The Impact of Digital Finance on Total Factor Productivity of Enterprises

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Abstract. As a new financial service mode integrating traditional finance and technology, digital finance has an important impact on the high-quality development of micro enterprises. Based on the relevant data of China's A-share listed companies from 2011 to 2019, this paper empirically tests the impact of digital finance on total factor productivity. The research finds that: (1) Digital finance is significantly positively correlated with total factor productivity of enterprises, that is, digital finance can improve total factor productivity of enterprises; (2) The mechanism test shows that the development of digital finance can effectively reduce the degree of financial mismatch and promote technological innovation of enterprises, so as to improve the total factor productivity of enterprises; (3) After analyzing the heterogeneity of individual characteristics of enterprises, it is found that when enterprises are under low government control, high financing constraints, and enterprises are high-tech enterprises, the role of digital finance in promoting total factor productivity of enterprises will be more significant. The research conclusion provides a certain reference basis for improving the quality and efficiency of financial services in the real economy, total factor productivity of enterprises and promoting the high-quality development of China's economy.

Keywords: Digital Finance; Total Factor Productivity of Enterprises; Financial Mismatch; Technological Innovation.

1. Introduction

In recent years, with the gradual aging of China's population structure, the insufficient effective supply of labor, the rapid urbanization process and the increasingly tense land resources, the contribution of traditional factors to economic growth has gradually decreased. The report of the 19th National Congress of the Communist Party of China clearly pointed out that "China's economy has changed from a high-speed growth stage to a high-quality development stage, and we should promote the quality, efficiency and power changes of China's economic development, and improve total factor productivity". Therefore, under the “new normal” of economic development, improving the total factor productivity of enterprises is the focus of China's high-quality economic growth and an important way for China to overcome the "middle-income trap" (Cai Fang, 2013). There is no doubt that China's economy and enterprises need to rely on the endogenous growth transformation of total factor productivity improvement, which is the key to breaking through the bottleneck of development. However, empirical research shows that the growth of total factor productivity of Chinese enterprises is more from enterprise growth, and the growth space is shrinking. Therefore, there is an urgent need for a new growth model with improved resource allocation (Yang Rudai, 2015; Yi Gang et al., 2003), which requires stable and sufficient financial resources as the guarantee of development. In the Chinese market, due to the widespread financial mismatch and other problems in traditional financial services, Chinese enterprises are always facing the dilemma of resource constraints in the process of innovation and development (Li Jun and Wan Junbao, 2019), which to a large extent restricts the potential driving force of market players to improve total factor production rate. Therefore, how to improve the allocation of financial resources, improve the effectiveness of financial services to the real economy, and then improve the total factor productivity of enterprises is a practical problem of high-quality economic development under the new development pattern.

At present, with the vigorous development of digital economy, artificial intelligence, blockchain, big data and other technologies have also made the deep integration of Finance and emerging technologies possible, and digital finance came into being. Digital finance generally refers to the interaction between traditional financial institutions and Internet companies, using digital technology to achieve online payment, investment and financing and other new financial business models. Specifically, digital finance optimizes traditional financial services and improves data processing capabilities from three dimensions: scale, speed and accuracy. Among them, the new format of digital finance represented by third-party payment and mobile payment has greatly improved the speed of information production and dissemination. At the same time, it also makes all kinds of information in the trading market more transparent, effectively reduces the financing cost and the degree of financial mismatch of enterprises, and then improves the efficiency of the financial industry. The improvement of the efficiency of the financial industry will produce various spillover effects, and ultimately promote the efficiency of the whole society. For the above reasons, the concept of digital finance has become a policy focus and research hotspot since its birth. The G20 Hangzhou summit also adopted the "High-level Principles of Digital Inclusive Finance" to guide countries to carry out corresponding digital finance practices. It can be seen that studying the role of digital finance in promoting the high-quality development of enterprises has important theoretical value and practical significance for the current deepening of financial reform and the development of digital economy.

According to the literature review, the current research on digital transformation mainly focuses on the impact of digital Finance on economic growth, enterprise innovation, household consumption, resource mismatch and enterprise efficiency (tenglei and Ma Degang, 2020; Beck et al., 2018; Karlan &zinman, 2010; Tang Song et al., 2020; Huang et al., 2018), while the research on the relationship between digital finance and total factor productivity is relatively scarce, and mainly focuses on the macro level. In view of this, this paper focuses on the total factor productivity of micro enterprises. Taking China's A-share non-financial listed companies from 2011 to 2019 as samples, combined with logical and mathematical derivation, this paper explores the deep relationship between digital finance and total factor productivity, and studies two indirect mechanisms: first, digital finance reduces the degree of enterprise financial mismatch; Second, digital finance promotes enterprise innovation; And based on the differences of enterprise ownership attributes, financing constraints and technological innovation, the heterogeneity analysis is carried out.

Compared with the existing literature, the possible marginal contributions of this paper are as follows: first, the existing literature mostly studies the total factor productivity of enterprises from the perspective of traditional financial development, financial mismatch and financial friction, or mostly discusses the impact of digital Finance on economic development and enterprise innovation. Therefore, this paper enriches the research perspective of total factor productivity drivers and the research direction of digital finance developing economy; Second, from the perspective of micro enterprise, this paper expands the existing research on digital finance and total factor productivity, discusses the mechanism through which digital finance can improve total factor productivity of enterprises under a unified framework, and studies the heterogeneity according to the differentiation characteristics of enterprises, so as to provide a new empirical basis for digital finance to serve the real economy; Thirdly, on the practical level, the research conclusions of this paper have certain enlightenment significance for the government and enterprises to promote the construction of digital economy, and can provide a reliable theoretical basis and policy reference for further optimizing the high-quality development of digital financial service economy.

2. Literature review

2.1 Total factor productivity

Total factor productivity, also known as the rate of technological progress, was first proposed by Solow (1957), which refers to the increase in output caused by technological progress and capacity realization in addition to capital, labor and other factor inputs. Therefore, total factor productivity can better reflect the quality of economic growth than quantitative indicators of economic growth such as GDP (Ye Yumin, 2002). Since the reform and opening up, relying on a large number of demographic dividends, high investment and high export development model, China's economic development has made great achievements, but China's capital formation ratio has basically reached the limit, and the "extensive" development model is not sustainable (Cai Fang, 2013). After China's economy enters the "new normal", it must rely on the endogenous growth transformation of total factor productivity improvement to achieve sustainable and stable growth (caiweixing, 2019). At present, the total factor productivity of Chinese enterprises is generally not high. Based on the data of Chinese industrial enterprises from 1998 to 2009, Yang Rudai (2015) calculated that the overall total factor productivity growth rate of China's manufacturing industry is between 2% and 6%, and the annual fluctuation is large. However, if China's resource allocation efficiency reaches the level of the United States, the total factor productivity of enterprises can be increased by 30% - 50% (Hsieh & Klenow, 2009). At present, the research on total factor productivity mainly focuses on three aspects: market perspective, enterprise perspective and government perspective (Wang Daoping and Liu Linlin, 2021). From the perspective of market, financial development (Lin Yifu and sun Xifang, 2008) and market environment (Zhang Li et al., 2019) promote total factor productivity; From the perspective of enterprises, technology research and development (Wu Yanbing, 2008) and human capital (Yao Xianguo and Zhang Haifeng, 2008) occupy the main aspects; For the government, government incentives (Zhang Yan and Gong Liutang, 2005) and infrastructure construction (Liu Yong, 2010) play an important role in improving the total factor productivity of enterprises. Combined with the research content of this paper, this paper mainly discusses the impact of financial markets on total factor productivity of enterprises.

Scholars at home and abroad have conducted extensive research on the impact of financial development on total factor productivity of enterprises, and produced rich research results. However, in terms of conclusions, different studies have differences. On the one hand, some scholars believe that financial development will promote the total factor productivity of enterprises: Zhang Jun and Jin Yu (2005) believe that the deepening of financial intermediation will increase the liquidity of investment and improve the return rate of financial resources; Merton & Bodie (1995) demonstrated that financial development will reduce the transaction cost of financial investment, which will lead to an increase in investment and ultimately improve productivity; Li Qingyuan et al. (2013) used the estimation method of systematic generalized moment panel to verify that financial development will promote the efficiency of capital allocation in China's real economy, thereby improving the total factor productivity of the whole region. On the other hand, some studies believe that financial development has little impact on the total factor productivity of enterprises. For example, pan Wenqing and Zhang Wei (2003) used panel data to analyze time series and cross-sectional data, and concluded that there is a weak correlation between China's financial development and capital allocation efficiency; Shen Kunrong and Sun Wenjie (2004) believe that although the correlation between financial development and economic growth has increased since the 1990s, the improvement of the financial system on investment efficiency and savings conversion efficiency is extremely limited. In addition, some scholars believe that financial development will "squeeze out" enterprise entity investment, thereby inhibiting enterprise technological innovation, and in the long run, it will inhibit the total factor productivity of enterprises (Wang Hongjian et al., 2017); At the same time, most studies believe that excessive financialization will shift the industrial focus from the real economy to the virtual economy, forming an industrial hollowing out, which will inhibit the development of enterprises (pally & Thomas, 2008). Ortiz (2014) even believes that financialization is like a virus, which will replicate and strengthen itself by occupying economic resources and restricting the development of other real economic sectors.

2.2 Digital Finance

In recent years, with the progress of digital technology and its deep integration with financial services, digital finance has developed rapidly. At present, the research on digital finance and macro-economy at home and abroad is relatively more abundant. Tenglei and Ma Degang (2020) evaluated the high-quality development level of 30 provinces in China from 2012 to 2017 in combination with the digital finance index, and found that digital finance can promote high-quality development, and also improve the level of regional innovation and opening-up. Moreover, the "incentive effect" of digital Finance on the level of regional innovation will be more prominent when the development of digital finance is mature and the level of human capital is high (niexiuhua et al., 2021). Beck et al. (2018) took mobile payment in digital finance as an example, and by building a general equilibrium model, confirmed that mobile payment can enhance innovation and entrepreneurship, thereby promoting the overall economic development. In addition, mobile payment can also reduce the liquidity constraints of residents' consumption, thereby promoting residents' consumption and improving the real economy (Karlan &zinman, 2010). At the micro level, digital finance can make up for the shortcomings of traditional financial services through scenarios and data, give play to the advantages of "low cost, fast speed and wide coverage", significantly reduce the cost and service threshold of financial services, improve the financing environment of enterprises, especially small and medium-sized enterprises, and better play the role of Inclusive Finance (Huang Yiping and Huang Zhuo, 2018). Tang Song et al. (2020) believe that digital finance can show a stronger effect of enterprise innovation driving in regions with poor financial endowment, and can correct the problems of "stage mismatch", "field mismatch" and "attribute mismatch" in traditional finance. For individual merchants, Huang et al. (2018) found that the e-commerce microfinance provided by ant financial services significantly improved the service level of merchants and significantly promoted their sales and trading volume. Although many studies have demonstrated that digital finance has a positive effect on the development of enterprises and individual industry and commerce, in terms of residents' income, Wang Xiuhua and Zhao Yaxiong (2020) believe that there is a Matthew effect in digital finance by comparing poor households with non poor households, which will aggravate residents' income inequality.

At present, there is still a lack of research on digital Finance on total factor productivity. Tang Song et al. (2019) conducted an empirical study based on the panel data of 31 provinces and cities in China, and found that digital finance helped improve the total factor productivity of the region by alleviating information asymmetry. In addition, other studies believe that the rise of regional total factor productivity is mainly due to the pure technological progress brought by digital finance, and this promotion is stronger in economically underdeveloped and low-level innovation areas (Qiu Zixun and Zhou Yahong, 2021). In terms of financial institutions, Song Min and other researchers (2021) believe that digital finance can rely on technology to empower traditional financial institutions, ease corporate financing constraints, and improve the efficiency of credit resource allocation of financial institutions. For example, the Bank of America using digital finance can process mortgage loan applications 20% faster than other banks (Fuster et al., 2019). The promotion of digital finance is also applicable to China's commercial banks. Shen Yue and Guo pin (2015) proved that digital finance has significantly improved the total factor productivity of China's commercial banks, especially joint-stock commercial banks, based on the technology spillover theory. However, there is little literature on the impact of digital Finance on total factor productivity of micro enterprises, so what is the relationship between the two? What is the intermediate mechanism of this relationship? Is there heterogeneity due to differences in the nature of enterprises? These problems are worth digging and refining.

3. Theoretical analysis and research hypothesis

Referring to the existing literature and research conclusions, this paper examines the indirect mechanism of digital finance affecting the total factor productivity of enterprises, and qualitatively infers that digital finance may improve the total factor productivity of enterprises by reducing the financial mismatch and increasing technological innovation.

3.1 Mitigate financial mismatches

The development of China's financial market is not perfect, the efficiency of resource allocation is low, and the transmission mechanism is not perfect. Specifically, traditional financial institutions have exposed some structural problems in the process of financing enterprises. First, because the financing mode of traditional finance is mainly indirect financing, traditional financial institutions lack fairness in the allocation of financial resources due to the pro cyclical preference of the industry and the prudent risk assessment system. Specifically, enterprises with relatively large market scale contributions are easier to obtain funds, which makes small and medium-sized enterprises in a "financing difficult" situation; And because large enterprises often have a far-reaching basis for cooperation with financial institutions, financial institutions have their own information and the cost of adjustment is small. On the contrary, the financial disclosure of small and medium-sized enterprises is often not perfect. Banks and other financial institutions will increase the financing cost of small and medium-sized enterprises out of risk considerations, making them face the situation of "financing is expensive". Second, there are great differences in the guarantee ability, collateral and market prospects of enterprises at different stages, while traditional financial institutions have a "backward" preference in lending, that is, lending and credit according to the current asset situation and market share of enterprises, which will make the growth enterprises with huge development prospects unable to get the funds they deserve, and to a great extent restrict the development of market players.

As an efficient, convenient and wide-ranging financial service model, digital finance provides an effective solution to the problem of corporate financial mismatch. Digital finance can make up for the shortcomings of traditional finance. First, relying on the Internet and big data, it can effectively reduce the degree of information asymmetry and moral hazard between investors and financiers, and improve the efficiency of capital use and reduce transaction costs as much as possible through pre screening and post supervision. Secondly, digital finance helps to guide the flow of social funds, optimize the allocation of financial resources, promote the optimization and transformation of industrial structure, further reduce the financial mismatch at the social level, break the obstacles of financing constraints to the production process of the physical sector, and finally promote the improvement of total factor production rate of enterprises.

3.2 Enhance technological innovation

Digital finance promotes technological innovation mainly in the following three aspects: first, digital finance improves the willingness of enterprises to technological innovation. Enterprise technological innovation is a high-risk activity with the characteristics of sunk input, irreversible process and uncertain output, so it needs sufficient and stable R & D funds as a guarantee. However, the imbalance and inadequacy of traditional finance often make it difficult for enterprises to obtain sufficient cash flow to support their R & D expenditure, which curbs the willingness of market players to innovate and start businesses. Digital finance reduces enterprise financing costs through accurate user portraits, refined risk pricing and intensive business processes (Demertzis et al., 2018), making it possible for long tail groups to break through various thresholds of financial services. In addition, digital finance also enriches the financing channels of enterprises, relieves the financing constraints of innovative enterprises, and provides a solid foundation for enterprises to carry out technological innovation activities. Second, digital finance improves the technological innovation ability of enterprises, and the improvement of innovation ability is the main means to improve total factor productivity. Digital finance combines artificial intelligence, big data, blockchain and other technologies, and can collect, summarize and analyze all kinds of massive non standardized and unstructured information, thus alleviating the problem of information asymmetry within and between enterprises. With the support of digital finance, enterprises can improve their ability to collect and integrate information, judge the market situation more accurately and quickly, and then improve the effectiveness of enterprise technological innovation decisions. Third, digital finance improves the sales revenue of enterprises and promotes technological innovation. Online payment promotes the development of e-commerce, and microfinance and Internet Finance meet the consumption needs of low-income groups, thereby stimulating consumption and promoting the upgrading and diversity of China's consumption structure, which is conducive to increasing the sales revenue of enterprises. Considering that the upgrading of consumption structure will strengthen technological innovation, enterprises will transform consumption upgrading into industrial upgrading. Specifically, small and medium-sized enterprises are more flexible and can quickly adjust the industrial structure to adapt to market changes, so small and medium-sized enterprises are more able to carry out technological innovation than large enterprises (Xie Xueyan and Zhu Xiaoyang, 2021). The technological innovation of enterprises plays an important role in promoting the improvement of total factor productivity. On the one hand, the innovation and entrepreneurship activities of enterprises enhance their independent research and development ability, which can directly improve the production efficiency of enterprises; On the other hand, the increase of technological innovation ability can reduce the production cost of enterprises, reduce their dependence on basic production factors, and then improve the total factor productivity of enterprises. Based on the above analysis, this paper puts forward the following assumptions:

H1: With other conditions unchanged, the development of digital finance is conducive to the improvement of total factor productivity of enterprises.

H2: With other conditions unchanged, digital finance can improve the total factor productivity of enterprises by alleviating financial mismatches.

H3: With other conditions unchanged, digital finance can enhance the total factor productivity of enterprises by enhancing technological innovation.

4. Research design

4.1 Sample selection and data source

This paper selects the relevant data of China's A-share listed companies from 2011 to 2019 as the research sample, and makes the following adjustments: (1) excluding ST and *ST with abnormal financial data, as well as financial and insurance samples; (2) Eliminate samples with missing required indicators; (3) Excluding extreme values, all continuous variables were subjected to tailing treatment at the upper and lower 1% level, and finally 9621 groups of observed values were obtained. The data used in this paper mainly comes from two aspects. The company level data are from CSMAR and wind databases; Digital finance adopts the "Digital Inclusive Financial Index" issued by the Digital Finance Research Center of Peking University. The software used in the study is Stata 16.0.

4.2 Variable selection

4.2.1 Explained variable

Total factor productivity (*tfp*). The measurement methods of total factor productivity of enterprises mainly include OLS, FE, OP and LP. However, Lu Xiaodong and Lian Yujun (2012) pointed out that the OLS method based on C-D production function has simultaneous bias and sample selectivity bias in estimating enterprise total factor productivity, and the FE method can not effectively solve the endogenous problem in OLS estimation. Therefore, most studies adopt the method based on consistent semiparametric estimation proposed by Olley and Pakes (1996), Levinsohn and Petrin (2003). In addition, because OP method will lead to a large amount of data being discarded, LP method does not require all enterprises to have positive investment every year, which effectively solves the problem of data loss. Therefore, referring to the practices of Jiang Hongli and Jiang Pengcheng (2021), this paper selects LP method to measure the total factor productivity of enterprises.

C-D production function is often expressed by $Y_{\mathrm{it}} = A_{it} L_{it}^{\alpha} K_{it}^{\beta}$, Y_{it} refers to output, and it is measured by the actual GDP of prefecture level cities; Input variables include the fixed capital stock K_{it} of prefecture level cities and the total urban employment population L_{it}; A_{it} is total factor productivity. LP method takes the input index of intermediate goods as the proxy variable of unobservable productivity impact, and establishes the relationship between the current capital stock of enterprises and the input of intermediate goods: $K_{it+1} = (1-\delta)K_{it} + I_{it}$. Among δ Is the depreciation rate;; I_{it} is the input of intermediate products. After the input variables and output variables are obtained, the logarithm of the residual can be obtained by fitting the production function, that is, the logarithm of the total factor productivity of each prefecture level city.

4.2.2 Explanatory variables

Digital Finance (*df*). Peking University worked with ant financial to compile a "Digital Inclusive Financial Index" that includes three levels: provincial, city and county. The index takes into account both the breadth and depth of digital finance, and measures the development of digital finance in various regions of China from multiple dimensions (Guo Feng et al., 2020). This paper takes it as the proxy variable of digital finance development, normalizes it, and adopts the digital finance development index at the provincial level in the theme regression (Xie Huali et al., 2018).

4.2.3 Intermediary variables

(1) Financial mismatch (*fc*). Based on the research of Shao Ting (2010), the degree of financial mismatch undertaken by enterprises can be reflected by the deviation of their capital cost from the average capital cost. The calculation formula is financial mismatch indicator = [interest expense / (liabilities - accounts payable) - industry average interest rate] / industry average interest rate. Since the index is negative, the absolute value is taken. The greater the absolute value, the greater the degree of financial mismatch of the enterprise.

(2) Technological innovation (*inno*). In order to ensure the observability of the regression coefficient, the total number of patents is logarithmicized (Tang Song et al., 2020).

4.2.4 Control variables

The control variables selected in this paper are: (1) The age of the company (*age*) ,mesuared by the natural logarithm of the establishment of the company; (2) Return on Assets (*roa*), measured by the ratio of net profit to total assets; (3) Asset Liability Ratio (*det*), that is, the ratio of total liabilities to total assets; (4) Property Right Nature (*soe*), enterprises are divided into state-owned enterprises and non-state-owned enterprises, in which the value of state-owned enterprises is 1 and the value of non-state-owned enterprises is 0; (5) Factor Intensity (*cap*), measured by the logarithm of per capita real net fixed assets; (6) The Enterprise's Cash Earning Capacity (*slack*), that is, the ratio of net cash flow from operating activities to total assets; (7) Growth of Operating Revenue (*growth*), measured by (growth of operating revenue / total operating revenue of the previous year)×100%. In addition, this paper also sets the enterprise virtual variable (*firm*) and the annual virtual variable (*year*).

4.3 Model construction

This paper constructs the following benchmark regression model to study the impact of digital Finance on total factor productivity of enterprises:

$$tfp_{it} = \alpha_0 + \alpha_1 df_{it} + \alpha_2 CV_{it} + \alpha_3 firm_i + \alpha_4 year_t + \varepsilon_{it} \ldots \quad (1)$$

Among them, subscript *i* refers to the enterprise and *t* refers to the year. The explained variable tfp_{it} is the total factor productivity of the target enterprise in year *t*; The explanatory variable df_{it} is the digital financial index of the target enterprise in year *t*, which adopts the current data. *CV* is the set of control variables, *firm* is the fixed effect of enterprises, *year* is the fixed effect of time,ε_{it} is a perturbation term.

Based on the practice of Wen Zhonglin et al. (2004), the following two groups of mediation effect models are constructed:

$$fc_{it} = \beta_0 + \beta_1 df_{it} + \beta_2 CV_{it} + \beta_3 firm_i + \beta_4 year_t + \varepsilon_{it} \ldots \quad (2)$$

$$tfp_{it} = \gamma_0 + \gamma_1 df_{it} + \gamma_2 fc_{it} + \gamma_3 CV_{it} + \gamma_4 firm_i + \gamma_5 year_t + \varepsilon_{it} \quad \ldots \tag{3}$$

$$inno_{it} = \beta_0 + \beta_1 df_{it} + \beta_2 CV_{it} + \beta_3 firm_i + \beta_4 year_t + \varepsilon_{it} \quad \ldots \tag{4}$$

$$tfp_{it} = \gamma_0 + \gamma_1 df_{it} + \gamma_2 inno_{it} + \gamma_3 CV_{it} + \gamma_4 firm_i + \gamma_5 year_t + \varepsilon_{it} \ldots \tag{5}$$

Among them, fc_{it} represents the absolute value of the financial mismatch index of enterprise *i* in year *t*, which measures the degree of financial mismatch of enterprises; $inno_{it}$ is the technological innovation level of *i* enterprise in year *t*, and the meaning of other variables is the same as that of formula (1). In the formula (1), α_1 significance is the premise of mediating effect test, (2) and (3) test whether digital finance can improve the total factor productivity of enterprises by alleviating the financial mismatch of enterprises; (4) formula and (5) test whether digital finance can improve the total factor productivity of enterprises by promoting technological innovation. These two groups of mediating effects are regressed and concerned whether β_1 and γ_1 is significant or not. If both are significant, it proves that assumptions 2 and 3 are true.

5. Empirical results and analysis

5.1 Descriptive statistics

Table 1 reports the descriptive statistical results of variables. The statistical results show that the maximum value of *tfp* of enterprises calculated by LP method is 10.43 and the minimum value is 3.78, indicating that there are great differences in total factor productivity of different enterprises; In addition, the degree of digital financialization (*df*) of different enterprises has a large gap, the maximum value is 399, the minimum value is 33.41, and the variance is as high as 83.17; At the same time, it can be seen that the difference of financial mismatch degree (*fc*) between different enterprises is small, with an average of 3748; In terms of technological innovation, the gap between enterprises is large, with the maximum value of 8.88 and the minimum value of 0.

Table 1. Descriptive Statistical Results of Variables

Type	Name	Symbol	Size	Mean	SD	Min	Max
Explained Variable	Total Factor Productivity	*tfp*	9261	6.925	2.08	3.776	10.429
Explanatory Variable	Digital Finance	*df*	9261	237.687	83.167	33.41	399.003
Intermediary Variables	Financial Mismatch	*fc*	8565	3.748	0.236	3.057	4.318
	Technological Innovation	*inno*	9261	3.154	1.413	0	8.875
Control Variables	Establishment Time of the Company	*age*	9261	2.77	0.353	1.609	3.434
	Return on Assets	*roa*	9261	0.06	0.051	-0.103	0.222
	Asset Liability Ratio	*det*	9261	0.387	0.194	0.05	0.852
	Property Right Nature	*soe*	9261	0.31	0.462	0	1
	Factor Density	*cap*	9261	0.216	0.141	0.01	0.649
	Cash Acquisition Ability	*slack*	9261	0.047	0.063	-0.123	0.227
	Growth Rate of Operating Revenue	*growth*	9261	0.181	0.334	-0.398	1.923

5.2 Basic regression results of digital finance and total factor productivity

Table 2 reports the regression results of model (1) digital finance and enterprise total factor productivity. Among them, columns (1), (2) and (3) are the results of adding main explanatory variables, adding control variables and further controlling years respectively. Whether control variables and fixed effects are added or not, the coefficient of digital finance is significantly positive at the level of 1%, indicating that the higher the level of digital finance, the greater the total factor productivity of enterprises, which supports hypothesis 1.

In addition, the symbols of control variables are also basically in line with expectations. From the regression results, the coefficient of the company's establishment years (*age*) is significantly positive at the level of 1%, because the longer the duration of the enterprise, it shows that its business ability is relatively high, it has accumulated a wealth of experience, and the reputation advantage can reduce its financial costs, so as to improve total factor productivity. The coefficient of return on assets (*roa*) is significantly positive at the level of 1%, because enterprises with strong profitability have better cash flow, which enables enterprises to make decisions more conducive to their development, thereby improving total factor productivity. In addition, factor intensity (*cap*) is significantly negatively correlated with total factor productivity at the level of 1%, which may be due to the negative externalities such as pollution, crowding and resource mismatch caused by factor agglomeration.

Table 2. Regression Results of Basic Model

Variables	(1) *tfp*	(2) *tfp*	(3) *tfp*
df	0.0031*** (16.4615)	0.0009*** (4.8238)	0.0008*** (3.9398)
age		2.1541*** (23.0591)	0.5525*** (2.7258)
roa		20.6085*** (61.1183)	20.5806*** (61.2576)
det		0.3014*** (2.2572)	0.3965*** (2.9678)
soe		0.0931 (0.6523)	0.0293 (0.2058)
cap		-1.5128*** (-8.3860)	-1.2628*** (-6.9585)
slack		-0.1345 (-0.5800)	-0.1079 (-0.4636)
growth		0.2557*** (7.1159)	0.2378*** (6.5975)
_cons	6.1800*** (131.9843)	-0.3585 (-1.4857)	3.2161*** (5.4623)
firm	yes	yes	yes
year	no	no	yes
N	9261	9261	9261

Note: * * *, ** *, * respectively indicate significant at the level of 1%, 5% and 10%, and t value is in brackets, the same below.

5.3 Robustness Test

5.3.1 Replace the explained variable

Table 3. Robustness Test of Substituted Explanatory Variables

Variables	(1) *tfp_op*	(2) *tfp_op*	(3) *tfp_op*
df	0.0030*** (15.896)	0.0009*** (4.374)	0.0007*** (3.404)
_cons	6.2049*** (132.104)	-0.3086 (-1.269)	3.9822*** (6.716)
controls	no	yes	yes
firm	yes	yes	yes
year	no	no	yes
N	9261	9261	9261

The benchmark regression model uses LP method to measure total factor productivity. In order to ensure the robustness of the research results, this paper refers to the practice of Wang Daoping and Liu Linlin (2021), and then uses the total factor productivity measured by OP method as the explanatory variable to regression equation (1). No matter what measurement method is adopted, the coefficient of the impact of digital Finance on the total factor productivity of enterprises is positive at the significant level of 1%, indicating that digital finance significantly promotes the total factor productivity of enterprises, and the result of this paper is still valid.

5.3.2 Replace explanatory variables

Because different measurement methods of digital finance may have great differences, which may affect the conclusion of this paper, this paper takes the breadth and depth of digital finance as explanatory variables to regress with the total factor productivity of enterprises, and the result is still valid. In addition, considering that different cities in the same province have different levels of economic and financial development, which may also affect the conclusion (Chen Zhongfei and Jiang Kangqi, 2021), this paper uses the digital financial development index at the municipal level as the explanatory variable for regression, and the results are consistent with the previous text, which verifies the conclusion of this paper again.

Table 4. Robustness Test of Replacement Explanatory Variables

Variables	*tfp*	*tfp*	*tfp*
df_breadth	0.001*** (4.150)		
df_depth		0.001*** (3.048)	
df			0.0008*** (3.940)
_cons	3.712*** (7.488)	3.588*** (7.257)	3.2161*** (5.462)
controls	yes	yes	yes
firm&year	yes	yes	yes
N	9261	9261	9261

5.3.3 By time period

Referring to the practice of Jiang Hongli and Jiang Pengcheng (2021), this paper divides the sample regression time into two periods: 2011-2013 and 2013-2019, in order to prevent structural changes in the development of digital finance around 2013, because the industry generally believes that the emergence of Alipay in 2013 represents the beginning of digital finance. The results show that digital finance has a significant positive effect on the total factor productivity of enterprises in both periods. After 2013, due to the development and popularization of digital finance, its promotion effect on total factor productivity is significantly greater than that before 2013.

Table 5. Robustness Test of Time Segment Estimation

Variables	*tfp*	
	2011-2012	2013-2019
df	0.0002** (2.306)	0.0008*** (3.297)
_cons	5.3732*** (47.592)	4.9875*** (64.079)
controls	yes	yes
firm&year	yes	yes
N	1397	7864

5.4 The Mechanism of Digital Finance Promoting Total Factor Productivity

The embedding of big data, blockchain, artificial intelligence and other technologies in digital finance enables digital finance to reduce the uncertainty of financial information, improve the financing efficiency of enterprises and reduce the financing costs of enterprises, especially small and medium-sized enterprises. At the same time, crowdfunding, microfinance and other methods also expand the financing channels of enterprises. Therefore, it is reasonable to speculate that digital finance can improve the total factor productivity of enterprises by alleviating the financial mismatch of enterprises. In addition, digital finance eases the financial mismatch of enterprises, makes it easier and more convenient for enterprises to obtain funds for innovative research, and thus improves the total factor productivity of enterprises. In order to verify these two mechanisms, the following regression is carried out for formula (2), (3), formula (4) and formula (5). It can be seen from table 6 that the coefficient of digital finance in (1) is significantly positive, and the prerequisite for intermediary effect analysis is established. From columns (2) and (4), it can be seen that digital finance significantly reduces the degree of financial mismatch and improves the technological innovation of enterprises. From columns (3) and (5), it can be seen that financial mismatch significantly inhibits the total factor productivity of enterprises, and technological innovation significantly improves the total factor production rate. Therefore, it can be concluded that digital finance can improve the total factor productivity of enterprises by alleviating the degree of financial mismatch and improving technological innovation. Assumptions 2 and 3 are true.

Table 6. Intermediary Effect Test

		(2)—(3)Financial mismatch mechanism		(4)—(5)Technological innovation mechanism	
Variables	(1) *tfp*	(2) *fc*	(3) *tfp*	(4) *inno*	(5) *tfp*
df	0.0008*** (3.940)	-0.0001* (-1.673)	0.0007*** (3.476)	0.0003** (1.972)	0.0008*** (3.865)
fc			-0.105*** (7.203)		
inno					0.101*** (6.765)
_cons	3.2161*** (5.462)	0.607** (2.214)	3.185*** (5.056)	2.334*** (9.096)	3.012*** (5.131)
controls	yes	yes	yes	yes	yes
firm&year	yes	yes	yes	yes	yes
N	9261	8565	8565	9261	9261

6. Further analysis: heterogeneity analysis of enterprise characteristics

Although the above research has verified that digital finance can significantly improve the total factor productivity of enterprises, due to the existence of financial discrimination and financial mismatch, the improvement of economic efficiency of micro entities has been restrained to a certain extent. Based on the nature of enterprise ownership, financing constraints and whether it is a high-tech enterprise, this paper uses the cross product term method to test the differences of the impact of financial technology on total factor productivity in different industry characteristics, which not only helps to indirectly verify the rationality of the theoretical mechanism, but also provides theoretical support for policy recommendations.

On the one hand, considering the political endorsements of state-owned enterprises, non-state-owned enterprises are more vulnerable to financing constraints than state-owned enterprises, so the nature of enterprise ownership may affect the promotion effect of digital Finance on total factor productivity. According to the type of enterprise registration, enterprises are divided into state-owned enterprises and non-state-owned enterprises. Taking property rights *soe* as the adjustment variable, State-owned enterprises are recorded as soe=1, and non-state enterprises are recorded as soe=0, and the measurement model (6) is constructed. On the other hand, considering the heterogeneity of enterprise financing constraints, the greater the financing constraints, the more difficult it is for enterprises to obtain funds through traditional channels and turn to digital finance channels, which ultimately affects the effect of digital Finance on total factor productivity. This paper selects the absolute value of *SA* index to measure the degree of financing constraints of enterprises, and takes *SA* as a regulating variable to build an econometric model (7). In addition, whether the enterprise is a high-tech enterprise will also cause heterogeneity. The characteristics of low physical assets, high intangible assets and high R & D risk of high-tech enterprises are contrary to the credit concept of traditional financial institutions, so high-tech enterprises are more vulnerable to financing constraints than non high-tech enterprises. Based on the classification standard of Huang Rui et al. (2020), the listed enterprises in C27, C39, I and M industries in the industry classification guidelines for listed companies (CSRC 2012 Edition) are classified as high-tech enterprises, and the rest are non high-tech enterprises. Construct the dummy variable *cp*, which is recorded as *cp*=1 for high-tech enterprises and *cp*=0 for non high-tech enterprises, and construct the measurement model (8). The regression results are shown in Table 7:

$$tfp_{it} = \lambda_0 + \lambda_1 df_{it} + \lambda_2 soe_i + \lambda_3 df_{it} \times soe_i + \lambda_4 CV_{it} + \lambda_5 firm_i + \lambda_6 year_t + \varepsilon_{it} \ldots \quad (6)$$

$$tfp_{it} = \lambda_0 + \lambda_1 df_{it} + \lambda_2 SA_i + \lambda_3 df_{it} \times SA_i + \lambda_4 CV_{it} + \lambda_5 firm_i + \lambda_6 year_t + \varepsilon_{it} \ldots \quad (7)$$

$$tfp_{it} = \lambda_0 + \lambda_1 df_{it} + \lambda_2 cp_i + \lambda_3 df_{it} \times cp_i + \lambda_4 CV_{it} + \lambda_5 firm_i + \lambda_6 year_t + \varepsilon_{it} \ldots \quad (8)$$

Table 7. Heterogeneity Analysis

Variables	(1) *tfp—soe a*s adjusting variable	(2) *tfp—SA a*s adjusting variable	(3) *tfp—cp as* adjusting variable
df	0.001*** (4.299)	-0.011*** (-3.658)	-0.001*** (-3.394)
soe	0.152 (0.947)		
SA		-0.095*** (-3.179)	
cp			-0.606*** (-5.163)
interact	-0.001** (-2.007)	0.003*** (3.980)	0.002*** (3.917)
_cons	3.848*** (7.670)	2.395*** (3.611)	4.397*** (24.991)
controls	yes	yes	yes
firm&year	yes	yes	yes
N	9261	7896	9261

According to the regression results, the front coefficient of the interaction term $df_{it} \times soe_i$ is significantly negative, indicating that digital finance has a stronger driving effect on the total factor productivity of private enterprises. The reason may be that the policy endorsement of state-owned enterprises makes it easier for them to obtain funds from traditional financial institutions. Compared with private enterprises, state-owned enterprises choose less digital financial financing channels; In addition, according to Shen Hongbo et al. (2010), private enterprises are more likely to be driven by the goal of profit maximization, and they will make more efficient allocation of external financing, resulting in a greater increase in marginal total factor productivity. At the same time, column (2) shows that the front coefficient of the interactive item $df_{it} \times SA_i$ is significantly positive, indicating that the increase of financing constraints will strengthen the role of digital finance in promoting total factor productivity. The reason may be that enterprises subject to greater financing constraints will turn to digital finance, which can effectively reduce financing costs, broaden financing channels, and reduce the threshold of financial services, thus greatly improving the total factor productivity of enterprises. In addition, the front coefficient of the interaction item $df_{it} \times cp_i$ is significantly positive, indicating that digital finance has a stronger driving effect on the total factor productivity of high-tech enterprises. It may be because high-tech enterprises are facing more severe financing constraints and the degree of information asymmetry, and digital finance can better match resources with the risk characteristics of high-tech enterprises by using big data, blockchain and other information technologies, and alleviate the problems of information asymmetry, difficult financing and expensive financing.

7. Conclusions and suggestions

Using the relevant data of China's A-share non-financial listed companies from 2011 to 2019, this paper examines the impact of digital Finance on total factor productivity of enterprises. The research results show that the development of digital finance has a significant impact on improving the total factor productivity of enterprises, which is mainly reflected in: Digital finance can improve the total factor productivity by alleviating the financial mismatch of enterprises and improving the technological innovation of enterprises. Further research found that under other conditions unchanged, the role of digital finance in promoting total factor productivity of private enterprises is stronger than that of state-owned enterprises, and the stronger the financing constraints, the more enterprises and high-tech enterprises can feel the role of digital finance in promoting total factor productivity.

Based on the above empirical research results, this paper puts forward the following policy recommendations: first, we should speed up the layout of digital finance, a new financial service model, in China's capital market. The government should be market-oriented, encourage Internet enterprises and traditional financial institutions to deeply integrate, continuously improve the breadth and depth of financial services through technology and product innovation, and provide support policies for technology and financial integration. Second, promote the construction of new infrastructure and develop digital economy infrastructure represented by 5g and cloud computing. The government should increase investment in the digital economy, use financial funds to provide a good basic environment for enterprises' digital transformation, and encourage enterprises to carry out digital transformation through the demonstration and pilot of typical enterprises. Third, we should pay attention to the balanced development of digital finance among regions, and we cannot ignore the pilot tests in the central and western regions and rural areas. Therefore, local governments should actively intervene and implement the development concept of Inclusive Finance. Fourth, the government should strengthen Macro Prudential Management, balance the relationship between financial risks and supporting the real economy, implement incentive compatible regulatory policies, and build a scientific and efficient regulatory system with the help of regulatory technology, digital technology and artificial intelligence. Finally, improve the profitability of small and medium-sized enterprises and encourage them to carry out technological innovation. For example, the government can establish an incubation mechanism for e-commerce enterprises to encourage enterprises to carry out e-commerce and industrial transformation; Or through financial subsidies, personnel training, centralized management and other ways to encourage and guide, through a variety of means to alleviate the financing constraints faced by small and medium-sized enterprises.

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