Financial Economics Research; Vol.3, No.2; 2026
E-ISSN: 3006-3663 P-ISSN: 3006-3655
DOI: https://doi.org/10.70267/fer.250302.5259
Published by: Zeus Press

The Impact of 5G Factory Construction on Corporate Financial Efficiency— An Empirical Analysis Based on Manufacturing Listed Companies on the Shanghai and Shenzhen A-Share Markets

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Abstract

In the era of digital economy, 5G factories, as the core carrier of intelligent manufacturing, represent an important manifestation of the transformation and upgrading of the manufacturing industry. This paper takes the manufacturing listed companies in Shanghai and Shenzhen stock markets from 2020 to 2024 as the sample. Using the "5G Factory List" released by the Ministry of Industry and Information Technology as the experimental group, a multi-period difference-in-differences model is employed to empirically examine the impact of 5G factory construction on the financial efficiency of enterprises. The research found that the construction of 5G factories significantly enhanced the total factor productivity of manufacturing enterprises. This conclusion remained robust after undergoing Parallel Trend Tests, Propensity Score Matching–Difference-in-Differences Model, and Placebo Tests. The Mechanism Test shows that although individual production, inventory or innovation indicators did not show significant changes in the short term, the 5G factory improved overall efficiency through systematic resource allocation optimization. This study provides microeconomic evidence for understanding the empowerment of the real economy by digital technologies.

Keywords

5G factory, total factor productivity, difference-in-differences method, digital transformation

1. Introduction

The academic community has conducted numerous theoretical and empirical studies on the relationship between digital transformation and enterprise efficiency. The "task model" proposed by Acemoglu and Restrepo in the early days laid the theoretical foundation for the assertion that automation technologies enhance productivity [1]. After the evolution of digital technology, digital transformation has been regarded as the core driving force for high-quality economic development. Shostak et al. pointed out that it not only changes the organizational operations, but also enhances overall efficiency through technological innovation [2].

At the micro-enterprise level, the financial efficiency empowerment effect of digital transformation has been well verified: Moolkham et al. have confirmed that it can increase enterprise value by enhancing financial efficiency and effectiveness. Mavlutova et al. believe that it can boost operational efficiency. Ajmal et al. have discovered that emerging digital technologies can improve enterprise profitability and optimize inventory efficiency [3-5]. Hossain pointed out that the Internet of Things can enhance the efficiency of enterprise investment [6].

2. Literature Review and Research Hypotheses

In terms of the influencing mechanism, the generation of innovation and the allocation of resources are the key paths: Yang Peng et al. found that digital technology can enhance knowledge acquisition and collaborative innovation capabilities, and improve the innovation efficiency of enterprises. Li Xuan believes that it can alleviate financing constraints and promote innovative output. Liu et al. confirmed that the digital transformation of finance can solve information asymmetry, reduce costs, and improve financial performance [7-9].

Regarding China's manufacturing industry, the studies conducted by Cao Xiaojing et al., Wu Xianfu et al., and Zhao Chen all demonstrate that digital transformation can significantly boost the total factor productivity of manufacturing enterprises [10-12]. The synergy of digital finance cannot be ignored either, as it provides macro-environmental support for related construction [13, 14]. However, digital transformation also has potential negative impacts. Bai Peiwen and Yu Li found that it might intensify market competition and reduce the price markup of enterprises [15]. It can be seen that the impact of 5G factory construction on the financial efficiency of enterprises is a complex system optimization process, and it is not a simple linear relationship.

In the era of digital economy, it is widely recognized that automation and intelligent technologies have reshaped the production function. Acemoglu and Restrepo's “task model” has laid the theoretical foundation for the enhancement of production efficiency through automation technologies [1]. 5G factories, as an advanced form of industrial internet, restructure the manufacturing process based on the characteristics of 5G technology. In theory, this can reduce marginal costs and optimize resource allocation. Based on this, an assumption is proposed.

H1: The construction of 5G factories significantly enhances the financial efficiency of manufacturing listed companies.

Based on the relevant research on how digital transformation enhances enterprise efficiency, this paper identifies three core paths through which 5G factories affect financial efficiency. On the path of improving production efficiency, digital transformation serves as a booster for operational efficiency improvement, and the application of industrial internet can further drive the growth of total factor productivity in the manufacturing industry [4, 10, 11]. The 5G factory achieves intelligent transformation of the entire production process, realizes equipment interconnection and process optimization, and enhances output while reducing losses. On the path of supply chain optimization, emerging digital technologies can optimize inventory efficiency, and the Internet of Things can enhance supply chain collaboration and investment efficiency [5, 6]. 5G factories break through the data barriers of each link in the supply chain, enabling real-time perception of demand and dynamic optimization of inventory. In the path of R&D innovation promotion, digital transformation enhances enterprise efficiency through technological innovation. Digital technology can also improve innovation efficiency, alleviate financing constraints, and promote innovation [2, 7, 8]. The 5G factory is not only an enterprise's digital and intelligent innovation practice but also provides technical and data support for R&D. Based on this, Hypothesis 2 is proposed.

H2: The 5G factory achieves a synergistic improvement in the financial efficiency of manufacturing enterprises through three paths: enhancing production efficiency, optimizing the supply chain, and promoting R&D innovation.

3. Research Design

This article selects the manufacturing companies listed on the Shanghai and Shenzhen stock exchanges from 2020 to 2024 as the initial sample. The 5G factory data is derived from the “2023 5G Factory List” and “2024 5G Factory List” released by the Ministry of Industry and Information Technology. The financial data is sourced from the CSMAR and Wind databases. After eliminating samples of the ST type, financial type and those with missing values, and conducting 1% and 99% tail trimming on the continuous variables, a total of 13,663 observations were finally obtained.

The core dependent variable of this article is total factor productivity (fe_tfp), and the explanatory variables are the difference-in-differences terms (did). The specific variable definitions are shown in Table 1.

Table 1: Variable Definition Table

Variable type	**Variable name**	**Symbol**	**Explanation**
The dependent variable	Total Factor Productivity	fe_tfp	The TFP calculated using the LP method reflects the efficiency of input-output.
Explanatory variable	5G Factory Effect	did	Treatment×Period
Control variables	Enterprise size	size	The natural logarithm of the total assets at the end of the period
	Asset-liability ratio	lev	Total liabilities at the end of the period / Total assets at the end of the period
	Shareholding Concentration	top1	The shareholding ratio of the largest shareholder
	Research and development investment	rd	Research and development expenditure / operating revenue
	Growth potential	growth	Growth rate of operating income
	Independence	Indep	Number of independent directors / Total number of the board of directors
	Enterprise age	age	Observation year - Year of enterprise establishment + 1
Mechanism variable	Production efficiency	product	Per capita operating income
	Supply chain efficiency	inventory	Inventory turnover rate
	Innovation capability	patent	The logarithm of the number of annual patent applications increased by 1

Data source: Compiled based on CSMAR and Wind databases.

This paper constructs the following multi-period difference-in-differences model:

$$FE_{i,t} = \alpha_0 + \alpha_1 \cdot DID_{i,t} + \sum \alpha_k \cdot Controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

Among them, fe_tfp represents the dependent variable, α_1 is the core concern coefficient, and μ_i and λ_t are the individual and year fixed effects respectively.

4. Analysis of Empirical Results

4.1 Descriptive Statistics

Table 2 presents the descriptive statistics of the main variables. The mean of total factor productivity is 8.959, with a standard deviation of 1.012, indicating significant differences in efficiency among manufacturing enterprises. The mean of the core explanatory variables is 0.0126, suggesting that approximately 1.26% of the observations in the sample are in the state after the implementation of the 5G factory policy. This is consistent with the reality that 5G factories in China are still in the pilot and promotion stage.

Table 2: Descriptive Statistics of Key Variables

Variable	Sample size	Mean value	Standard deviation	Minimum value	Maximum value
fe_tfp	13,663	8.959	1.012	6.955	11.850
did	13,663	0.0126	0.111	0.000	1.000
size	13,663	22.24	1.153	20.19	25.84
lev	13,663	0.393	0.188	0.061	0.866
age	13,663	23.48	5.784	10.00	40.00
rd	13,663	6.171	5.578	0.160	34.34
growth	13,663	0.169	0.453	-0.624	2.515
top1	13,663	31.60	13.85	8.359	69.92
indep	13,663	0.393	0.077	0.250	0.600

Note: The data has been rounded to the 1st and 99th decimal places.

4.2 Baseline Regression Results

Table 3 presents the benchmark regression results. Column (1) shows that, after controlling for the individual fixed effects of enterprises, the fixed effects of years, and relevant control variables, the coefficient of the core explanatory variable "did" is 0.040, and it is statistically significant at the 1% level (t = 2.61). This means that, compared to the control group, the construction of 5G factories has significantly increased the total factor productivity of manufacturing enterprises by approximately 4%, verifying hypothesis H1, which states that the construction of 5G factories significantly enhances the financial efficiency of manufacturing listed companies. In terms of controlling variables, the size of the enterprise significantly promotes TFP, while the debt ratio and the intensity of R&D investment have a negative impact. This might be related to the fact that the current investments have not been promptly converted into outputs.

Table 3: Baseline Regression Results

Variable	(1)fe_tfp
did	0.040***
	(2.61)
size	0.588***
	(31.18)
lev	-0.120**
	(-2.40)
rd	-0.050***
	(-19.89)
growth	-0.015**
	(-1.97)
top1	0.001
	(1.06)
indep	-0.015
	(-0.50)
_cons	-3.788***
	(-8.96)
Sample size	13,427
R-squared	0.976
Individual fixed effect	YES
Fixed effect of year	YES

*Note: The values in parentheses are t-values. ***p<0.01, **p<0.05, *p<0.1.*

4.3 Robustness test

4.3.1 Parallel trend test, PSM-DID test and placebo test

In order to verify the underlying assumptions of the DID model, this paper examines the dynamic effects before and after the implementation of the policy. The results shown in Table 4 indicate that before the implementation of the policy (Pre_3), the coefficient was significantly negative (-0.052), suggesting that the experimental group had lower efficiency before the establishment of the factory and there was a certain "catch-up effect". However, in the year of policy implementation (Current) and subsequent years (Post_1), the coefficient turned positive. Although due to the short sample period, the statistical significance was not fully conclusive, the overall trend indicates that the construction of 5G factories has reversed the efficiency disadvantage, conforming to the dynamic characteristics of the parallel trend assumption, and further verifying the rationality of the DID model set in this paper.

Table 4: Results of Parallel Trend Test

Variable	Coefficient	t-value	P>|t|
pre_3	-0.052**	-2.05	0.040
pre_2	-0.036*	-1.94	0.052
current	0.014	0.98	0.328
post_1	0.003	0.10	0.921
post_2	(omitted)	-	-

Considering that the declaration of the 5G factory list is not completely random, there might be a "self-selection bias", meaning that enterprises with larger scale and better management are more likely to be selected as 5G factories. To address this endogenous issue, this paper employs a combination of propensity score matching and difference-in-differences methods for the test.

This study examines whether an enterprise is a 5G factory (treatment) as the dependent variable, and selects control variables such as enterprise size and debt ratio (lev) as covariates for Logit regression. The 1:1 nearest neighbor matching method is used to find featureally similar control groups for the experimental group.

The matching result table 5 shows that after matching, the vast majority of samples are within the common support domain, while only a very small number of samples fall outside this range. This indicates that the matching effect is good, and the feature differences between the experimental group and the control group have been effectively eliminated. The average treatment effect (ATT) for the treatment group was 0.036. This value is very close to the coefficient of 0.040 in the baseline regression, indicating that after eliminating the sample selection bias, the positive impact of 5G factory construction on enterprise efficiency remains robust. The results of the benchmark regression are not solely driven by the inherent qualities of the sample, but rather are indeed attributed to the policy effects of the construction of 5G factories.

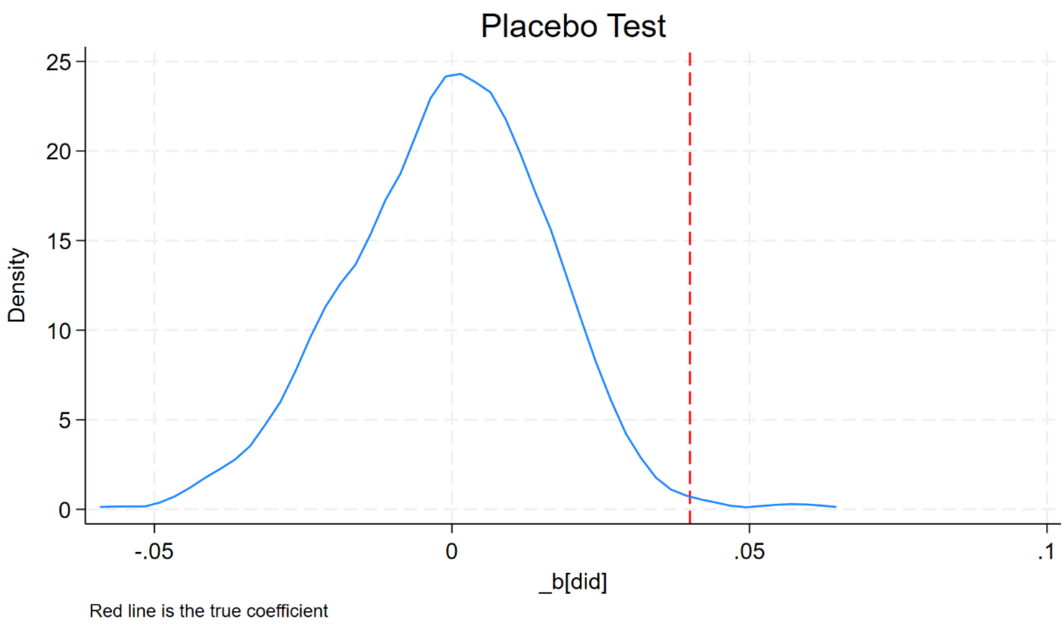
Table 5: PSM-DID Matching Results

Variable	Unmatched	ATT	Difference	S.E.	T-stat
fe_tfp	9.967	9.960	0.036	0.075	0.48

In order to further eliminate the interference of unobservable omitted variables on the research conclusions and ensure that the baseline regression results are not caused by random factors, this paper employs the Random Permutation Test for placebo verification.

Specifically, this paper maintains the control variables and fixed effects unchanged, randomly reassigns the allocation of the core explanatory variable "did" among the sample enterprises, constructs a false experimental group and a policy time interaction term, and then conducts regression estimation again. This process was repeated for 500 times to obtain 500 sets of false regression coefficient estimates. The results of the placebo test are shown in Figure 1.

Figure 1: Kernel density distribution map of the placebo test



As can be seen from Figure 1, the false regression coefficients generated through 500 random simulations (the blue curve) exhibit a standard normal distribution centered at 0. This indicates that, after randomly altering the processing status, the average impact effect of 5G factory construction on the financial efficiency of enterprises approaches zero.

The red dotted line in the figure represents the true estimated coefficient (0.040) of the baseline regression in this article. It can be clearly observed that this true coefficient is located at the far right tail of the kernel density distribution graph, completely separate from the randomly generated coefficient distribution area. According to the statistical results of the Monte Carlo permutation test, in 500 random samplings, only 2 simulations had coefficients greater than the actual observed values. The two-sided test's P-value was 0.008. This indicates that the probability of obtaining the current significant positive result under random conditions is less than 1%.

In conclusion, the core conclusion of this paper - "The construction of 5G factories enhances the financial efficiency of enterprises" - is not the result of accidental factors or unobservable omitted variables. The research conclusion is highly robust.

4.3.2 Change the Dependent Variable

Replace TFP with asset net profit ratio (ROA), total asset turnover ratio (TAT), and cost and expense profit margin (CPM). The results shown in Table 6 indicate that the 5G factory had no significant impact on these individual financial indicators. This result contrasts with the significant increase in TFP observed in the baseline regression, revealing the structural characteristics of the enabling effect of 5G factories. The significant increase in total factor productivity indicates that 5G technology has indeed optimized the production process, reduced redundant losses, and enhanced "technical efficiency". However, no significant improvement was observed in the single-factor financial indicators (particularly ROA and TAT). The possible reasons for this are as follows: The construction of 5G factories is a capital-intensive investment. During the initial stage of construction, enterprises need to purchase expensive intelligent equipment and base stations (resulting in an increase in the denominator of total assets), and the conversion of technological dividends into book net profits has a certain lag. Therefore, in the short term, 5G factories mainly represent a "qualitative" leap in the technical efficiency of the production and manufacturing process, rather than an immediate and significant increase in the accounting financial return rate. This further indicates that using TFP (Total Factor Productivity) as the core indicator can more accurately capture the real efficiency contribution of digital transformation.

Table 6: Regression Results of Replaced Dependent Variable

Variable	(1)fe_roa	(2)fe_tat	(3)fe_cpm
did	0.001	-0.003	0.009
	(0.34)	(-0.31)	(0.80)
Controls	YES	YES	YES
FE	YES	YES	YES
N	13,427	13,427	13,427
R-squared	0.744	0.905	0.792

4.4 Mechanism Verification

To verify the research hypothesis H2, this paper examined three paths of influence: production efficiency (product), supply chain efficiency (inventory), and innovation capability (patent). The results in Table 7 showed that the DID coefficients corresponding to the three mechanism variables were all not significant. Therefore, the research hypothesis H2 was not supported by the empirical results. The reason for this outcome lies in the fact that the construction of 5G factories is a systematic digital transformation that covers the entire production and operation chain of the enterprise. From the commissioning of intelligent equipment, the adaptation of personnel skills to the full-scale reconfiguration and implementation usually requires a 1-3 year integration period. The list of 5G factories in this sample was released in 2023, and the observation period only extends to 2024. The observation window after policy implementation is relatively short. In the short term, the efficiency improvement effect of a single link is difficult to manifest. At the same time, indicators such as patent applications and inventory turnover rate have strong lagging characteristics and cannot fully capture the enabling effect of 5G technology in the short term. This result also complements and corroborates the baseline regression, indicating that the improvement in enterprise efficiency by 5G factories is not achieved through an immediate burst in a single link, but is ultimately reflected as an improvement in total factor productivity through the optimization of systematic resource allocation throughout the entire chain. Currently, enterprises are still in the transitional period of digital transformation, and the improvement of a single indicator has a significant time lag.

Table 7: Results of Mechanism Test Regression Analysis

Variable	(1) product	(2) inventory	(3) patent
did	-42111.2	-0.115	0.007
	(-0.25)	(-0.75)	(0.06)
Controls	YES	YES	YES
FE	YES	YES	YES
N	13,427	13,427	13,427

Note: product refers to per capita revenue, inventory refers to inventory turnover rate, and patent refers to the number of patent applications.

5. Conclusion

This paper takes the manufacturing companies listed on the Shanghai and Shenzhen stock exchanges from 2020 to 2024 as the sample. Based on the “2023 5G Factory List” of the Ministry of Industry and Information Technology, a quasi-natural experiment was constructed. Using the multi-period difference-in-differences model for empirical testing, it was found that the construction of 5G factories can significantly enhance the total factor productivity of manufacturing enterprises. This conclusion still holds after undergoing a series of robustness tests; At the same time, this efficiency improvement exhibits significant structural and systematic characteristics. In the short term, it mainly manifests as the improvement of technical efficiency at the production end. It has not yet fully translated into an increase in book financial performance, and it is not achieved through immediate breakthroughs in single links such as production, supply chain, and innovation. Instead, it stems from the systematic optimization of resource allocation throughout the entire chain. It is recommended that enterprises maintain their strategic determination for digital transformation and attach importance to the long-term systematic benefits of 5G factory construction.

This study still has certain limitations: Firstly, the observation window of the sample is relatively short, covering only the data from 1 to 2 years after the implementation of the policy, which makes it difficult to fully capture the long-term dynamic effects of the construction of 5G factories; Secondly, the core explanatory variables only use the dummy variable indicating whether a company is included in the list, failing to distinguish the construction scale and application depth of 5G factories; Thirdly, the sample only covers A-share manufacturing listed companies and does not include small and micro enterprises, so the generalizability of the conclusions needs to be expanded; Fourthly, the mechanism research only examines three basic paths and fails to further decompose the specific channels for systematic resource allocation optimization.

In response to the aforementioned limitations, future research can proceed in the following ways: First, extend the sample observation period to clarify the long-term change patterns and profit conversion cycles of the 5G factory empowerment effect; second, refine the multi-dimensional measurement indicators for 5G factory construction, and conduct heterogeneity analyses for different enterprises and industries; third, expand the sample coverage to include small and micro enterprises to complete the research on all entities; fourth, deepen the examination of the mechanism of action, and simultaneously expand the research perspective to further explore the impact of 5G factory construction on enterprise risks, green transformation, and industrial chain competitiveness, and more comprehensively evaluate the comprehensive value of 5G factory construction.

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Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.

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