compared to other banks. These unique characteristics could also affect the relationship between digital finance and bank efficiency. In 2017, *China's Financial Stability and Development Committee* included four state-owned banks (Industrial and Commercial Bank of China, Agricultural Bank of China, Bank of China, and China Construction Bank) as systemically important banks. Therefore, we removed these four banks from the regression analysis and reconducted the analysis. The results are presented in Columns (5) and (6) of Table 5. Overall, the regression results in each column of Table 5 are consistent with the baseline regression results. The results are significant at the 1% level, indicating that the empirical conclusions are robust.

5.2.3. Instrumental variable test

The baseline regression may have a problem of reverse causality, as changes in bank efficiency could lead to a shift in the management style of traditional financial institutions. This will promote the digital process of traditional financial institutions, thus promoting the development of digital finance. To address this issue, we employ two instrumental variables, namely, the spherical distance between the location of the enterprise registration and the provincial capital and the average spherical distance between the location of the enterprise registration and the three core cities of Beijing, Hangzhou, and Shenzhen. A geographic information system (GIS) was used to calculate the data for these instrumental variables. These two types of instrumental variables are highly correlated with the development of digital finance. First, provincial capitals are the economic development centers of their respective provinces. They are also the areas where infrastructure is constructed and new things are disseminated the fastest. Therefore, the digital business of banks and new financial services develop rapidly in these areas. The closer a city is to the provincial capital, the higher the level of digital finance development in that city should be. Second, in recent years, digital finance in Beijing, Shenzhen, and Hangzhou has developed rapidly. Hangzhou and Shenzhen are the headquarters of *Alibaba* and *Tencent*, respectively. These cities have a higher level of digital finance development. Additionally, these three cities are geographically dispersed, and the average distance between the sample cities and the three cities can be used to objectively measure the level of digital finance in various regions.

Next, we explain the exogeneity of these instrumental variables. While the three core cities are only a part of China's developed cities, proximity to these cities does not necessarily indicate greater economic development, thus satisfying exogeneity. However, the distance to provincial capitals may be related to economic development. Therefore, we control for economic development variables at the regional level (as discussed above under "Control Variables") to eliminate the potential link between instrumental variables and bank efficiency, thereby achieving exogeneity. Secondly, geographical distance is determined by the externality of natural geographical conditions. Although new economic geography emphasizes the relationship between economy and geographical distance, with the continuous improvement of transportation facilities, the correlation between geographical distance and economy is gradually weakening, indicating that this instrumental variable has certain externality.

Additionally, distance variables are constants that do not change over time and cannot be used directly as instrumental variables for panel data. Digital finance is a variable that changes with time, and the trend of digital finance in different regions should be similar. The development of digital finance outside the local region can well map the development level of local digital finance, and has a certain degree of externality. Therefore, we interact the two types of distance-based instrumental variables with the average digital finance development level (excluding the local area) for the current year and use them as new instrumental variables. We then regress both types of instrumental variables separately and report the results in Table 6. The results in Table 6 show that the regression coefficient of DFI is still significantly positive, and the F-value of the first stage is significantly positive, indicating that the instrumental variables meet the correlation characteristics.

Table 6. Instrumental variable test

Variables	(1)	(2)	(3)
	DFI	Y_1	Y_2
distance to provincial capital city × *DFI*	–0.2840***		
	(0.0093)		
DFI		0.0108**	0.0970**
		(0.0049)	(0.0384)
Control Variables	YES	YES	YES
Fixed Effect	YES	YES	YES
N	3,363	3,363	3,363
F	23.70		

Notes: This table presents the results of instrumental variable tests. Column (1) is the result of the first stage regression, and columns (2)–(3) is the results of the second stage regression. The regression of another instrumental variable here, with similar results, is omitted for space limitations. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

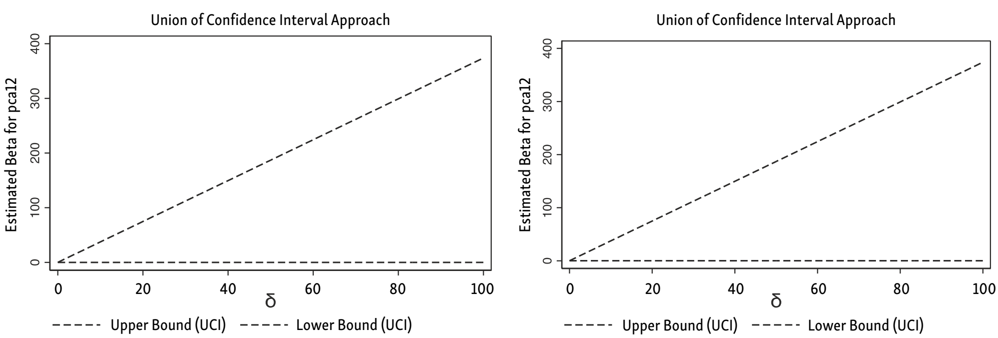
In reality, it is difficult to find an instrumental variable that is completely unrelated to the dependent variable, so we relax the assumption that the instrumental variable is "strictly exogenous" and construct the following two-stage Equation:

$$Y_{it} = \kappa_0 + \kappa_1 DFI_{it} + \kappa_2 iv_{it} + \gamma Control_{jit} + u_i + \tau_t + \varepsilon_{it}\,, \tag{37}$$

$$DFI_{it} = \nu_0 + \nu_1 iv_{it} + \gamma Control_{jit} + u_i + \tau_t + \varepsilon_{it}\,, \tag{38}$$

where, *iv* represents the instrumental variable, if $\kappa_2 \neq 0$, indicating that *iv* is not strictly exogenous; If $\kappa_2 \approx 0$, indicates that iv approximates exogenesis. We use the confidence interval set method (UCI) introduced by Conley et al. (2012) to set κ_2 an expected range in advance, and estimate κ_1 point estimates and confidence intervals under the premise of economic logic. The advantage of this method is high flexibility. The UCI method allows researchers to set different confidence intervals based on different assumptions and prior knowledge. This method can consider the case of incomplete exogenesis of instrumental variables, and obtain the final confidence interval by estimating the confidence interval of a series of coefficients and combining them. The disadvantages of this method are its dependence on assumptions and complexity of calculation. The validity of the UCI method depends on the strength and specific form of the exogenous assumptions made about the instrumental variables. If these assumptions do not hold, then the confidence intervals derived by the UCI method may not be accurate.

Further, the distribution and value of κ_2 will change, rather than always changing along some interval. We report the variation of DFI regression coefficient with variation of κ_2. As shown in Figure 2, the horizontal coordinate is the standard deviation δ of κ_2, and the vertical coordinate is the coefficient of DFI. The Figure on the left shows the confidence interval of DFI coefficient under UCI assumption when the dependent variable is cost efficiency; The figure on the right shows the confidence interval of the DFI coefficient under the UCI assumption when the dependent variable is revenue efficiency. When δ = 100, the upper limit of the confidence interval for the DFI coefficient in the left Figure is 373.8820 and the lower limit is 0.0084; In the Figure on the right, the upper limit of DFI coefficient is 373.9809, and the lower limit is 0.0896, with little difference between the two. The results show that with the increase of δ, that is, the externality of the instrumental variable becomes weaker and weaker, the coefficient of κ_1 is still significantly positive. Even if the value of κ_2 continues to change, the impact of DFI on cost and revenue efficiency is always positive. It should be noted that we have pointed out that instrumental variables have a certain externality and given the corresponding reasons. Therefore, even if the assumption that the instrumental variable is "strictly exogenous" is relaxed, the confidence interval for the corresponding coefficients of DFI should be in the first half of Figure 2, that is, when the DFI coefficient is small. The confidence interval corresponding to δ = 100 is only a theoretical calculation result and has no practical significance. To sum up, relaxing the exogenous conditions of instrumental variables is an important means to solve the problem of iv incomplete exogenesis at present. Even after attempting to admit iv incomplete exogenesis, the baseline regression results are still robust.



Notes: The cost efficiency coefficient is on the left and the revenue efficiency coefficient is on the right.

Figure 2. Confidence intervals under UCI assumptions

5.3. Policy effect analysis

On April 7, 2018, the People's Bank of China, together with the China Banking and Insurance Regulatory Commission, the China Securities Regulatory Commission, and the State Administration of Foreign Exchange, officially released the "Guiding Opinions on Regulating Asset Management Business of Financial Institutions" (hereinafter referred to as the Asset Management New Regulations), which regulate financial market behaviors from the perspective of recognizing qualified investors, breaking rigid redemption, solving term mismatch, removing fund pool operations, suppressing channel businesses, etc. We use the Asset Management New Regulations as an example to explore whether the implementation of regulatory policies affects the role of digital finance in bank efficiency. Since the regulatory business object of the new regulation is the asset management business, we can't establish a typical experimental and control group scenario across banks, making a standard difference-in-differences model a non-starter. However, the new asset management regulations strictly regulate bank financial products, which may have different impacts on banks with different financial scales. Therefore, this paper constructs the following generalized DID model for empirical analysis according to the scale of bank financial services before the policy impact. The specific model is as follows:

$$Y_{it} = \beta_0 + \beta_1 Post \times Fin_{it} \times DFI_{it} + \gamma Control_{it} + u_i + \tau_t + \varepsilon_{it}, \tag{39}$$

where, *Post* is the time dummy variable, according to the implementation time of the new asset management regulations, where the value of *Post* is 1 in 2008 and later, otherwise it is 0. Fin_{it} is the proxy variable of the average scale of bank i's wealth management business at the end of the three years before the implementation of the new asset management regulation. This paper uses the proportion of the scale of bank wealth management business and the total asset scale to measure. The regression results in Table 7 show that cross term coefficient is positive in all models and significant at the 5% level, indicating that the positive relationship between digital finance and bank efficiency is strengthened by the AMR policy. As the first unified and strict regulatory policy for the asset management industry, the AMR policy has further regulated bank wealth management products and digital finance derivative products, which will affect the relationship between digital finance and traditional banking business and thus affect bank efficiency. From the liability side, the AMR policy has shaken the advantage of high-yield, low-risk internet wealth management products and encouraged risk-averse users to choose safer bank deposits. From the asset side, this policy has suppressed the development of shadow banking, promoted the flow of funds to real businesses, and enabled banks to regain loan business that was previously replaced by shadow banking, which helps to increase bank income and enhance the promoting effect of digital finance on bank efficiency.

In addition, the application of the differential model needs to meet the parallel trend test. As far as this study is concerned, it is necessary to ensure the consistency of the impact of digital finance on the efficiency of banks with different wealth management scales before the implementation of policies. We add the interaction terms of 2016 (Pre2016) and 2017 (Pre2017) dummy variables with bank wealth management scale (Fin_{it}) and digital finance (DFI_{it}) in model (37), respectively. The regression results are shown in Table 8. The coefficients of the newly added interaction terms are not significant and pass the parallel trend test.

Table 7. Policy impact of digital finance on bank efficiency

Variables	(1)	(2)	(3)	(4)
	Y_1	Y_2	Y_1	Y_2
$\text{Post} \times Fin_{it} \times DFI_{it}$	0.0048**	0.0158***	0.0064**	0.0335***
	(0.0024)	(0.0050)	(0.0026)	(0.0065)
Control Variables	NO	NO	YES	YES
Fixed effect	YES	YES	YES	YES
N	3,363	3,363	3,363	3,363
Pseudo R^2	–0.8499	2.1265	–1.2777	2.1662

Notes: This table presents results from regressions of bank efficiency on digital finance taking into account policy factors. Columns (1) and (3) are the results of the cost efficiency, and columns (2) and (4) are the results of the revenue efficiency. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 8. Parallel trend test

Variables	(1)	(2)	(3)	(4)
	Y_1	Y_2	Y_1	Y_2
$Post \times Fin_{it} \times DFI_{it}$	0.0067***	0.0335***	0.0064**	0.0335***
	(0.0026)	(0.0065)	(0.0026)	(0.0065)
$Pre2016 \times Fin_{it} \times DFI_{it}$	0.0077	–0.0220		
	(0.0065)	(0.0164)		
$Pre2017 \times Fin_{it} \times DFI_{it}$			0.0061	-0.0202
			(0.0065)	(0.0165)
Control Variables	YES	YES	YES	YES
Fixed effect	YES	YES	YES	YES
N	3,363	3,363	3,363	3,363
Pseudo R^2	–1.2780	2.1666	–1.2790	2.1663

Notes: This table presents parallel trend test. Columns (1) and (3) are the results of the cost efficiency, and columns (2) and (4) are the results of the revenue efficiency. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

6. Heterogeneity analysis

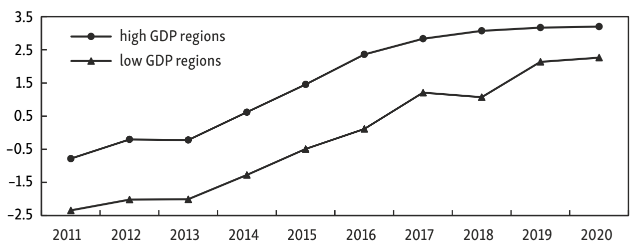
6.1. Regional analysis

Due to differences in natural resources, infrastructure, and industrial structure, the economic conditions in different regions are also different, which directly affect the supply and demand environment of banks in different regions. This difference also affects the impact of digital finance on bank efficiency. In developed areas, financial resources are relatively sufficient, and there are more types of banking businesses. We divided the sample into high GDP per capita (GDP per capita above the median) and low GDP per capita (GDP per capita below the median). The trends of digital finance averages by region from 2011 to 2020 are shown in

Figure 3. From the spatial dimension, the development of digital finance in low GDP areas is weaker than that in high GDP areas. With the continuous development of digital finance, the gap between the two types of regions is gradually narrowing. This illustrates the inclusiveness of digital finance.

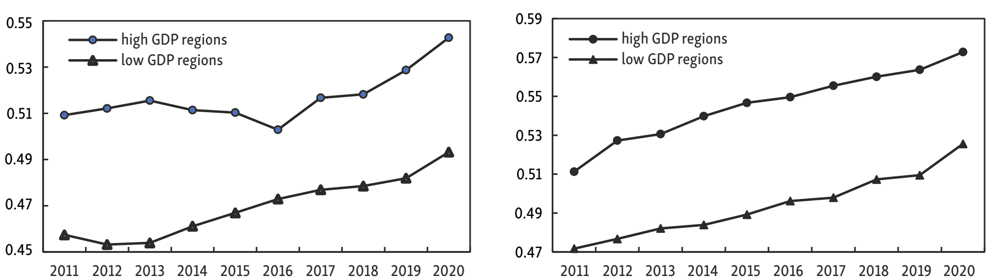
Figure 4 shows the bank efficiency in different regions. From the spatial dimension, the cost efficiency and revenue efficiency in high GDP areas are higher than those in low GDP areas. The bank efficiency in the high GDP regions is on a fluctuating upward trend. The growth rate of bank efficiency in low GDP areas is lower than that in high GDP areas, but it also shows a growth trend. Thus, banks' efficiency in high-GDP areas may be more sensitive to changes in digital finance.

We include the cross-term between digital finance and GDP per capita in the baseline regression. The results are shown in Table 9. The DFI coefficients in Table 9 are all negative, and the cross-item DFI * GDP coefficients are significantly positive at the 1% level. This shows that the positive effects of digital finance on cost efficiency and profit efficiency are more obvious in high GDP regions. Thus, digital finance can improve the efficiency of banks in different regions. In developed areas, there are more financial resources and businesses of all kinds, and banks are more likely to be inefficient. Digital technology in digital finance can effectively help banks optimize all kinds of processes; therefore, the optimization of bank efficiency in these areas is stronger.



Note: The figure presents the trend of digital finance in high GDP and low GDP regions.

Figure 3. Trend chart of average digital finance in different regions



Notes: The figure reports the trend of bank efficiency in high GDP and low GDP regions. For ease of comparison, we only calculate banks that have annual data. The left figure presents the trend of cost efficiency, and the right figure presents the trend of revenue efficiency.

Figure 4. Trend chart of average bank efficiency in different regions

Table 9. The impact of digital finance on bank efficiency in different regions

Variables	(1)	(2)
	Y_1	Y_2
DFI	–0.0755***	–0.2951***
	(0.0236)	(0.0600)
*DFI*GDP*	0.0061***	0.0289***
	(0.0021)	(0.0053)
Control variables	YES	YES
Fixed effect	YES	YES
N	3,363	3,363
Pseudo R^2	–1.2759	2.1735

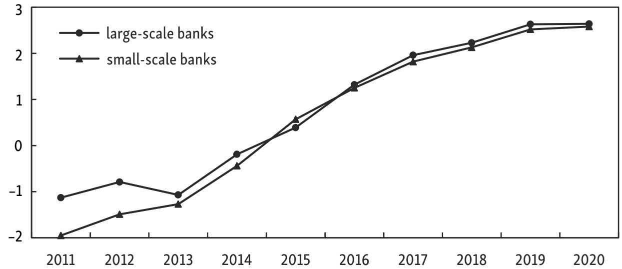
Notes: The table presents the results from regressions of bank efficiency on digital finance taking into account regional factors. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

6.2. Scale analysis

Large banks have a stable supply chain of financial resources, long-term cooperative relationships with various enterprises, and more lending businesses. However, this kind of bank management is relatively solidified. Its capital competition pressure is slight, so it is difficult to play the maximum capital value. The difference in management style caused by the different scales of banks will also affect the impact of digital finance. We divided the sample by bank size into large-scale banks (banks larger than the median) and small-scale enterprises (banks smaller than the median), and trends in digital finance averaged with different bank sizes are shown in Figure 5. In the early stage, digital finance in the region where small-scale banks are located is weaker than that in the region where large-scale banks are located. Large-scale banks are often located in more developed regions, which provides a good prerequisite for the development of digital finance. Then, with the popularization of digital finance, digital finance in small-scale banks catches up with that in large-scale banks, and the development gap between the two is very small.

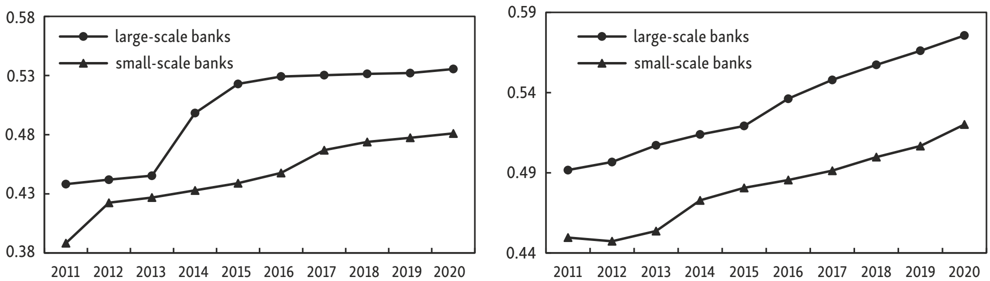
Figure 6 shows the efficiency of banks of different sizes. Regarding spatial factors, large-scale banks demonstrate higher cost and profit efficiency compared to small-scale banks. The bank efficiency of the large-scale banks is on a fluctuating upward trend. Small banks' efficiency gains lag behind larger ones, yet exhibit positive progression. As a result, the efficiency of large banks may be more sensitive to changes in digital finance.

We select the cross-term between the logarithm of SIZE and digital finance to add to the baseline regression, and the results are shown in Table 10. The DFI coefficients in Table 10 are all negative and significant at the 1% level. The cross-item DFI * SIZE coefficients are significantly positive. For large-scale banks, the positive effects of digital finance on cost efficiency and revenue efficiency are more obvious. Cloud computing and big data technology based on digital finance can help banks not only identify high-quality growth enterprises and provide financial resources but also manage themselves effectively and improve the efficiency of bank funds. Large-scale banks easily obtain funds, have relatively fixed management and are more prone to inefficient problems, so the role of digital finance in improving these banks is stronger.



Notes: The figure presents the trend of digital finance of large-scale banks and small-scale banks.

Figure 5. Trend chart of average digital finance with different sizes



Notes: The figure reports the trend of bank efficiency of large-scale banks and small-scale banks. For ease of comparison, we only include banks that have annual data in the calculation. The left figure presents the trend of cost efficiency, and the right figure presents the trend of revenue efficiency.

Figure 6. Trend chart of average bank efficiency with different sizes

Table 10. The impact of digital finance on bank efficiency in different sizes

Variables	(1)	(2)
	Y_1	Y_2
DFI	–0.0193***	–0.0535***
	(0.0059)	(0.0149)
*DFI*SIZE*	0.0176**	0.0327*
	(0.0078)	(0.0194)
Control Variables	YES	YES
Fixed Effect	YES	YES
N	3,363	3,363
Pseudo R^2	–1.2786	2.1568

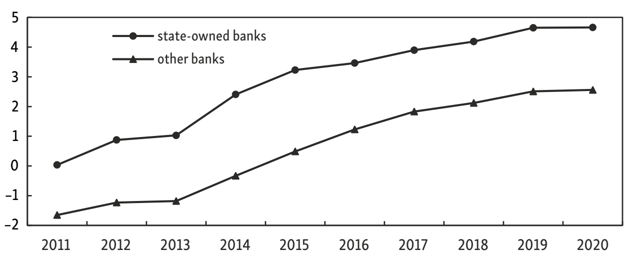
Notes: The table presents the results from regressions of bank efficiency on digital finance taking into account scale factors. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

6.3. Ownership analysis

Bank ownership also affects the impact of digital finance on bank efficiency (Ferri & Liu, 2010). State-owned banks are large in scale and have strong connections with other financial institutions (Yang & Shen, 2024). They can provide key services that are hard to replace in the financial system. Such banks are also different from other banks in their responsiveness to novelty (Cui & Xu, 2003), so digital finance also works differently for such banks (Dapp, 2015). We grouped state-owned banks and nonstate-owned banks. The trends of the digital financial averages with different ownership banks are shown in Figure 7. From the spatial dimension, digital finance in the area where the state-owned banks are located is higher than that in other areas. The trend of digital finance in the two areas is similar, and the gap has been narrowed.

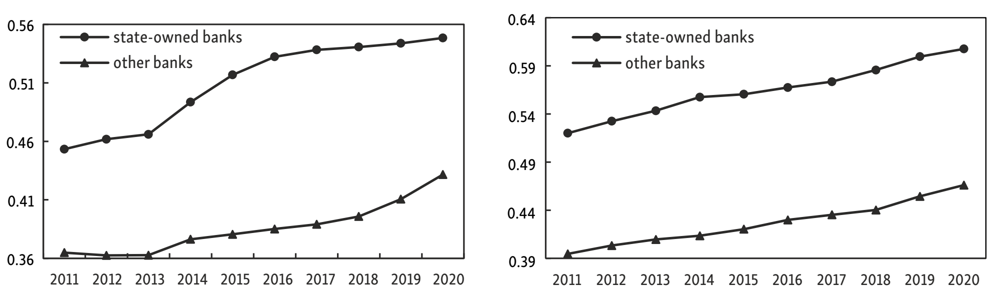
Figure 8 shows the efficiency of banks with different types of ownership. In terms of space, the cost efficiency and profit efficiency of state-owned banks are higher than those of nonstate-owned banks. The fluctuation of bank efficiency of nonstate-owned banks rises, but the increase is less than that of state-owned banks. Therefore, the bank efficiency of state-owned banks may be more sensitive to changes in digital finance.

We add a cross-term of state-owned bank virtual variable *soedum* (which is set at 1 for state-owned banks and 0 for nonstate-owned banks) and digital finance to the baseline regression, and the results are shown in Table 11. In Table 11, the DFI coefficients are all



Notes: The figure presents the trend of digital finance of state-owned banks and other banks.

Figure 7. Trend chart of average digital finance with different ownership



Notes: The figure reports the trend of bank efficiency of state-owned banks and other banks. For ease of comparison, we only include banks that have annual data in the calculation. The left figure presents the trend of cost efficiency, and the right figure presents the trend of revenue efficiency.

Figure 8. Trend chart of average bank efficiency with different ownership

significantly positive, and the cross-term *DFI * soedum* coefficients are significantly positive. This shows that the positive effect of digital finance on cost efficiency and revenue efficiency is more obvious in state-owned banks. The deposits of state-owned banks mainly come from the companies and users that cooperate with for a long time, and the competition pressure is less. The strategic management aspect is relatively slow and inflexible in state-owned banks; therefore, the effect of digital finance on this kind of bank is stronger.

Table 11. The impact of digital finance on bank efficiency in different ownership

Variables	(1)	(2)
	Y_1	Y_2
DFI	0.0072***	0.0317***
	(0.0025)	(0.0064)
*DFI*soedum*	0.0277***	0.0384*
	(0.0078)	(0.0199)
Control Variables	YES	YES
Fixed Effect	YES	YES
N	3,363	3,363
Pseudo R^2	–1.2772	2.1661

Notes: The table presents the results from regressions of bank efficiency on digital finance taking into account ownership factors. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

7. Mechanism analysis

Theoretically, the influence of digital finance on bank efficiency comes from its impact on both the liability and asset sides of banks. As digital finance develops, the way banks manage their assets and liabilities will change. Next, we discuss the impact of digital finance on bank efficiency from the debt side and the asset side.

7.1. Impact on the liability side of banks

To investigate how digital finance affects the liability structure of banks, we use the interbank liability ratio (the ratio of interbank liabilities to interest-bearing liabilities) and the cost of deposits (the ratio of interest expenses to interest-bearing liabilities) as the dependent variables instead of the original baseline regression. The results are shown in Table 12. The first column indicates that the development of digital finance has reduced banks' reliance on interbank liabilities, resulting in a higher deposit ratio. The second column shows that the coefficient of digital finance (*DFI*) is -0.0973, implying digital finance growth has lessened banks' operational expenses.

Digital finance provides consumers with more investment options, and some consumers tend to prefer high-yield internet wealth management products over low-yield bank deposits, which harms the deposit absorption of banks. Although the liberalization of interest rates allows banks to adjust deposit rates, the difference in asset properties makes it difficult for bank deposits to compete with the yield rates of internet wealth management products. To counterbalance the rise of digital finance, commercial banks have launched various wealth management products, further reducing the number of bank deposits. However, digital finance fosters economic growth and brings in more financial resources.

Table 12. Impact of digital finance on the liability side of commercial banks

Variables	(1)	(2)
	interbank liabilities	depost cost
DFI	–0.0276*	–0.0973*
	(0.0145)	(0.0512)
Control variables	YES	YES
Fixed effect	YES	YES
N	3,363	3,363
R^2	0.0231	0.1223

Notes: The table presents the results from regressions of the liability side on digital finance. Columns (1) and (2) show the results for interbank liabilities, and Columns (3) and (4) show the results for depost cost. Fixed effects models are used for all regressions in the table, as below. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

7.2. Impact on the asset side of banks

We examine the impact of digital finance on the asset side of a bank. We used the nonperforming loan ratio (the ratio of nonperforming loans to total loan balances) and the risk asset ratio (the ratio of risk-weighted assets to total assets) in place of the original regression's dependent variables. Among them, the nonperforming loan ratio measures the bank's ex post risk, and the risk asset ratio measures the proportion of the bank's risk assets. The results are shown in Table 13. The results in Column (1) and (2) show that the DFI coefficient is significantly positive. Findings indicate a notable rise in bank risk appetite linked to online

Table 13. Impact of digital finance on risk-taking of commercial banks

Variables	(1)	(2)
	nonperforming loan	risk assets
DFI	0.0410**	0.0833*
	(0.0176)	(0.0437)
Control Variables	YES	YES
Fixed Effect	YES	YES
N	3,363	3,363
R^2	0.0838	0.0064

Notes: The table presents the results from regressions of risk-taking on digital finance. Columns (1) and (2) show the results for nonperforming loans, and Columns (3) and (4) show the results for risky assets. The regression results omit the constant term; standard errors are in parentheses below; ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

finance. A possible reason for this is that the competitiveness of digital financial products forces banks to reduce their profit margins, forcing them to engage in some high-risk and high-yield business activities to earn full profits. This increases banks' risk-taking.

In summary, digital finance has strengthened the cost advantage of commercial banks on the liability side and aggravated risk-taking on the asset side. Drawing from the baseline model's findings, the core driver behind enhancing bank efficiency lies in the fact that digital finance's positive impact on the liability side outweighs its diminishing influence on the asset side. In other words, the benefits of optimizing liabilities through digital finance more than compensate for any drawbacks experienced on the asset front. After the new asset management regulations were implemented, digital finance enhanced the mitigation effect on bank financing costs, reduced bank risk, and increased bank income.

8. Conclusions

Digital finance has made financial services more accessible to people who previously had no access to them. It has also decreased the cost of financial services, which has disrupted traditional financial modes. This study explores the influence of digital finance on bank efficiency from the perspective of resource allocation and builds a theoretical model to investigate how digital finance affects bank efficiency through liabilities and assets. A sample including 406 commercial banks ranging from 2011 to 2020 is selected and used to measure their efficiency with the SFA method, and a three-dimensional digital finance index is constructed to empirically examine the impact of digital finance on bank efficiency. The results clearly indicate that digital finance has really improved the efficiency of Chinese commercial banks. Furthermore, the impact of the digital revolution isn't uniform; it varies across different regions, scales, and types of ownership. It is also found that developed areas, large-scale banks, and state-owned banks have a relatively strong effect on bank efficiency. Because of the numerous banking businesses in developed areas, the problem of low efficiency is more easily caused, which makes bank efficiency more sensitive to changes in digital finance. Large-scale banks and state-owned banks have less competitive pressure on funds, and their management mode is relatively fixed, so digital finance impacts bank efficiency more significantly.

Furthermore, the mechanism analysis shows that digital finance has altered the original liability structure of commercial banks, resulting in a smaller proportion of interbank liabilities as digital finance becomes more advanced. This change not only reduces the operating costs of banks but also affects the asset side of banks. In the pressure of digital finance, banks are forced to engage in high-risk activities to pursue higher returns, thus increasing their risk burden. The way digital finance really boosts bank efficiency hinges primarily on its knack for revamping liabilities more effectively than it dampens assets. Our research enriches the literature on digital finance and however, due to data limitations, we only used a sample of 406 banks, which did not cover all banks in China. Following the conclusion of this study, some suggestions are proposed:

First, digital finance companies should be proactive in promoting innovative development and continually regulating the relevant institutions. Digital finance has integrated into every aspect of the human society, providing convenience for people's daily lives; however, incidents such as "*P2P* fraud" still occur from time to time. To develop the digital finance further, companies should adhere to the risk bottom line, strengthen governance, accelerate the pace of innovation, reform and improve existing institutions, actively protect consumer rights, and promote healthy industry development.

Second, commercial banks should be prepared to address the impact of digital finance and accelerate the process of comprehensive digitalization. Facing the rapid development of digital finance, commercial banking institutions should embrace digital technology and integrate it with traditional financial services to maximize advantages of digitized finance. Specifically, commercial banks really need to jump on the digital finance bandwagon. It's crucial they wisely allocate funds to specific companies and make sure that high-performing businesses with serious borrowing needs get al. the financial backing they require. Additionally, by fully utilizing the superior characteristics of digital technology, commercial banks can effectively identify high-quality enterprises and provide them with a continuous flow of funds. The excellent attributes of these enterprises can guarantee timely repayment, thus forming a virtuous cycle. Commercial banks should also actively use financial technology to accelerate innovation and promote the construction of online platforms, which can not only save labor costs but also help attract financial resources more widely.

Third, the supervision of digital finance should be strengthened to promote its healthy development. On the one hand, regulations and management norms related to digital finance should be introduced to facilitate its healthy development. Regulators need to keep up with the times, strike a balance between the digital finance development and risk prevention, develop sustainable and targeted policies, and monitor the financial system in real-time to implement effective intervention measures when necessary. However, they should avoid using excessive intervention measures that could disrupt the financial market's balance. On the other hand, in terms of infrastructure, the government should actively improve computer systems and communication network facilities, thus ensuring a stable supply of hardware and software for digital finance development and promoting its rapid and healthy growth.

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Data availability statement

The data of this study can be obtained in the CSMAR (China Stock Market & Accounting Research Database) and Wind Database, available at: https://data.csmar.com and https://www.wind.com.cn/

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APPENDIX

This table describes the definition of main variables used in the empirical analyses.

Table A1. Variable definitions

Variables	Definitions
Y_1	The cost efficiency computed using stochastic frontier analysis (SFA method) following Sun et al. (2013).
Y_2	The revenue efficiency computed using stochastic frontier analysis (SFA method) following Sun et al. (2013).
DFI	The digital finance index is measured in three dimensions.
LDR	The ratio of total bank loans to total deposits.
CAR	The ratio of total bank capital to risk-weighted assets.
SIZE	The logarithm of total bank assets at the end of the year
DAR	The ratio of outstanding loans to total bank assets at the end of the year.
GDP	The logarithm of per capita GDP.
GDP1	The share of GDP from the primary industry.

This table describes descriptive statistics of the input-output variables used in measuring efficiency. Each variable is deflated with 2011 as the base period. It can be seen from the table that the loanable fund price is higher than the operating input price, and the standard deviation of the loanable fund price is larger, which is 15.5726, indicating that the loanable fund price has a large fluctuation. The average and maximum size of bank deposits are higher than the size of loans. The average non-interest income is significantly lower than that of deposits and loans.

Table A2. Descriptive statistical of input-output variables

Variables	Symbol	N	Mean	SD	Min	Max
Price of loanable funds	W_{1it}	3363	2.6543	15.5726	0.0097	7.2905
Price of operating inputs	W_{2it}	3363	0.0214	0.0927	0.0006	0.0329
Total loans (trillion yuan)	X_{1it}	3363	0.2408	1.3025	0.0002	0.5279
Total deposits (trillion yuan)	X_{2it}	3363	0.3371	1.7880	0.0002	0.7425
Other earning assets (trillion yuan)	X_{3it}	3363	0.2635	0.5323	0.0001	1.6785
Noninterest income (trillion yuan)	X_{4it}	3363	0.0176	0.0673	0.0001	0.0279