Proceedings of ICFTBA 2026 Symposium: Digital Government, Finance, Accountability, and Sustainable Economic Development
DOI: 10.54254/2754-1169/2026.AB39282

The Impact of Digital Inclusive Finance about Enterprise Total Factor Productivity: Based on China A-Share Listed Companies' Experimental Evidence

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Abstract. Total Factor Productivity (TFP) is an important indicator for measuring high-quality economic development. Exploring the impact of fintech on enterprise TFP, against the background of digital technologies and the financial sector, has certain practical significance. Based on the data of A-share listed companies in China from 2011 to 2023, this paper uses the Peking University Digital Inclusive Finance Index to measure the level of fintech development at the city level, employing a two-way fixed-effects panel model and applying standard error clustering for evaluation. After strict screening, this study empirically examines the impact of fintech on enterprise TFP and the differences therein. This study finds that, after taking into account macro environment fluctuations and robust standard errors, fintech and TFP still have a positive correlation. Based on the above conclusion, this article suggests that governments should deepen the penetration of fintech and implement differentiated financial support policies, and that companies should actively embrace digital transformation and improve digital financial services for the real economy.

Keywords: Fintech, total factor productivity, new quality productive forces

1. Introduction

Total Factor Productivity (TFP) is a key indicator for measuring a firm's production efficiency and the quality of economic growth. China's national leaders have clearly stated that a significant increase in TFP serves as the core indicator, with innovation as its feature, quality as its key, and advanced productive forces as its essence [1]. In recent years, digital technologies such as big data, cloud computing, AI, and blockchain have deeply integrated with the financial industry, giving rise to the emerging field of fintech. Because of fintech, real-world financial markets are now undergoing historic transformations. In 2025, the increment of aggregate financing to the real economy (AFRE) reached 35.60 trillion yuan. Among this, the increment of direct financing reached 16.71 trillion Chinese Yuan (CNY), accounting for 46.94%. This proportion has significantly increased by 7.83 percentage points compared to 2020 [2]. In the past, indirect finance was dominant in China's financing market, while the share of direct financing remained relatively low for a long time. Because of high risk, banks were not willing to provide financing channels for small and medium-sized companies. Meanwhile, as an alternative financing method, fintech could provide

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DOI: 10.54254/2754-1169/2026.AB39282

more direct and convenient channels and big data can reach financing demands from different angles [3].

In this process, fintech needs more continuous research and development. Currently, fintech focuses more on technological application, which means using the deep integration of artificial intelligence technology and financial services to solve the long-term issue in the financial market, thereby lowering the difficulty of financial services and expanding their inclusiveness, and providing technical support for improving the quality and efficiency of the real economy [4]. At the same time, fintech also changes companies' financing environment and business decisions through innovative financial service models and by reducing information asymmetry. Based on this context, conducting research on the impact of fintech on corporate TFP and its mechanism of action has important theoretical value and practical significance for understanding the microeconomic effects of fintech, determining whether to utilize fintech channels for financing, and promoting the financial industry to serve the real economy.

So far, many scholars have researched this respect. However, most studies discuss the impact of fintech on TFP, and specific research directions still have areas for further improvement. Existing research has primarily focused on individual mechanisms, with insufficient attention to differences between enterprises, particularly between state-owned and non-state-owned firms. In addition, some studies rely on limited datasets covering relatively short periods, highlighting the need for longer-term data to support more comprehensive analysis.

In summary, based on the analysis, this study employs Chinese A-share listed companies from 2011 to 2023 as the research sample, using the Peking University Digital Inclusive Finance Index as a proxy variable for fintech development levels, and using a two-way fixed-effects panel model to empirically test the impact of fintech on firm TFP.

This paper's research structure is as follows: the first part summarizes scholarly literature research on fintech; next, it proposes and elaborates on the two-way fixed-effects panel model; then, it uses this model to analyze the results; finally, suggestions and conclusions regarding the relationship between fintech and company TFP are presented.

2. Literature review

2.1. Evolution of measurement methods for TFP in enterprises

The measurement of enterprise TFP has evolved a lot. Early research created the OP method, which uses investment as a proxy variable. It handles endogeneity well, but in real data, many firms have zero investment, which causes sample loss and affects accuracy [4]. To solve this problem, later research proposed the LP method uses intermediate inputs as a proxy. This approach addresses endogeneity issues and preserves a larger sample size, thereby improving the stability of the results [5]. Domestic studies also show that the LP method works better in China's context. It has become the main method in micro-level research for measuring TFP [6].

2.2. Theoretical basis and mechanisms

Exploring how fintech affects enterprise TFP, the basic theories of this study are information asymmetry and credit rationing theory. In the traditional financial system, information asymmetry between banks and firms easily leads to adverse selection and moral hazard, causing banks to ration credit and making small and medium-sized enterprises face serious financing constraints [3, 7]. Fintech, based on big data and AI, can find alternative data and ease information asymmetry, helping

DOI: 10.54254/2754-1169/2026.AB39282

break the credit rationing limit [8]. In this situation, existing papers test the mechanisms: fintech significantly raises enterprise TFP by easing financing constraints and increasing technological innovation [9, 10]. At the same time, it works through other channels to help increase production efficiency, such as cutting agency costs, offsetting the negative shocks of rising labor costs, and deepening supply chain finance [11-13].

2.3. Ownership heterogeneity and the theoretical space to deep talk

Existing literature shows that fintech's enhancing effect is more significantly for private firms and medium-sized and small enterprises. However, further research is needed to investigate why some non-state-owned enterprises located in regions with higher levels of fintech development still experience limited improvements in TFP. Academic circles always combining soft budget constraints and ownership discrimination theories to explain.

State-owned enterprises can easily obtain hidden resource support, so their financing channels are relatively smooth, and fintech brings them only limited marginal improvement [9, 14]. In contrast, non-state-owned enterprises face long-term ownership discrimination in the financial system, and fintech delivers a larger marginal effect in easing their financing constraints [8]. This divergence in marginal utility caused by ownership differences directly affects how efficiently firms turn fintech dividends into actual productivity.

3. Research methods and data sources

Fintech should have a positive effect on enterprise TFP. It works through channels such as easing financing constraints and cutting transaction costs [15]. However, firms with different ownership types have different resources and financing environments, so this positive effect may be heterogeneous. For medium-sized and small enterprises, to some extent, fintech can solve their financing problems [7]. Based on the analysis, this paper references the model framework used in previous research and builds the following regression model based on a two-way fixed-effects panel model:

$$TFP_{it} = \alpha_0 + \beta_1 \times Fintech_{jt} + \beta_2 \times Age_{it} + \beta_3 \times SOE_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

i is the firm, t is the year, and j is the city. FinTech is the core explained variable, meaning the fintech level of city j in year t ; Age and SOE are firm age and ownership type, they are the two control variables; μ_i is the firm fixed effect, controlling for firm features that do not change over time. λ_t is the year fixed effect, controlling for macro change over time. ε_{it} is the error term.

Following the method used in previous research, this study uses the LP method (Levinsohn-Petrin) to measure enterprise TFP [9]. The Digital Financial Inclusion Index from Peking University is used as a proxy for fintech development. This index measures regional digital finance from three dimensions: coverage, usage depth, and digitalization. This index has good reliability and validity and has been widely used in fintech research. Previous studies are followed to select the following control variables [6, 8, 12]. The Age is calculated as the current year minus the firm's first listing year. If the actual controller is state-owned, SOE equals 1 and 0 otherwise. Firm size and LP method TFP both include total operating revenue, with a correlation of 0.94, showing a high mechanical correlation. To avoid multicollinearity and estimation bias, the main regression does not include firm size.

DOI: 10.54254/2754-1169/2026.AB39282

The data used in this paper mainly come from two sources. First, enterprise TFP and listed company financial data come from the CSMAR database. The sample covers Chinese A-share listed companies from 2011 to 2023, with 4,537 firms and 36,492 observations. Second, fintech data come from the Digital Financial Inclusion Index by Peking University, covering 337 prefecture-level cities in mainland China from 2011 to 2023.

For data processing, Chinese A-share listed companies from 2011 to 2023 are used as the initial sample. The following screening is performed. First, sample screening. Because the LP method for TFP relies mainly on main business, financial firms are not excluded (only 1 observation). Also, to keep the sample complete, ST, *ST, or delisted firms are not excluded (1,161 observations). After excluding listing year data (0 observations), all are kept. Second, missing values and matching. Observations that failed city matching (3,966), missing SOE (229), and duplicate observations (15) are dropped. This removes 4,180 observations in total. Third, outlier treatment. To reduce extreme outliers, continuous variables are winsorized at the 1% and 99% levels. After these steps, the initial sample becomes 36,492 observations and 4,537 firms.

4. Results and analysis

4.1. Descriptive statistical results

Table 1 shows the descriptive statistical results of the main variables. The mean value of TFP is 8.34, and the standard deviation is 1.09. The mean value of Fintech is 252.63, and the standard deviation is 79.71. This shows that the level of fintech development differs across regions. Regarding the control variables, the mean value of Age is 11.18 years, and the mean value of SOE is 0.1. This indicates that about 10% of the sample consists of state-owned enterprises, so non-state-owned companies make up the majority of the sample.

Table 1. Descriptive statistics of core and control variables

Variable	Sample Size	Mean	Standard Deviation	Minimum	Median	Maximum
TFP	36492	8.34	1.09	6.01	8.25	11.20
FinTech	36492	252.63	79.71	59.31	271.24	363.22
Age	36492	11.18	7.89	1	10	29
SOE	36492	0.10	0.30	0	0	1

4.2. Variable correlation and visualization analysis

From Table 2, FinTech and enterprise TFP have a correlation of 0.12, with $p<0.01$, which means a significantly positive correlation at the 1% level. This shows that fintech development and higher productivity are related. Meanwhile, Age and SOE also show significantly positive correlations with TFP at the 1% level. This reflects that older firms and state-owned firms have higher productivity levels. Then, the correlation between FinTech and SOE is -0.11. This means that SOE and fintech have a negative linear relationship.

Table 2. Variable correlation coefficient matrix

Variable	TFP	Fintech	Age	SOE
TFP	1			

DOI: 10.54254/2754-1169/2026.AB39282

Table 2. (continued)

Fintech	0.12***	1		
Age	0.28***	0.05***	1	
SOE	0.15***	-0.11***	0.15***	1

Figure 1 presents the scatter plot and linear fit. The red fitted line slopes upward to the right, indicating a positive correlation between the two variables. Figure 2 further shows that fintech maintained a continuous upward trend during the sample period. Enterprise TFP also generally increased from 2011 to 2020, exhibiting a similar temporal trend. Notably, however, the fintech index continued to rise after 2021, whereas the average enterprise TFP exhibited a certain pullback. In addition, the sample points in the scatter plot are widely dispersed, suggesting that this positive relationship is confounded by macroeconomic conditions and firm-specific characteristics.

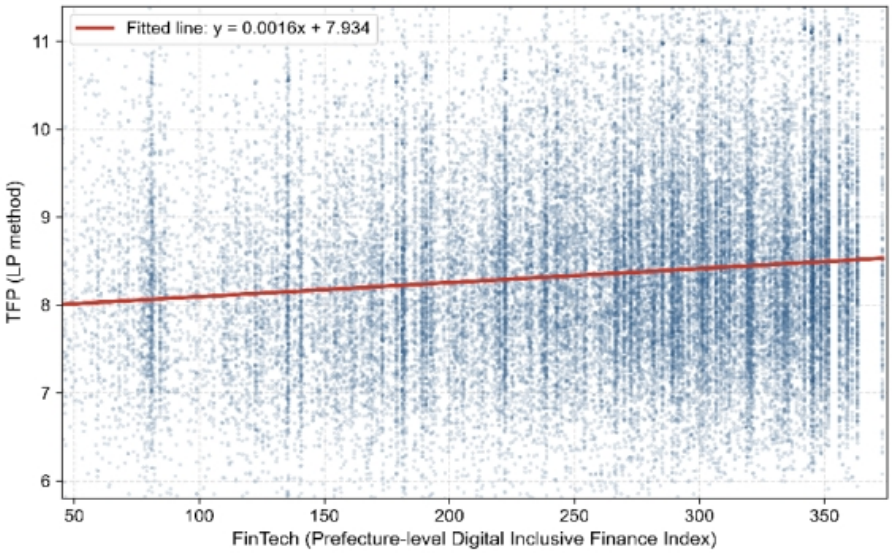

Figure 1. Scatter plot and linear fit of corporate TFP versus the fintech index of prefecture-level

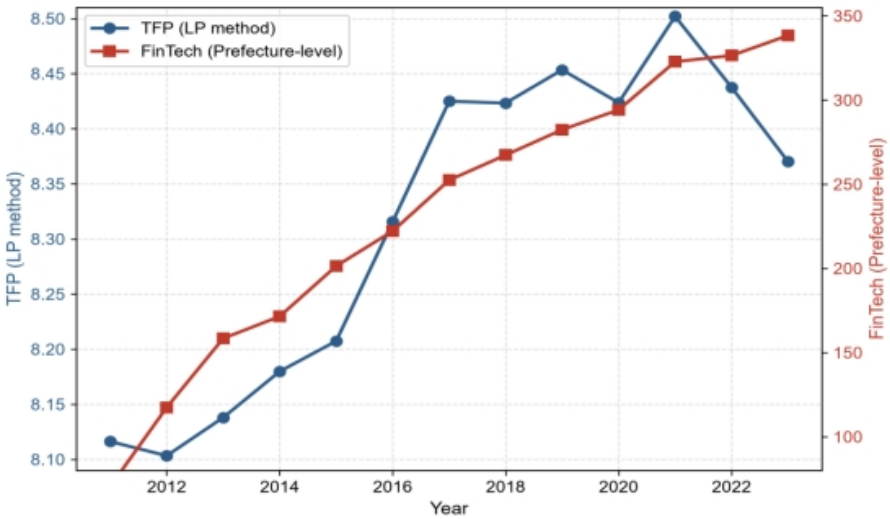

Figure 2. Annual mean trends of corporate TFP and FinTech indices from 2011 to 2023

DOI: 10.54254/2754-1169/2026.AB39282

4.3. Grouped comparative analysis

The left side of Figure 3 shows that the average TFP of state-owned firms is 8.82, higher than the 8.29 of non-state-owned firms. This is mainly because state-owned firms have natural talent in resources, scale, and policy support [14]. However, the right side of Figure 3 shows that the average fintech level for non-state-owned firms is higher than state-owned firms, which is same with Table 2.

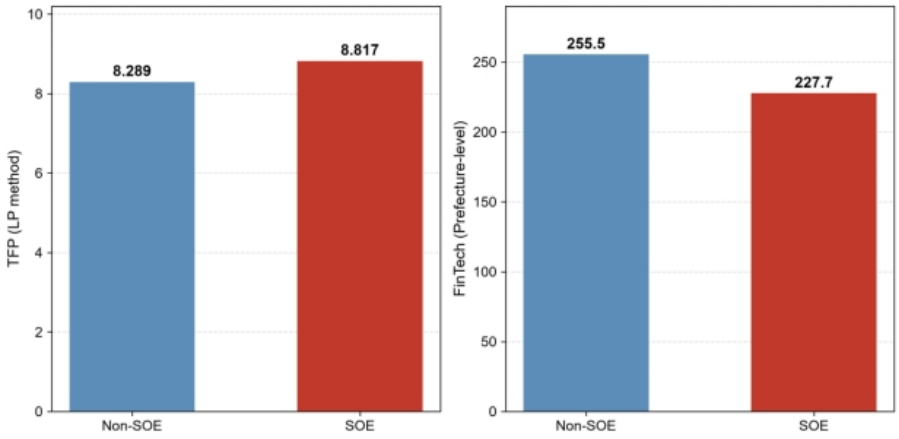

Figure 3. Mean TFP and Fintech values between state-owned and non-state-owned enterprises

4.4. Discussion of results

The main regression results in Table 3 show that the coefficient of FinTech is 0.003, with a standard error of 0.001. It is significantly positive at the 5% level. The 95% confidence interval is [0.000, 0.005], which does not include 0. This result is consistent with the significant positive correlation in Table 2 and the upward-sloping fit line in Figure 1. It shows that, after controlling for firm and year fixed effects, fintech development can help enterprise TFP growth. The p-value is 0.024, smaller than the 0.05 significance level. This is a small probability event. Therefore, this positive effect is confirmed to be true and reliable in statistical terms. In addition, the Within and Overall R-squared values of the model show that the model has good explanatory power for the sample data.

Table 3. Summary of the main regression model results

Variable	Coefficient	Standard error	t Value	P Value	Lower limit of the 95% CI	Upper limit of the 95% CI	Significance
Fintech	0.003	0.001	2.253	0.024	0.000	0.005	**
Age	0.044	0.035	1.278	0.201	-0.024	0.112	
SOE	0.090	0.021	4.327	0.000	0.049	0.131	***

Although Figure 2 shows that average TFP falls after 2021, the regression controls for year fixed effects, which effectively mitigates the negative impact of macroeconomic changes on TFP. On this basis, the FinTech coefficient remains significantly positive. This indicates that fintech still has a significant and independent effect on improving TFP.

Regarding the control variables, the coefficient of Age is not significant. It should be noted that, after adding year fixed effects, Age, as a variable that increases with time, has part of its effect absorbed by year fixed effects. Therefore, this insignificant coefficient does not simply imply that

DOI: 10.54254/2754-1169/2026.AB39282

firm survival time has no impact on TFP. In addition, the coefficient of SOE is 0.090, with p<0.01, which is significantly positive at the 1% level. This means that, after removing the FinTech effect, state-owned firms still have significantly higher TFP than non-state-owned firms, possibly because of the resource access and scale effects under China's current capital market.

To explore the difference in fintech's impact, Table 4 reports the regression results after classifying the sample into state-owned and non-state-owned groups. The results show that the FinTech coefficient for non-state-owned firms is 0.003, significantly positive at the 5% level, while the FinTech coefficient for state-owned firms is -0.001. These results echo the findings in Table 2 and Figure 3. This misalignment between environmental advantage and lower productivity shows that non-state-owned firms have not fully released their ability to turn fintech dividends into results. Because non-state-owned firms face stronger financing constraints, fintech has a larger marginal effect by easing information asymmetry and widening financing channels. In addition, in the state-owned group, the Age coefficient is 0.143 and significantly positive. While in the non-state-owned group, it is 0.044 and not significant. This means that state-owned firms rely more on long-accumulated resources, while non-state-owned firms rely more on external factors.

Table 4. Results of grouped regression analysis for state-owned and non-state-owned enterprise

Variable	State-owned enterprises	Non-state-owned enterprise
Fintech	-0.001	0.003**
	（0.004）	（0.001）
Age	0.143**	0.044
	（0.069）	（0.040）
Sample Size	3744	32748
R^2 (within)	0.060	0.096

In Table 5, Age and SOE are removed, and the regressions are rerun. The results show that the main regression coefficient is 0.002, the coefficient after removing Age is 0.002, and the coefficient after removing SOE is 0.002. Although the FinTech coefficient changes only slightly across the three models, the change remains within a small range. At the same time, the significance level and standard error remain highly consistent, all significantly positive at the 5% level. The sign and significance of the core coefficient indicate that the positive effect of fintech on enterprise TFP is somewhat reliable.

Table 5. Robustness test with control variable adjustments

Variable	Main Regression	No Age	No SOE
Fintech	0.002**	0.002**	0.002**
	（0.001）	（0.001）	（0.001）
Age	0.044	-	0.044
	（0.035）	-	（0.034）
SOE	0.090***	0.090***	-
	（0.021）	（0.021）	-
R^2 (within)	0.133	0.174	0.128

DOI: 10.54254/2754-1169/2026.AB39282

5. Suggestion

5.1. Suggestion for government

The government should continue to improve fintech development while adapting to local conditions. The results of this study show that fintech overall raises enterprise TFP. Therefore, the government should continue to promote the application of big data, blockchain, and other technologies in finance. Importantly, however, these results are based on listed companies. When applying them to small and medium-sized firms, the government should first pilot such applications in regions with better conditions. Blind expansion should be avoided, and efforts should focus on guiding financial resources to non-state-owned enterprises. At the same time, regulators should guide financial institutions to change their traditional collateral-based lending mindset and use big data to develop credit products suitable for companies. To prevent potential risks arising from credit sinking, policies should be advanced steadily within a controllable risk framework.

5.2. Suggestion for corporate

Research shows that fintech plays a significant timely-support role for non-state-owned enterprises, but not so much for state-owned ones. Therefore, non-state-owned enterprises should be encouraged to improve their absorptive capacity for fintech benefits. Although non-state-owned enterprises are mostly located in developed fintech areas, their TFP remains low, indicating a problem of insufficient conversion. Consequently, enterprises should reduce their reliance on external financing and actively utilize digital payments and supply chain finance to improve capital management efficiency. They need to transform external funds into real R&D investment and production efficiency.

5.3. Suggestion for individual

Individuals should improve their digital financial literacy, keep up with new fintech technologies, and contribute to the growth of financial talent. The improvement of enterprise TFP cannot be achieved without individual support. Managers and employees need to be well informed about new technologies, which helps them use digital tools more efficiently for management and services. Meanwhile, entrepreneurs and business leaders should engage with new financial tools such as big data, AI, and blockchain. By keeping pace with the times, they can inspire entrepreneurship and make forward-looking decisions for their firms.

6. Conclusion

This study examines the relationship between fintech development and enterprise TFP based on panel data from Chinese A-share listed companies between 2011 and 2023. Using the Peking University Digital Financial Inclusion Index to measure regional fintech development, a two-way fixed-effects model is employed to investigate the relationship between fintech and enterprise productivity. The empirical results reveal a significant positive association between fintech development and enterprise TFP, suggesting that the development of digital financial services is closely related to improvements in corporate production efficiency. Furthermore, the heterogeneity analysis indicates that this positive relationship is more significant among non-state-owned enterprises, while the corresponding coefficient for state-owned enterprises is not statistically significant. These findings highlight the importance of fintech development in improving financial

DOI: 10.54254/2754-1169/2026.AB39282

accessibility and supporting enterprise productivity, particularly for enterprises facing greater financing constraints.

However, several limitations remain in this study. First, the research sample focuses exclusively on Chinese A-share listed companies, which may limit the generalizability of the findings to small and medium-sized enterprises and unlisted firms. Second, although the two-way fixed-effects model controls for firm-specific characteristics and common time effects, potential endogeneity issues and omitted variables may still affect the estimation results. Third, the study mainly examines the overall relationship between fintech development and enterprise TFP, without directly testing specific transmission mechanisms, such as financing constraints, technological innovation, and resource allocation efficiency. In addition, the limited number of control variables may restrict the model's ability to capture other factors influencing enterprise productivity.

Future research could extend the sample to include unlisted enterprises and small and medium-sized firms to provide a more comprehensive understanding of the economic effects of fintech. Moreover, more advanced econometric methods, such as instrumental variable estimation and difference-in-differences approaches where suitable identification conditions are met, could be applied to address potential endogeneity and strengthen causal inference. Further studies could also explore the mechanisms through which fintech development influences enterprise productivity, particularly by examining financing constraints, technological innovation, and resource allocation. Finally, additional heterogeneity analyses across industries, regions, and enterprise characteristics could help identify the conditions under which fintech contributes more effectively to productivity growth.

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