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The Effect and Influence Path of Fintech on Total Factor Productivity of Enterprises

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Abstract:
The critical transition phase from factor-driven to efficient-driven is being experienced by the Chinese economy. Total factor productivity (TFP), as the core measurement index to measure the high-quality economic transformation and development and Fintech has opened up a new path for enterprises to improve production and operation efficiency. Although existing research has gradually focused on the relationship between fintech and enterprise efficiency, obvious deficiencies still exist in both the integrity of the research framework and content.: First, most studies rely on provincial fintech metrics, which cannot accurately capture the actual situation of fintech services available to enterprises at the prefecture level; Secondly, most studies stay at the level of correlation analysis and fail to identify the causal relationship through methods such as policy shocks. Firstly, this paper selects non-financial listed companies in China's A-share market from 2011 to 2018 as the research object and empirically verifies that the development of fintech has A significantly positive impact on corporate total factor productivity. To further identify the causal relationship, the Difference in Difference (DID) model is constructed with the 2016 the 'Development Plan for Promoting Inclusive Finance (2016-2020)' as the policy shock to confirm the causal promoting effect of fintech on corporate TFP. On the one hand, this study provides empirical support for fintech to empower the real economy at the micro enterprise level; On the other hand, the results have important policy implications for optimizing the allocation of regional financial resources.

Keywords: Financial technology; total factor productivity; DID; panel fixed effect model.

1. Introduction

China's economy, which has long relied on traditional production factors such as capital and land, is facing unprecedented development constraints and transformation problems as it enters the stage of

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high-quality development. In this critical period of development model upgrading, total factor productivity (TFP) has emerged as the core evaluation metric for achieving the transition from factor-driven to efficiency-driven growth, making it the primary means to break development constraints and ensure sustainable economic growth. As the micro subjects of the real economy, the TFP level of enterprises directly determines the macroeconomic efficiency [1].

Fintech provides innovative solutions for small and medium-sized market players and all kinds of enterprises to solve business difficulties at a time when market players have diversified demands [2]. From 2011 to 2018, the average annual number of existing fintech enterprises in prefecture-level administrative regions of the Chinese mainland reached 382, but the median was only 18, revealing the uneven regional development. In order to alleviate this imbalance and promote fintech to empower the real economy, in 2016, The State Council issued The Development Plan for Promoting Inclusive Finance (2016-2020), which clearly proposed to "optimize the supply of financial services by relying on fintech, focusing on regions with weak financial resources". The implementation of this policy has laid an ideal foundation for quasi-natural experiment analysis to clarify the causal mechanism between corporate TFP and fintech from an empirical perspective [3].

Although existing research has begun to explore the connection between fintech and enterprise efficiency, there are still two key gaps: first, most studies use fintech indicators at the provincial level, which makes it difficult to accurately capture the service availability of the prefecture-level city where the enterprise is located; Second, most studies stay at the level of correlation analysis and fail to identify the causal relationship through methods such as policy shocks [4-6]. It is difficult to exclude the reverse causal interference that „regions with high TFP of enterprises are more likely to attract fintech companies to settle in". [7]

Based on the aforementioned research gap, the initial sample of this paper selects A-share listed companies in Shanghai and Shenzhen from 2011 to 2018, and through multiple rounds of systematic screening, 15,761 annual observations of companies are finally obtained for benchmark regression. Considering that a large number of fintech platforms exited or transformed abnormally due to the concentration of P2P industry in 2018, the data of 2018 were further excluded, and the final DID observation value was 13,466 [8]. In order to deeply analyze the transmission mechanism of fintech affecting total factor productivity (TFP) of enterprises, this paper takes the original number of fintech companies in prefecture-level cities as the core explanatory variable, conducts systematic empirical analysis with the panel fixed effect model and the DID method, and scientifically defines the causal association with the help of the policy impact of the inclusive financial policy in 2016.

The main contributions of this study are reflected in three aspects: first, in the measurement of variables, the original number of fintech companies in prefecture-level cities is used to replace the traditional provincial indicators, and the details of variables without log transformation are clearly marked to improve the micro suitability of indicators; second, in terms of causality identification, the 2016 ,the Development Plan for Promoting Inclusive Finance , is taken as the policy impact, and the treatment group is defined as the enterprises whose digital economy development level in the city in 2015 is lower than the median. Thirdly, in terms of sample processing, this study distinguishes the sample scope of the benchmark regression and DID regression and eliminates the data of 2018 to avoid the problem of too short post-policy observation period, so that the empirical design is more consistent with the time characteristics of policy transmission.

2. Literature Review and Research Hypotheses

2.1 Section Headings

Total factor productivity is often used as a core indicator to characterize the productive efficiency of an economy, and its improvement is the comprehensive result of technological progress, management optimization and improvement of resource allocation efficiency [9]. Various TFP measurement paradigms have been constructed by scholars, including Olley-Pakes based TFP measurement method (OP method) and Levinsohn-Petrin based TFP measurement method (LP method).

As the integration product of digital technology and financial services, fintech has reconstructed the core links of financial services through technological innovation, providing a new way to solve this dilemma [2]. Big data technology can integrate multi-dimensional information such as enterprise financial data, supply chain flow and tax records to build a more accurate risk assessment model [10]. Artificial intelligence drives intelligent investment, automatic approval and other tools shorten the credit process, shorten the financing cycle of enterprises, and significantly improve the efficiency of capital use [1]. Quantitative analysis tools generated by fintech can be deeply embedded in all aspects of enterprise production and operation, and at the same time, their own risk management characteristics can significantly reduce inefficient investment behaviors of enterprises.

Based on the above analysis, fintech can affect TFP through multiple mechanisms: on the one hand, the expansion of fintech companies in prefecture-level cities reflects the continued improvement of the adequacy of financial service supply; Fintech tools can directly optimize inventory management, production processes and risk management, and reduce operating costs.

Relying on the above logic, this paper puts forward the core assumptions as follows.

H1: The development of fintech, measured by the number of fintech companies in a prefecture-level city, has a significant positive impact on enterprise total factor productivity.

In addition,the‘Development Plan for Promoting Inclusive Finance (2016-2020)’formally implemented, can significantly strengthen the above effects: For the regions with a low level of digital economy, after the introduction of the policy, they have a higher probability of improving the service supply through the growth of the number of fintech-related enterprises, which ultimately accelerates the growth process of total factor productivity, which also lays a logical premise for the subsequent DID test.

3. Literature References

3.1 Sample Selection and Data Sources

In this paper, the initial sample included 2011-2018 Shanghai and shenzhen two city a-share non-financial listed companies. On the one hand, it is to adapt to the DID model with the policy impact of 2016, and on the other hand, it is to match the development stage of fintech. After 2011, China‘s fintech entered the stage of large-scale development, and its substantial impact on enterprise TFP can be observed, while the industry was still in the embryonic stage before 2011. There is a lack of heterogeneity in the data. In addition, the following criteria are combined to screen and optimize the data: excluding listed companies with financial abnormalities in ST and *ST states and excluding listed companies in the real estate and financial industries; Excluding insolvent enterprises whose asset-liability ratio exceeds 100%; Samples with missing core variables are eliminated. After screening, the benchmark regression finally obtains 15761 company-year observations; The DID regression further excludes the data of 2018, and the final number of observations is 13,466.

3.2 Model Setting

Firstly, a significant positive relationship between fintech development and firm TFP is verified using a benchmark regression analysis model:

$$TFP_{i,t} = \partial_0 + \alpha_1 FintechN_{m,t} + \alpha_2 X_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t} \quad (1)$$

Specifically defined as: TFP_i,t represents the total factor productivity of enterprise i in period t, and the measurement methods are LP (LP) and OP (OP); FintechN_k,t refers to the fintech development level of the prefecture-level city k in period t; X_i,t is the vector of control variables.λ_t represents the annual fixed effect;ε_i,t denotes the random error term.

Relying on the exogenous policy shock of’ the‘Development Plan for Promoting Inclusive Finance (2016-2020)’. This paper sets a DID model to accurately define the causal association between fintech and TFP of enterprises:

$$TFP_{i,t} = \beta_0 + \beta_1 Treat_i \times Post_t + \beta_2 X_{i,t} + \mu_i + \lambda_t + \epsilon_{i,t} \quad (2)$$

In detail, Treat_i is set as a treatment group dummy variable: 1 if the digital economy level of the prefecture-level city where an enterprise was registered in 2015 is below the median, and 0 if not;Post_t is the dummy variable of the policy time, and 1 after 2016 and 0 before 2016;Treat_i x Post_t is treatment group and the interaction of policy point item, the coefficient of beta $_1$ said policy impact on treatment group enterprise net impact of the total factor productivity.

Based on the enterprise’s total factor productivity as explained variable, the corresponding LP is calculated with the OP is calculated in two ways, the enterprise city (prefecture) of the original financial science and technology enterprise quantity used as a measure of financial development level of science and technology.

At the same time, the DID variable is constructed based on the 2016 ‘the Development Plan for Promoting Inclusive Finance ‘: for the policy treatment group (Treat), if the digital finance index of Peking University in 2015 in the prefecture-level city where the enterprise is located is ≤ the median, the variable is assigned the value of 1., otherwise it is 0; In the post-policy period (Post), 2016 is taken as the break point, which is 1 for 2016 and after and 0 for before, matching the policy nodes; Policy effect (Treat_Post) Treat_i with Post_t paid by item, intuitive depiction group policy to deal with the net effect of the enterprise.

At the micro level of the company, the core characteristic variables that may affect enterprise productivity are systematically controlled. Specifically, it includes enterprise Size, enterprise Age, return on assets, operating cash flow (OCF), financial leverage ratio, business growth (BG) and board independence (BI).

Control variables at the regional macro level include EconoDev and FinDev: EconoDev represents the overall economic development level of the region, and FinDev reflects the development level of the regional financial market. In addition, to ensure the purity of the regression results, this paper further controls the number of off-site fintech companies within a 200-kilometer radius centered on the prefecture-level city where the enterprise is located (FinN200).

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4. Empirical Results

4.1 Model Setting

As shown in Table 1, LP value of 16.4862, standard deviation is 1.0948, the OP a value of 14.5882, standard deviation is 0.9870 Both reflect significant productivity differences among sample enterprises, providing a heterogeneous basis for testing the impact of fintech. The average value of FintechN reached 382.0443, with a median value of 180,000 and a standard deviation of 1,328.3560. All statistical indicators were within a reasonable range. This is in line with the normal operation of listed companies and will not cause extreme interference with the core return.

Table 1. Descriptive statistics of main variables

VarName	Obs	Mean	SD	P5	Median	P95
LP	15761	16.4862	1.0948	14.8239	16.3850	18.5567
OP	15761	14.5882	0.9870	13.0913	14.5120	16.4442
FintechN	15761	382.0443	1328.3560	0.0000	18.0000	2376.0000
Size	15761	22.1137	1.2903	20.3424	21.9319	24.5865
Roa	15761	0.0426	0.0466	-0.0217	0.0375	0.1239
Age	15761	10.7155	6.6933	2.0000	10.0000	22.0000
BG	15761	0.2242	0.5135	-0.2344	0.1274	0.9089
OCF	15761	0.0428	0.0697	-0.0751	0.0421	0.1589
BI	15761	0.3729	0.0530	0.3333	0.3333	0.4545
LEV	15761	0.4297	0.2110	0.1008	0.4243	0.7826
FinDev	15761	0.0749	0.0378	0.0340	0.0647	0.1662
EconoDev	15761	0.0940	0.0261	0.0660	0.0880	0.1450
FinN200	15761	4.6703	1.8445	1.7918	4.8122	7.8091

4.2 Benchmark Regression Results

The benchmark regression results are shown in Table 2. The positive impact of fintech on the total factor productivity of enterprises is statistically significant: When be explained variable for LP, FintechN coefficient is 0.0464 * * * (P< 0.01); The robustness test results with OP as the explained variable further verify the stability of this positive relationship. Size, ROA and OCF all have significant positive driving effects on firm total factor productivity, which is in line with relevant theoretical expectations.

Table 2. Benchmark regression results

	LP	OP
FintechN	0.0464***	0.0458***
	(2.8604)	(2.8047)
Size	0.3985***	0.3601***
	(21.7432)	(19.6941)
Roa	1.1785***	1.2088***
	(7.8915)	(8.1116)
Age	-0.0810	-0.1125*
	(-1.0334)	(-1.6644)
BG	0.1280***	0.1336***
	(11.8558)	(13.3946)
OCF	0.2117***	0.1918**
	(2.8385)	(2.5333)

BI	0.1778*	0.1927*
	(1.6793)	(1.7804)
LEV	0.4215***	0.4029***
	(8.5528)	(7.7856)
FinDev	-0.6378	-0.4112
	(-1.3529)	(-0.8444)
EconoDev	0.5024	0.5005
	(1.6454)	(1.6391)
FinN200	-0.0301	-0.0331
	(-1.4224)	(-1.5575)
_cons	8.5459***	7.8199***
	(7.7199)	(7.9372)
Year Effect	Yes	Yes
N	15761	15761
R^2	0.4604	0.3160

4.3 DID Analysis

Double difference regression results as shown in table 3, interaction of the regression coefficient is 0.0511, Treat by Post by the 5% level of significance test (P< 0.05). This suggests that the policy after implementation, the low level of financial development of science and technology area of enterprise (treatment group) significantly higher total factor productivity. The results not only confirmed the strong financial technology and enterprise total factor productivity of cause and effect, also successfully excludes the omitted variables, reverse causation and so naturally interference, make the estimate result more credibility.

Table 3. DID results of PBOC fintech pilot

	TFP_LP	TFP_OP	TFP_LP	TFP_OP
Treat_Post	0.0511**	0.0533***		
	(2.5901)	(2.7044)		
Treat_year2012			0.0005	0.0055
			(0.0236)	(0.2595)
year2013			-0.0136	0.1246
			(-0.0452)	(0.4809)
Treat_year2013			-0.0194	-0.0136
			(-0.9043)	(-0.6098)
year2014			-0.0419	0.0716
			(-0.1859)	(0.3674)
Treat_year2014			0.0251	0.0307
			(0.9550)	(1.1004)
year2015			-0.0254	0.0761
			(-0.1679)	(0.5823)
Treat_year2015			0.0348	0.0340
			(1.0964)	(1.0274)
year2016			0.0034	0.0624
			(0.0437)	(0.9199)
Treat_year2016			0.0432	0.0479

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			(1.1895)	(1.2883)
year2017			0.0000	0.0000
			(.)	(.)
Treat_year2017			0.0845**	0.0900**
			(2.5451)	(2.5789)
_cons	7.8451***	6.8350***	7.8254***	6.8102***
	(7.3736)	(7.2935)	(7.2760)	(7.2070)
Year Effect	Yes	Yes	Yes	Yes
N	13466	13466	13466	13466
R^2	0.4187	0.2814	0.4193	0.2821

5. Conclusion

This paper selects A-share non-financial listed companies in Shanghai and Shenzhen Stock exchanges from 2011 to 2018 as research samples and takes the number of fintech companies (FintechN) in prefecture-level cities as the proxy variable of fintech development level. In order to accurately measure the real situation of TFP, this paper uses two commonly used measurement methods, Levinsohn-Petrin (LP) and Olley-Pakes (OP), to determine its value, and uses the panel benchmark regression and DID model to conduct an empirical study on the effect of fintech on corporate TFP in stages.

Among them, the panel benchmark regression results show that the core explanatory variable is the development level of fintech (FintechN), and its estimated coefficients in the regression equations corresponding to TFP measured by LP method and OP method are 0.0464*** (p< 0.01) and 0.0458*** (p< 0.01), And all pass the significance test at the statistical level of 1%.This result is highly consistent with the theoretical logic of „technology empowerment can break the information barrier of traditional financial industry“, indicating that fintech can play a significant positive role in promoting the total factor productivity of enterprises.To more comprehensively avoid the influence of endogeneity issues and clarify the causal relationship between the two, this paper takes the official implementation of the „Plan for Promoting Inclusive Finance Development“ in 2016 as an exogenous policy shock and constructs a Difference-in-Differences (DID) model.The regression results show that the estimated coefficient of Treat×Post is 0.0511, which is statistically significant at 5% (P< 0.05).This result provides more convincing empirical evidence for the causal link between fintech and enterprise TFP. The benchmark regression verifies the positive correlation between fintech and TFP of enterprises, and the DID model further excludes endogeneity and confirms the causal relationship between the two.

In terms of practical implications, for policy makers, aiming at the unbalanced regional development of fintech, they can increase the investment in digital infrastructure in low-level regions, reduce the cost of technology implementation through differentiated supervision pilot, and guide credit resources to serve entities more accurately. For enterprises, they should take the initiative to connect with local fintech services, use them to optimize the matching efficiency of production resources and capital, and help TFP improve, which is in line with the core goal of economic efficient-driven transformation.

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