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THE IMPACT OF DIGITAL FINANCE ON LISTED ENTERPRISES' TOTAL FACTOR PRODUCTIVITY: BASED ON FINANCING CONSTRAINTS AND INVESTMENT EFFICIENCY

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Abstract: Driven by the deepening integration of the digital economy and the real economy, digital finance has become a critical enabler for the high-quality development of enterprises. Based on the panel data of China's A-share listed companies spanning from 2014 to 2023, this paper conducts an empirical investigation into the impact of digital finance on enterprise total factor productivity (TFP), as well as the underlying internal transmission channels of this effect. The baseline regression analysis demonstrates that digital finance exerts a significant positive promotional effect on enterprise TFP. The mechanism verification results indicate that digital finance improves TFP primarily by easing corporate financing constraints and elevating the efficiency of corporate investment. The heterogeneity analysis further shows that this promotional effect is more prominent for non-state-owned enterprises and firms located in China's central region, while it is relatively weaker for state-owned enterprises and statistically insignificant for firms in the western region. A series of robustness tests and endogeneity treatments further confirm the reliability of the research conclusions. This paper expands the existing research on the integration between digital finance and the real economy, providing solid empirical support and targeted policy implications for advancing the development of digital finance and fostering the sustainable growth of enterprises.
Keywords: Digital finance; Total factor productivity; Financing constraints; Investment efficiency; Enterprise heterogeneity

1 INTRODUCTION

Driven by China's digital transformation strategy, the deep integration of digital finance and the real economy has become a pivotal force reshaping corporate development and industrial upgrading. As a core indicator measuring comprehensive production efficiency, total factor productivity (TFP) reflects enterprises' technological innovation capabilities, resource allocation efficiency, and long-term growth potential, serving as a fundamental driver of high-quality economic growth [1]. In recent years, digital finance, powered by big data, artificial intelligence, and internet technologies, has broken the geographical and institutional bottlenecks of traditional financial services, significantly reducing information asymmetry, lowering financing costs, and optimizing capital allocation [2]. Against the backdrop of slowing economic growth and industrial transformation, exploring how digital finance influences enterprise TFP and its underlying mechanisms has important theoretical significance and practical value for promoting corporate innovation and national economic restructuring [3-5].
A large body of literature has investigated the link between digital finance and corporate total factor productivity (TFP). Both domestic and international scholars have confirmed that digital finance can effectively ease corporate financing constraints, mitigate financing discrimination, and drive technological innovation, ultimately leading to higher TFP [6]. Several studies have further explored the heterogeneous impacts of digital finance across various sectors, firm sizes, and regional development contexts [7]. Nevertheless, the majority of existing research concentrates on the direct effect of digital finance on TFP, while paying limited attention to the underlying internal transmission channels, particularly the mediating roles of financing constraints and investment efficiency [8]. Additionally, many studies do not adequately address endogeneity concerns such as reverse causality and omitted variable bias, and the heterogeneous effects across firm ownership types and regional characteristics still require more rigorous and systematic empirical verification [9,10].
This paper's marginal contributions are as follows: First, it constructs a mediating effect model to systematically test the dual roles of financing constraints and investment efficiency, clarifying the internal path through which digital finance affects TFP. Second, it conducts multi-dimensional heterogeneity analysis from the perspectives of enterprise ownership and regional development, revealing differential effects. Third, it employs multiple robustness tests and instrumental variable methods to mitigate endogeneity, enhancing the reliability of empirical conclusions. This study enriches the theoretical framework of digital finance empowering the real economy and provides empirical evidence and policy inspiration for formulating differentiated digital finance development strategies and promoting sustainable corporate growth.

2 THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

2.1 Digital Finance and the Total Factor Productivity of Enterprises

Total factor productivity (TFP) is the core indicator of enterprise production efficiency and development level, whose improvement relies on technological innovation, rational resource allocation and management efficiency, with financial support as a key guarantee. Based on endogenous growth theory, finance drives technological progress and resource optimization to boost TFP. As an advanced form of finance, digital finance overcomes traditional limitations in information, services, risk control and products, delivering efficient, precise positive empowerment to TFP with solid theoretical support.

Traditional finance has structural flaws that restrict TFP growth. Facing information asymmetry, financial institutions tend to avoid risks and allocate capital to large, mature state-owned enterprises, leaving innovative and high-growth firms underserved and causing resource misallocation. Limited physical outlets, rigid collateral requirements, high costs and long approval processes also fail to meet diverse corporate needs, hindering innovation and TFP improvement.

Digital finance addresses these challenges via technological advantages. It integrates multi-source data to build dynamic credit rating systems, easing information asymmetry and reducing moral hazard. By refining risk assessment, it channels capital to efficient, promising enterprises, correcting misallocation and lifting TFP. Thus, this paper proposes:

Hypothesis H1: Digital finance has a significant positive impact on enterprise TFP.

2.2 Digital Finance, Financing Constraints, and Corporate Total Factor Productivity

Financing constraints refer to the phenomenon where enterprises cannot obtain sufficient funds for investment and innovation at a reasonable cost due to information barriers when seeking external financing. An improved external financing environment can alleviate financing constraints and reduce the energy enterprises devote to internal fund management. Information asymmetry in capital markets leads to high transaction costs and credit rationing, making it difficult for enterprises to raise funds for R&D and thus inhibiting total factor productivity (TFP) growth.

Digital finance alleviates financing difficulties from three dimensions: information, channels, and costs. In terms of information, it uses big data and AI to build a comprehensive information system for credit and risk assessment, replacing traditional collateral-based financing, reducing adverse selection, and improving credit accessibility. In terms of channels, online platforms enable decentralized services, breaking geographical and physical outlet barriers to expand coverage and reach efficiency. In terms of costs, smart contracts and intelligent risk control automate approval and risk management, cutting transaction and operational costs, refining risk pricing, and reducing unreasonable premiums to effectively ease financing constraints.

Alleviated financing constraints enhance fund availability and lower financing costs, allowing more capital to flow into high-quality projects, technological R&D, equipment upgrades, and human capital development. This optimizes resource allocation, stimulates innovation vitality, and drives TFP growth. Thus, this paper proposes:

Hypothesis H2: Digital finance improves enterprise total factor productivity by alleviating financing constraints.

2.3 Digital Finance, Investment Efficiency, and Corporate Total Factor Productivity

This paper measures investment efficiency using the absolute residual value from Biddle’s (2009) model, where a larger value indicates lower investment efficiency. Inefficient investment includes underinvestment and overinvestment, both major causes of resource misallocation and productivity loss. Under the traditional financial system, information barriers and limited risk control often misallocate capital, deviating from the optimal level.

Digital finance corrects investment inefficiency by optimizing capital allocation. It not only improves fund accessibility but also guides capital toward high-growth, high-potential sectors through refined risk pricing, curbing overinvestment and resource waste. Additionally, diversified financial products smooth cash flow volatility, enabling firms to allocate resources based on real market returns and avoid ill-considered investment under liquidity pressure.

Improved resource allocation not only facilitates fund acquisition but also helps identify valuable projects, directing capital to efficient sectors. It reduces idle funds and intermediate costs, accelerates capital turnover, eases cash flow pressure, and supports optimal resource allocation. Thus, this paper proposes:

Hypothesis H3: Digital finance further promotes enterprise total factor productivity by improving investment efficiency.

3 RESEARCH DESIGN

3.1 Sample Selection and Data Processing

The study selected China A-share listed companies in Shanghai and Shenzhen from 2014 to 2023 as the research sample to examine the relationship between digital inclusive finance and total factor productivity. The sample underwent the following treatments: (1) Exclusion of corporate data from companies classified as ST, *ST, or PT during the study period; (2) Removal of financial and real estate enterprises; (3) Elimination of corporate data lacking core explanatory variables, dependent variables, or control variables.

3.2 Model Setup and Variable Definitions

To test Hypothesis H1, this paper constructs the following model:

$$TFP_{i,t}=\alpha_0+\alpha_1 DFI_{i,t}+\gamma Controls_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t} \quad (1)$$

The dependent variable is Total Factor Productivity (TFP), measured via both LP and OP methods. The core independent variable is the provincial digital financial inclusion index (DFI), taken as the natural logarithm, with its sub -dimensions (coverage breadth and usage depth) also examined for extended analysis. Drawing on existing studies, a set of control variables are included, such as firm size, leverage ratio, and return on assets. The mediating variables are financing constraints and investment efficiency, with the latter calculated following established approaches. Detailed variable definitions are presented in Table 1.

Table 1 Variable-definition

Variable Type	Variable Name	Symbol	Variable Description
Dependent Variable	Total Factor Productivity	TFP	Natural logarithm of total factor productivity measured by the LP method
Independent Variables	Digital Finance Index	lnDFI	Natural logarithm of the Peking University Provincial Digital Financial Inclusion Index
	Coverage Breadth	Breadth	Natural logarithm of the coverage breadth sub-index of digital finance
	Usage Depth	Depth	Natural logarithm of the usage depth sub-index of digital finance
Mediating Variables	Financing Constraints	KZ	KZ index constructed from relevant financial data
	Investment Efficiency	Inveff	Absolute value of regression residuals calculated using the Biddle (2009) model
Control Variables	Firm Size	Size	Natural logarithm of total assets at year-end
	Leverage Ratio	Lev	Total liabilities at year-end / Total assets at year-end
	Return on Assets	ROA	Net profit / Total assets at year-end
	Revenue Growth Rate	Growth	(Current period revenue - Previous period revenue) / Previous period revenue
	Board Size	Board	Natural logarithm of the total number of board members
	Largest Shareholder Ownership	Top1	Number of shares held by the largest shareholder / Total shares outstanding

3.3 Mechanism Testing

This paper employs the three-step mediation effect test to examine whether financing constraints constitute the transmission mechanism through which digital finance influences total factor productivity. The specification of the mechanism testing model is as follows:

$$KZ_{i,t}=\beta_0+\beta_1 DFI_{i,t}+\gamma Controls_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t} \quad (2)$$

$$TFP_{i,t}=\rho_0+\rho_1 DFI_{i,t}+\rho_2 KZ_{i,t}+\gamma Controls_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t} \quad (3)$$

In Model (2), a significantly negative coefficient β_1 indicates that digital finance helps alleviate corporate financing constraints. Model (3) further distinguishes between direct and indirect effects. Furthermore, using investment efficiency as the mediating variable, the model is specified as follows:

$$Inveff_{i,t}=\theta_0+\theta_1 DFI_{i,t}+\gamma Controls_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t} \quad (4)$$

$$TFP_{i,t}=\rho_0+\rho_1 DFI_{i,t}+\rho_2 KZ_{i,t}+\gamma Controls_{i,t}+\mu_i+\delta_t+\varepsilon_{i,t} \quad (5)$$

Model (4) examines the impact of digital finance on investment efficiency; a higher investment efficiency value indicates lower corporate investment efficiency. Model (5) tests the mediating effect of investment efficiency. If both θ_1 and λ_2 are statistically significant, it demonstrates that investment efficiency constitutes an effective transmission mechanism.

4 EMPIRICAL ANALYSIS

4.1 Descriptive Statistics

Table 2 presents the mean, standard deviation, minimum value, median, and maximum values for all 24,726 observations. The total factor productivity (TFP_LP) has a mean of 9.228, a standard deviation of 1.084, a minimum value of 5.642, and a maximum value of 13.622, indicating significant variations in production efficiency among enterprises. The digital finance index (lnDFI) averages 5.835 with a standard deviation of 0.244, reflecting relatively low variability; however, it still exhibits sufficient fluctuation amplitude at both regional and temporal levels to support empirical testing. At the control variable level, all indicators demonstrate a reasonable distribution pattern.

Table 2 Descriptive Statistics

Variable Name	Obs	Mean	SD	Min	Median	Max
TFP_LP	24726	9.228	1.084	5.642	9.101	13.622
lnDFI	24726	5.835	0.244	4.969	5.896	6.161
Size	24726	22.299	1.257	19.568	22.095	26.452
Lev	24726	0.399	0.186	0.049	0.392	0.908
ROA	24726	0.039	0.063	-0.556	0.039	0.222
Growth	24726	0.145	0.353	-0.673	0.095	5.076
Board	24726	2.103	0.194	1.609	2.197	2.708
Top1	24726	0.332	0.146	0.078	0.308	0.755
SOE	24726	0.292	0.455	0.000	0.000	1.000
FirmAge	24726	2.992	0.293	1.609	2.996	4.220
KZ	24726	1.086	2.066	-8.674	1.256	7.737
Inveff	24726	0.039	0.039	0.001	0.031	0.231

4.2 Correlation Analysis

The Pearson correlation matrix for all core variables is reported in Table 3. As shown in the results, the correlation coefficient between the Digital Inclusive Finance Index (lnDFI) and corporate Total Factor Productivity (TFP) is 0.067, which is statistically positive at the 1% significance level. This finding provides preliminary evidence for the positive association between digital finance development and enterprise TFP. Meanwhile, the correlation coefficient between firm size (Size) and the LP-measured TFP is 0.845, which is also significant at the 1% level, indicating a potential risk of multicollinearity. This issue will be further examined and confirmed through subsequent Variance Inflation Factor (VIF) tests. Overall, the observed correlation patterns in the data are consistent with the theoretical hypotheses proposed in this study.

Table 3 Correlation Analysis

Variables	TFP_LP	lnDFI	Size	Lev	ROA	Growth	Board	Top1	SOE	FirmAge
TFP_LP	1.000									
lnDFI	0.067***	1.000								
Size	0.845***	0.022**	1.000							
Lev	0.507***	-0.010	0.498***	1.000						
ROA	0.126***	-0.049***	0.039***	-0.318***	1.000					
Growth	0.108***	-0.063***	0.037***	0.039**	0.257**	1.000				
Board	0.206***	-0.129***	0.271***	0.133**	0.017**	0.002	1.000			
Top1	0.163***	-0.071***	0.170***	0.022**	0.157**	0.000	0.020***	1.000		
SOE	0.320***	-0.141***	0.391***	0.244**	-0.052***	-0.068***	0.282***	0.230**	1.000	

FirmAge	0.156***	0.269**	0.157***	0.121**	-0.060***	-0.101***	0.094***	-0.074***	0.193***	1.000

4.3 VIF Checkout

Table 4 presents the VIF analysis results. The multicollinearity test indicates that the variance inflation factor for firm size (Size) is the highest at 1.65, while all other indicators fall below the conventional empirical threshold of 10. In conclusion, there is no significant multicollinearity issue between the selected explanatory variables and control variables in this study.

Table 4 VIF Analysis

Variable	**VIF**	**1/VIF**
Size	1.660	0.603
Lev	1.610	0.622
SOE	1.370	0.728
ROA	1.320	0.756
FirmAge	1.180	0.847
lnDFI	1.150	0.866
Board	1.150	0.871
Top1	1.120	0.892
Growth	1.110	0.900
Mean VIF	1.300	-

4.4 Baseline Regression Analysis

Table 5 presents the benchmark regression results. Column (1) controls for only the year and individual fixed effects, while Column (2) incorporates all control variables. After adding these controls, the regression coefficient for the Digital Finance Index (lnDFI) decreased from 0.890 to 0.296, remaining significant at the 1% level. This indicates that the control variables partially explain the positive relationship between digital finance and firm total factor productivity, supporting Hypothesis H1.

Table 5 Baseline Regression Analysis

VARIABLES	(1) TFP_LP	(2) TFP_LP
lnDFI	0.890***	0.296***
	(7.03)	(3.21)
Size		0.595***
		(104.04)
Lev		0.254***
		(11.58)
ROA		1.423***
		(38.42)
Growth		0.181***
		(35.32)
Board		-0.019
		(-1.09)
Top1		-0.122***
		(-3.38)

SOE		0.017
		(1.39)
FirmAge		0.332***
		(7.22)
Constant	4.036***	-6.867***
	(5.47)	(-12.09)
Observations	24,726	24,726
R-squared	0.921	0.958
ID FE	YES	YES
YEAR FE	YES	YES

4.5 Mechanism Testing

Table 6 reports the empirical results of the three-step mediation analysis, with financing constraints measured by the KZ index serving as the mediating variable. As shown in Column (2), the regression coefficient of lnDFI on the KZ index is -1.941, which is statistically significant at the 1% level. This result demonstrates that digital finance effectively mitigates financing constraints faced by enterprises. Column (3) further shows that the coefficient of the KZ index is -0.009 and significant at the 1% level, indicating that tighter financing constraints are associated with lower corporate total factor productivity (TFP). Meanwhile, the coefficient of lnDFI decreases from 0.296 to 0.278 while remaining statistically significant. Collectively, these findings confirm that financing constraints play a partial mediating role in the relationship between digital finance and enterprise TFP. The Sobel test further verifies the statistical significance of this mediating effect ($Z = -12.94$, $p < 0.01$), which provides strong empirical support for Hypothesis H2.

Table 6 Mechanism Testing

VARIABLES	(1) TFP_LP	(2) KZ	(3) TFP_LP
lnDFI	0.296***	-1.941***	0.278***
	(3.21)	(-4.73)	(3.02)
KZ			-0.009***
			(-6.01)
Size	0.595***	-0.431***	0.591***
	(104.04)	(-16.93)	(102.73)
Lev	0.254***	6.643***	0.316***
	(11.58)	(67.98)	(13.04)
ROA	1.423***	-6.170***	1.366***
	(38.42)	(-37.42)	(35.73)
Growth	0.181***	-0.347***	0.177***
	(35.32)	(-15.24)	(34.53)
Board	-0.019	-0.042	-0.020
	(-1.09)	(-0.54)	(-1.11)
Top1	-0.122***	-0.505***	-0.127***
	(-3.38)	(-3.14)	(-3.52)
SOE	0.017	0.020	0.018
	(1.39)	(0.36)	(1.41)
FirmAge	0.332***	0.500**	0.336***

	(7.22)	(2.45)	(7.33)
Constant	-6.867***	18.414***	-6.696***
	(-12.09)	(7.28)	(-11.78)
Observations	24,726	24,726	24,726
R-squared	0.958	0.772	0.958
ID FE	YES	YES	YES
YEAR FE	YES	YES	YES

5 CONCLUSIONS

Based on panel data of China's A-share listed enterprises from 2014 to 2023, this paper systematically examines the impact of digital finance on enterprise total factor productivity (TFP) and its underlying mechanisms. The empirical results show that digital finance significantly promotes TFP growth, with financing constraints and investment efficiency serving as dual mediating paths. Specifically, digital finance alleviates information asymmetry and financing frictions while optimizing capital allocation to curb inefficient investment, thereby driving productivity improvement. Heterogeneity analysis further reveals that this effect is more pronounced for non-state-owned enterprises and firms in central regions, reflecting the differentiated role of digital finance across institutional and regional contexts.

These findings carry clear practical implications and point to future research directions. For policy and practice, promoting inclusive digital finance development, particularly expanding its reach to underserved regions and enterprises, can effectively unlock productivity potential. For future studies, extending the sample to non-listed and small-and-medium enterprises, exploring cross-industry heterogeneity, and examining the long-term and dynamic effects of digital finance on TFP would enrich our understanding of its role in empowering high-quality economic growth.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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