

Studies on How the Growth of the Digital Economy Affects Businesses' Overall Factor Productivity

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Abstract

With the rapid development of digital technology and its extensive integration in various fields, the digital economy is increasingly becoming a core driving force for economic and social development. The difference-in-differences model (DID) is used to empirically examine the promotion effect and internal mechanism of the development of the digital economy on the total factor productivity of firms, based on sample data of all A-share listed companies from 2010 to 2022. According to the study, the growth of the digital economy can greatly increase an organization's total factor productivity, and there is a large mediating influence between the two that is mediated by the extent of business data factor utilization. The test of heterogeneity of firms' external environment shows that digital economy policies are more likely to promote the total factor productivity of enterprises in regions with a lower degree of market competition, while the test of heterogeneity of firms' internal characteristics shows that the total factor productivity of non-state-owned firms and firms with a high degree of dynamic capabilities are more affected by the government's digital economy policies. The study enriches the theory of the relationship between the total factor productivity of enterprises empowered by the digital economy, which can provide reference and reference for the formulation of China's digital economy policies and the practice of high-quality development of enterprises.

Keywords

Digital Economy Policy, Data Factor Utilization, Total Factor Productivity of Enterprises, Difference-in-Differences Model, China

1. Introduction

The quality of economic development primarily reflects the economic characteristics

of socialism with Chinese characteristics entering the new era, and high-quality development is a key strategic path for China's economic development. Enterprises, as the micro subjects of macroeconomic development and the cornerstone of meso-industrial development, enhancing their total factor productivity is becoming a key path to realizing high-quality economic development (Huang et al., 2018). Meanwhile, with the rapid development of digital technology and its extensive integration in various fields, the digital economy has increasingly become the core driving force for economic and social development, leading the direction of economic growth in the new era. The Chinese Government attaches great importance to the development of the digital economy and regards it as an important engine for promoting economic transformation and upgrading and realizing high-quality development. The China Digital Economy Development Research Report (2023) projects that by 2022, the country's digital economy will have grown to a size of RMB 50.2 trillion, or 41.5% of GDP, while sustaining a rapid growth rate of 10.3%. The report of the 20th CPC National Congress and the 14th Five-Year Plan for the Digital Economy Development both emphasize the need to actively promote the deep penetration of digital technology in a wide range of economic, social and industrial development fields, and to build a development pattern in which technological advancement promotes the enhancement of total factor productivity, and cross-sectoral applications lead to the continuous advancement of technology, strong policy support and strategic leadership for the development of the digital economy. Therefore, how to effectively realize the high-quality integration and development of the digital economy and real enterprises, promote the high-quality development of all aspects of the economy and society through digital technology (Li & Huang, 2022). The government and all spheres of society have been debating how to fully utilize the digital economy to propel China's superior development as a matter of urgency in recent times. Research on the relationship between the digital economy and high-quality development currently mostly focuses on the macro level, including how the digital economy affects and the mechanisms behind high-quality city development (Zhao et al., 2020; Lu et al., 2021), the impact of digital economy on high-quality development of the region (Lu et al., 2023), and how digital finance can promote the high-quality sustainable development of the regional economy (Meng & Zhang, 2022). Scholars have not yet fully discussed the question of "whether digital economy development affects high-quality development of enterprises". Moreover, existing studies have mostly approached the issue from a single perspective, such as studying the role of the digital economy on the ESG performance of enterprises (Bi et al., 2024), innovation performance (Jiang & Pan, 2022), innovation efficiency (Han et al., 2019), and the efficiency of resource allocation in enterprises (Wei, 2022), and the key to maintaining medium and high-speed economic growth and enhancing the quality of economic development is the enhancement of total factor productivity (Chen, 2023). In fact, in the booming development of the digital economy, the multiplier effect of data on improving production efficiency is constantly highlighted,

and it is becoming the most characteristic production factor of the times. Effective use of data elements will bring strong impetus to the high-quality development of the economy and provide solid support.

In particular, 2015 was a key year for the development of digital economy, and for the first time, China upgraded the development of digital economy to a national strategy, marking a new stage in the development of China's digital economy, and a deep understanding at the national level of the historical opportunities of digitalization in revitalizing the economy and promoting social development, and the development of China's digital economy has officially opened a new chapter since then. Based on the specific situation and background of China and the emphasis on "further releasing the value of data production factors" in the White Paper on the Development of China's Digital Economy (2023), combined with the digital economy policy, the experimental group and control group are divided into two groups based on the Guidelines for the Industrial Classification of Listed Companies (revised in 2012) and the Statistical Classification (2021) of the Digital Economy and its Core Industries, the experimental group and control group are divided, and the time point is 2015. The level of high-quality development of national A-share listed companies from 2010 to 2022 is measured, and the theoretical analysis framework is constructed from the perspective of data factor utilization level to empirically test the impact of digital economy development on total factor productivity of enterprise and its mechanism of action. The possible marginal contributions of this paper are as follows: first, a more comprehensive measurement of digital economy policies and total factor productivity of enterprise from the enterprise level, and a more detailed discussion of the impact relationship between the two. Second, it reveals the intrinsic mechanism of digital economy policies affecting total factor productivity of enterprise from the perspective of data factor utilization, deepening the existing literature. Third, considering the possible differences in the impact of digital economy development on total factor productivity of enterprise performance under different external environment characteristics and firm attributes, further heterogeneity analyses in terms of the degree of industry competition, firm ownership attributes, and dynamic capability attributes are conducted, aiming to complement how digital economy development differentially affects total factor productivity of enterprise in diversified firm backgrounds and industry environments.

2. Theoretical Framework and Research Hypothesis

2.1. The Direct Impact Effect of Digital Economy Development on Firms' Total Factor Productivity

Specifically, the role of the digital economy on the total factor productivity of enterprises is reflected in: The digital economy through big data analytics, cloud computing, intelligent algorithms and other technical means can significantly strengthen the business capacity of financial institutions in the acquisition of information, operational management and risk control, improve the transparency

of information between the two sides of the credit (Wei & Sun, 2021), to avoid the financial institutions due to the asymmetry of information is difficult to obtain a full range of information about enterprises and effective monitoring of the use of funds and repayment behavior of enterprises. Repayment behavior, and credit resource mismatch phenomenon between financial institutions and enterprises (Wei & Ma, 2022), which in turn reduces the cost of enterprise financing, provides enterprises with more transparent and efficient financing channels, and further realizes the total factor productivity of enterprises. In the new stage of “deep integration of digital technology with industry”, relying on the information service system of “cloud integration, network interconnection and terminal intelligence”, the vitality of data and information elements has been continuously activated, and the innovation resources and potentials previously confined to the internal sector have been effectively released (He & Liu, 2019), enterprises are able to accurately understand the subtle changes in market demand and cutting-edge trends in technological development, formulate forward-looking research and development plans, accelerate the leap in enterprise innovation capability, and help enterprises realize high-quality development.

Within the context of the burgeoning digital economy, constructing big data platform can effectively improve the transparency of enterprise information, relieve agency issues, and enhance the internal governance level of enterprises. When the goals of shareholders and management gradually converge, enterprises are more likely to implement innovative development strategies in pursuit of long-term gains and sustained advantage in competition (Wei & Ma, 2022). In addition, the application of digital technology and detailed data support can strengthen the internal and external information communication and collaboration, improve the accuracy and effectiveness of capital allocation decision-making, optimize the resource allocation pattern, improve the efficiency of production operations, and create a good information environment for the total factor productivity of enterprises (Li & Wang, 2021). The digital economy has led to a change in the mode of production and organization of enterprises, promoting the transformation of enterprise structure into an open “flat” structure, which is beneficial for improving management efficiency and enhancing adaptability to both internal and external environments of the enterprise. With the development of the digital economy, environmental monitoring systems, big data platforms and other technological platforms have been widely adopted, effectively compensating for the Government’s disadvantages in terms of information, thereby significantly improving the Government’s regulatory efficiency. The development of digital economy has brought about an improvement in the data processing capabilities of enterprises, smoother communication and deeper trust among stakeholders, which is conducive to monitoring the behavior of management, thus reducing the cost of trial and error, and contributing to the co-creation of enterprise value and the improvement of total factor productivity (Liu, 2022). Technological advances have accelerated the efficient flow of information in a wider range of time and

space dimensions, and the path of information dissemination has become flatter and more transparent, a process that has led to the reinforcement of external supervision and regulation of corporate governance behavior by social governance actors represented by small and medium-sized shareholders, market intermediaries, social media, and so forth (Chen & Hu, 2022).

In summary, hypothesis H1 is proposed: the development of digital economy can increase the level of total factor productivity of enterprises.

2.2. The Mediating Role of Data Factor Utilization Level in the Relationship between Digital Economy Development and Firms' Total Factor Productivity

Brynjolfsson, E. & McAfee, A. (2014) pointed out that the development of emerging technologies has broadened the way of information disclosure of listed companies to improve its convenience and provide a good information base for the decision-making of business stakeholders, effectively alleviating the information asymmetry between each other, enhance market information transparency and ultimately achieve optimal allocation of resources. With the rapid development of digital technology, data resources have become the fifth core production factor after land, labor, capital and traditional technology, which occupies a pivotal position in promoting the overall development of China's economy and society, and it can provide insights to help enterprises optimize their decision-making process and create new business models (Jin et al., 2024). The emergence of digital technologies, platforms, etc., provides more opportunities and possibilities for the collection, processing, analysis and application of data elements, and the demand of enterprises for the utilization of data elements is also increasing, such as enterprises can use advanced analytical tools to process and analyze a large amount of data in order to acquire valuable information and support business decision-making, and apply the data to improve the monitoring and management capabilities of the supply chain, reduce operational costs and increase operational efficiency. The development of advanced data processing technologies and artificial intelligence has led to a significant increase in automation in enterprises, reducing the need for manpower and impacting the workforce structure. The deep integration of the digital economy with the real economy is the result of the dual-wheel drive of digital technology and data elements (Hong & Ren, 2023).

With the improvement of the utilization level of data elements, the productivity, innovation ability and competitiveness of enterprises have been significantly improved. The significant reduction of the cost of data collection, processing and analysis, the scale of data resources has been continuously expanded, and data elements have gradually become the core driving force of a new round of technological revolution and industrial transformation (Goldfarb & Tucker, 2019). As a new type of essential productive factors, the level of utilization of data elements directly reflects the competitiveness and innovation ability in the digital age. Data elements lead the innovation of enterprise management mode and improve

productivity by optimizing the enterprise decision-making path and enhancing the effectiveness of organizational learning (Chen et al., 2020; Xie et al., 2020). The effective information contained in data elements helps to reduce uncertainty in enterprise operations and significantly improves the efficiency of resource allocation. At the same time, the integration of data elements and traditional production factors can promote the optimal allocation among production factors, form economies of scale and scope, and further promote the total factor productivity of enterprises (Wang & Fu, 2021). Data elements can promote the collision and integration of knowledge between different industries and fields, promote industries to realize in-depth transformation and upgrading, and provide a constant power for total factor productivity of enterprises.

In summary, hypothesis H2 is proposed: The digital economy can enhance the total factor productivity of enterprises by improving the utilization level of data elements.

3. Research Design

3.1. Sample Selection and Data Sources

This paper takes the core enterprises in the digital economy as the research object and collects relevant data of all A-share listed companies from 2010 to 2022 as samples. And excluding ST and ST* categories, financial industry companies and samples with severe missing data of major variable indicators, all continuous variables are subjected to 1% shrinking tail treatment to get 34,883 valid samples. The rest of the sample data comes from CSMAR, CNRDS database and annual reports of listed companies.

3.2. Model Construction

The difference-in-differences model can better avoid the endogeneity problem and identify the effect of policy action, and is mostly used in the study of policy impact. In order to examine the impact of the introduction of digital economy industrial policies on the total factor productivity of core enterprises in the digital economy, this paper constructs the following DID model:

$$DID_{it} = treat_{it} \times period_{it} \quad (1)$$

Treat is a dummy variable for whether the enterprise is a listed company in the digital industry, according to the industry classification standards of the Securities and Exchange Commission, if the enterprise's industry belongs to the internet and related services, telecommunications, radio and television broadcasting and satellite transmission services, computer, telecommunications and other electronic equipment manufacturing, software and information technology services, assigned a value of 1, otherwise it is 0. Dummy variable for time. For the selection of the sample period, this paper takes into account that 2015 is the opening year of the new period of China's digital economy development, as manifested in the confirmation of the historic opportunity and significant value of digitalization for renewed economic vitality and social development from the national strategic

level. Therefore, 2015 is chosen as the policy implementation period, i.e., 2015 and subsequent years are 1, otherwise 0.

$$TFP_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \sum \alpha_2 Controls_{i,t} + \sum industry + \sum year + \varepsilon_{i,t} \quad (2)$$

$$Dig_{i,t} = \beta_0 + \beta_1 DID_{i,t} + \sum \beta_3 Controls_{i,t} + \sum industry + \sum year + \varepsilon_{i,t} \quad (3)$$

$$TFP_{i,t} = \eta_0 + \eta_1 DID_{i,t} + \eta_2 Dig_{i,t} + \sum \eta_3 Controls_{i,t} + \sum industry + \sum year + \varepsilon_{i,t} \quad (4)$$

Equation (2) only adds control variables to test the impact of the digital economy on the total factor productivity of enterprises, Equation (3) to test the impact of the digital economic development degree of data factor utilization level; Equation (4) in the combination of Equation (2), Equation (3) on the basis of the determination of the mediating effect of the level of utilization of data factors exists or not. Among them, the dependent variable is the total factor productivity of enterprises level (TFP), the core independent variable is the digital economic development (DID), and ε is the random error term of the model. The model also controls dummy variables for year and industry to try to absorb the fixed effects of these factors.

3.3. Variable Definition

1) Explained variable. Enterprise Total Factor Productivity (TFP), It reflects the maximum output capacity that an enterprise can achieve within a certain period of time using all factors of production (including labor, capital, land, etc.). It measures the productivity index of total output per unit of total inputs, i.e., the ratio of total output to all factor inputs. There are three main core methods for measuring enterprise total factor productivity: the multi-indicator comprehensive evaluation method, the single-indicator method giving intermediate variables and the total factor productivity method. Compared with the first two methods, total factor productivity goes beyond the pure contribution of tangible factor inputs such as labor and capital, and captures the enhancement of intangible productivity including management mode optimization and industrial structure upgrading, which can gentleman the overall development quality of the enterprise with a more comprehensive perspective. Therefore, this paper draws on the LP method of [Levinsohn & Petrin \(2003\)](#) to measure the TFP.

2) Core explanatory variables. Digital Economy Development (DID), which views the implementation of digital economy policies as a quasi-natural experiment, takes the value of 1 if the firm belongs to the core industry firms of the digital economy and in the current year of 2015 and beyond, and 0 otherwise.

3) Mediator variable. Data factor utilization level (Dig) refers to the enterprise's ability to collect, store, process, analyze and apply data resources in the process of production and operation. The utilization level of data elements covers the degree of mastery and application ability of enterprises in multiple technical fields, which is specifically reflected in the key aspects of data collection, storage, purification, analysis and utilization. Draw on the research results of [Wu et al. \(2021\)](#), evaluates the investment and application intensity of data elements by counting the frequency

of the detailed entries of the five core indicators of artificial intelligence technology maturity, blockchain technology development level, cloud computing technology implementation status, big data technology capability and big data application practice publicly disclosed by the enterprises in their annual financial reports, and then adding them up. The higher the frequency of the above five indicators mentioned in the financial report, the higher the comprehensive capability and investment level of the enterprise in the utilization of data elements.

4) Control variables. For the sake of reducing the influence of endogeneity, the control variables are selected with reference to the studies of scholars such as Li (2021), Bi et al. (2024), Xie & Yu (2023), etc. The detailed calculation of the variables is shown in **Table 1**.

Table 1. Definition of variables.

Variable Type	Variable Name	Variable Symbol	Variable Description	Data Sources
Explained variable	Policy variables	treat	Enterprises in the core industries of the digital economy take 1, the rest take 0	Manual assignment of dummy variables
	Time variable	period	0 for 2010-2015 and 1 for 2016-2022	
Core explanatory variables	Total factor productivity of enterprises	TFP	Using LP method to calculate	the CSMAR database
Mediator variable	Data element utilization level	Dig	The frequency of data factor utilization level related indicators in financial reports	Annual financial reports of statistical enterprises
Control variables	Enterprise scale	Employee	Logarithm of enterprise staff size	CSMAR, CNRDS databases, and annual reports of listed companies
	Enterprise age	Firmage	The logarithm of the difference between the observation year and the establishment year plus one	
	Asset-liability ratio	Lev	Total liabilities/total assets	
	Return on assets	ROA	Net profit margin of total assets	
	Board size	Board	The number of the board of directors takes the logarithm	
	Proportion of independent directors	Indep	Number of independent directors/number of board members \times 100%	
	Combination of two positions	Dual	The chairman and the general manager are the same person with the value of '1', otherwise it is '0'	

4. Empirical Analysis

4.1. Descriptive Statistical Analysis

As can be seen from **Table 2**, the large difference between the maximum and minimum values of TFP indicates a significant difference in the high-quality level

Table 2. Descriptive statistical results.

Variable	N	Mean	p50	SD	Min	Max
TFP	34,883	8.355	8.253	1.053	6.119	11.20
treat	34,883	0.170	0	0.375	0	1
period	34,883	0.726	1	0.446	0	1
Dig	34,883	7.683	7.601	1.241	4.796	11.16
Employee	34,883	2.919	2.944	0.329	1.792	3.526
Firmage	34,883	0.429	0.422	0.206	0.0560	0.908
Lev	34,883	0.0390	0.0380	0.0660	-0.236	0.223
ROA	34,883	2.122	2.197	0.199	1.609	2.708
Board	34,883	37.66	36.36	5.373	33.33	57.14
Indep	34,883	0.282	0	0.450	0	1
Dual	34,883	8.355	8.253	1.053	6.119	11.20

of enterprises. In terms of the development of the digital economy, the average is 0.170, which means that only some companies are in the ranks of the digital economy, 72.6% of the sample is located in the year of the implementation of the industrial policy of the digital economy and the subsequent years. Further observing the Employee, the maximum value of is 11.16, the minimum value is 4.796, indicating significant differences in the size of listed companies; the maximum difference of Lev is 0.848, which indicates that there is a large difference in the level of indebtedness of listed companies; the large difference between the maximum and minimum values of Indep, this indicates that there is a significant difference in the proportion of independent directors among the sample companies, and the remaining variables do not differ much.

4.2. Regression Analysis

This paper first applies the univariate difference-in-differences method to preliminarily investigate the impact of digital economy policies on the total factor productivity of enterprises. Specifically, this study divides the core digital economy enterprises into an experimental group and the rest of the enterprises as a control group. Among them, the period before the introduction of the policy (2010-2014) is labeled as the Before period, after the introduction of the policy (2015-2022) is labeled as the After period. Based on this, the mean value of total factor productivity of the two groups are calculated respectively, and the t-test method is used to compare and analyze whether there are systematic differences between the two groups before and after the implementation of the policy, and the results are shown in **Table 3**. The mean value of total factor productivity of the enterprises in the control group is 8.253 before the implementation of the policy, and increases to 8.456 after the implementation of the policy; before and after the implementation of the policy, the correlation coefficient of the enterprises in the experimental group grows from 7.794 to 8.245. This shows, after the introduction

of the policy, the total factor productivity of the two groups of enterprises have increased, but the experimental group increases more significantly. Overall, the policy produces an effect value of 0.247 and is significant at the 1% level. This results together illustrate that the digital economy policy promotes the improvement of total factor productivity of the relevant firms and further promotes the high-quality development of enterprises in the core industries of the digital economy.

Table 3. Univariate double difference results.

	control group	experimental group	difference
Prior to policy implementation	8.253	7.794	-0.459*** (-15.39)
After policy implementation	8.456	8.245	-0.211*** (12.30)
DID	—	—	0.248*** (7.21)

Note: *, **, *** are significant at the 10%, 5%, and 1% levels, respectively, with t values in parentheses, as follows.

In conducting the benchmark regression analysis, a stepwise regression is carried out based on the model that has been set, the results are shown in **Table 4**. In model (1), only controlling the influence of time effect and industry effect, which indicates that the regression coefficient of digital economy development on TFP is 0.2171, and this result passes the significance test of 1%, showing a strong positive correlation; the model (2) continues to introduce control variables in order to more comprehensively capture the factors that affects the TFP, and then the regression coefficient is reduced to 0.1612. The reason for this change is that some of the factors that originally affected the TFP were absorbed by the newly introduced control variables. At this point, the t-statistic is 6.2095 and passes the 1% significance test, further strengthening the original conclusion. In summary, the development of digital economy has a significant positive effect on the TFP, that is, the core hypothesis of this paper is established.

Table 4. Double difference regression results.

	(1)	(2)
	TFP	TFP
DID	0.2171*** (6.3511)	0.1612*** (6.2095)
Employee		0.3362*** (22.0431)
Firmage		0.2606*** (3.2814)

Continued

Lev		0.7059*** (12.5878)
ROA		2.6062*** (33.0962)
Board		0.1268*** (2.8786)
Indep		0.0017 (1.4192)
Dual		-0.0064 (-0.5175)
_cons	7.7144*** (57.9560)	3.7284*** (13.4203)
<i>N</i>	34883	34883
industry	Yes	Yes
year	Yes	Yes
r2	0.2718	0.4709
r2_a	0.2710	0.4702

The previous section has verified that the development of the digital economy positively affects TFP, so through what mechanism do the two play a role? Based on the mechanism test methodology described above, **Table 5** shows the results of the effect played by the level of data factor utilization in the relationship between digital economy development and TFP. Based on the validation of the baseline regression in Column (1), Column (2) reveals that there is a positive correlation between digital economy development and the level of data factor utilization of enterprises, which is significant at the 1% level, implying that the digital economy development contributes to the level of data factor utilization of enterprises. Further, the results from Column (3) indicate that data factor utilization is positively correlated with TFP at the 1% level, which means that data factor utilization is conducive to promoting TFP. Together, these results point to the conclusion that the development of the digital economy promotes total factor productivity of enterprises by increasing the level of enterprise data factor utilization, which in turn promotes TFP.

Table 5. Regression results of the mediating effect of the level of utilization of data elements.

	(1)	(2)	(3)
	TFP	Dig	TFP
DID	0.1612*** (6.2095)	22.3644*** (12.3590)	0.1134*** (4.3097)

Continued

Dig			0.0021*** (5.9769)
Employee	0.3362*** (22.0431)	3.1239*** (7.1918)	0.3295*** (21.6273)
Firmage	0.2606*** (3.2814)	4.5672 (1.3647)	0.2508*** (3.1646)
Lev	0.7059*** (12.5878)	0.2065 (0.1336)	0.7055*** (12.6533)
ROA	2.6062*** (33.0962)	-4.4119** (-1.9991)	2.6156*** (33.1844)
Board	0.1268*** (2.8786)	3.9884** (2.1119)	0.1183*** (2.7038)
Indep	0.0017 (1.4192)	-0.0170 (-0.3406)	0.0018 (1.4635)
Dual	-0.0064 (-0.5175)	0.3519 (0.7520)	-0.0071 (-0.5810)
_cons	3.7284*** (13.4203)	-40.9975*** (-3.8509)	3.8160*** (13.7470)
<i>N</i>	34883	34883	34883
industry	Yes	Yes	Yes
year	Yes	Yes	Yes
r2	0.4709	0.2241	0.4742
r2_a	0.4702	0.2231	0.4735

4.3. Robustness Tests

To ensure the stability of the core assumptions in the previous section, this paper develops robustness tests in five areas: parallel trend test, placebo effect, PSM-DID, and lagged model:

1) Parallel trend test

This paper applies the event study method to verify the parallel trends, and the results are shown in **Figure 1**. Before the implementation of the policy, the coefficients are not significant. In the current period of policy implementation, the correlation coefficients begin to change significantly and pass the 5% significance test. This phenomenon reflects that before the development of the digital economy, the level of enterprise total factor productivity of enterprises in the experimental group and the control group maintains a similar parallel trend, but after the implementation of the policy, there is a significant difference in the performance of total factor productivity of enterprises between the two groups. From the perspective of dynamic impact, the impact of the development of digital

economy on total factor productivity of enterprises is characterized by time lag and long-term. In summary, before the implementation of the policy, there is a parallel development trend between the experimental group and the control group, which verifies the validity and applicability of the difference-in-differences model in this paper.

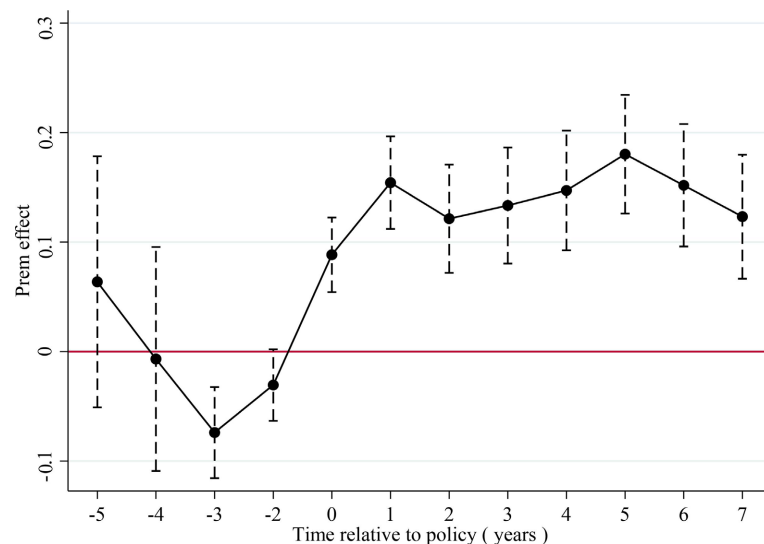


Figure 1. Parallel trend test results.

2) Placebo testing

In the baseline regression analysis of this paper, several variables that may affect the total factor productivity of pairs of firms have been adequately considered and controlled for, however, it is not entirely certain whether there are still important variables that have been omitted. To verify this potential problem, this paper uses a placebo test with random sampling. On the basis of keeping the order of arrangement of control variables unchanged, the experimental group of firms and policy time are randomly selected to simulate the construction of policy variables, and 1000 regression tests are carried out with strict control of time effects and industry effects. The results in **Figure 2**, and the regression coefficient equal to 0.1612 is a small probability event, i.e., it can be reasonably inferred that the omission of variables will not substantially affect the core conclusions of this paper.

3) Propensity score matching

Given the limitations of the double difference model in dealing with the sample bias problem, in order to effectively deal with the sample self-selection problem, this paper introduces the PSM-DID model, which aims at eliminating the potential impact of sample bias on the benchmark regression conclusions. This is done by firstly, carefully screening the matching variables through maximum likelihood estimation and selecting the control variables as key covariates. Second, the 1:1 neighbor matching method is used to limit the matching range to the control group in the same period, and the sample matching is performed through period-by-period propensity score matching, and the matching effect shows that the

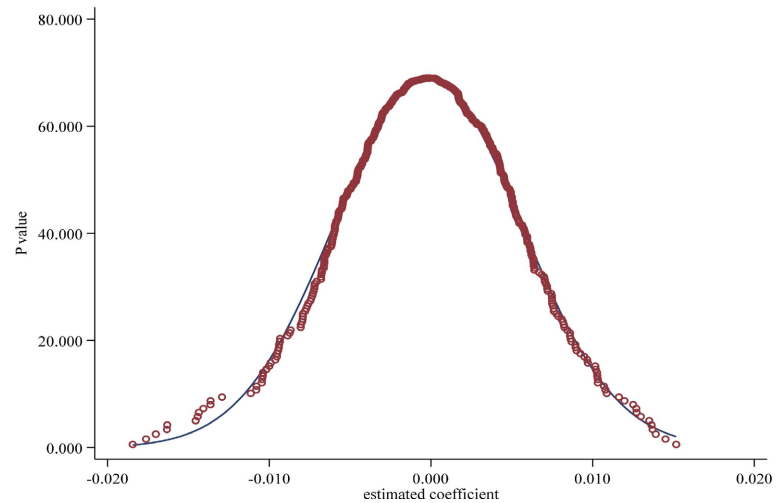


Figure 2. Placebo test results.

inter-sample bias has been effectively reduced; after completing the matching, the common support hypothesis and the balanced hypothesis test are carried out. The kernel density distribution plots before and after the matching shown in Figure 3 shows that the distribution deviation of the experimental group and the control group is effectively corrected during the matching process. Finally, the meta-benchmark regression model is re-estimated according to the matched samples. In Column (1) of Table 6, the impact coefficient of the observed term $\text{treat} \times \text{period}$ of the policy effect in the benchmark regression is 0.161 and is significantly positive at the level of 1%. There is no significant difference in the coefficient before matching, indicating that after eliminating the sample bias factor, the development of the digital economy still has a significant positive effect on the TFP, which is consistent with the conclusion of the benchmark regression, and further confirms the validity of the research hypothesis and model.

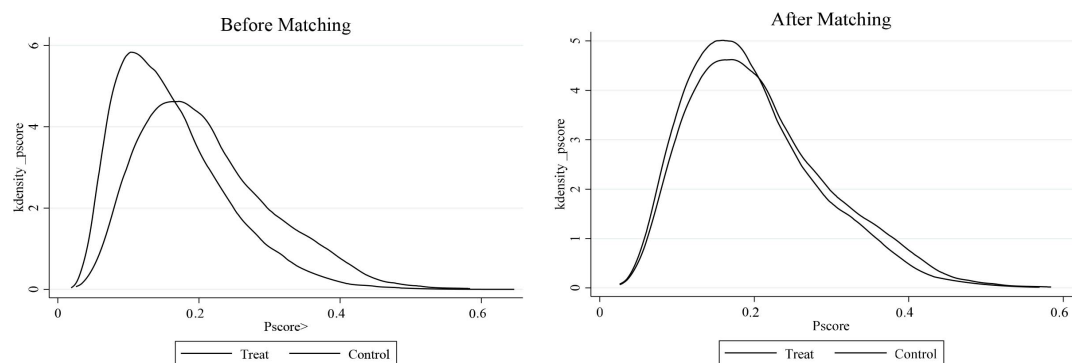


Figure 3. Kernel density distribution before and after matching.

4) Lag explanatory variables

In this study, for fully considering the possible lag effect of digital economic development on the level of the TFP, the explanatory variable (DID) is lagged from 1 to 2 periods, the results in Table 7 shows that the impact of DID on TFP

Table 6. Regression results after PSM matching.

	(1)	(2)
	TFP	TFP
DID	0.2176*** (6.3678)	0.1618*** (6.2351)
Employee		0.3363*** (22.1216)
Firmage		0.2609*** (3.2860)
Lev		0.7050*** (12.5938)
ROA		2.6069*** (33.1039)
Board		0.1295*** (2.9384)
Indep		0.0017 (1.4337)
Dual		-0.0065 (-0.5262)
_cons	7.7177*** (57.9535)	3.7236*** (13.3975)
N	34878	34878
industry	Yes	Yes
year	Yes	Yes
r2	0.2721	0.4714
r2_a	0.2713	0.4707

is highly significant, both in lag 1 and lag 2. This result indicates that the development of the digital economy has a sustained positive impact on the total factor productivity of firms, and this impact has not been significantly weakened by the passage of time.

Table 7. Lag explanatory variables.

	(1)	(2)	(3)	(4)
	TFP		TFP	
	DID lags one phse		DID lags two phase	
DID1	0.1764*** (5.4812)	0.1353*** (5.4740)		
DID2		0.3438*** (21.2079)	0.0971*** (3.1968)	0.0795*** (3.2960)

Continued

Employee		0.3438***		0.3474***
		(21.2079)		(19.2326)
firmage		0.2878***		0.3240***
		(3.3855)		(3.4753)
Lev		0.7134***		0.7039***
		(12.1843)		(11.4732)
ROA		2.5132***		2.4016***
		(31.2901)		(28.6748)
Board		0.1213***		0.1228***
		(2.6413)		(2.6166)
Indep		0.0022*		0.0024*
		(1.7301)		(1.8558)
Dual		-0.0059		-0.0056
		(-0.4761)		(-0.4483)
_cons	7.8526***	3.7138***	7.8672***	3.6314***
	(57.7188)	(12.3513)	(68.7475)	(11.1952)
N	29942	29942	25691	25691
industry	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
r2	0.2578	0.4594	0.2498	0.4471
r2_a	0.2569	0.4586	0.2490	0.4463

5. Heterogeneity Test

Firstly, the heterogeneity of industry competition. The degree of market competition, as an important variable of the external environment, has an important influence on the effectiveness of enterprises in utilizing the digital economy to improve total factor productivity of enterprises. In order to deeply understand the difference of its influence under different degrees of market competition, this paper further divides the sample into regions with a high degree and a low degree of market competition based on the median of the Herfindahl index, and the regression model is the same as in the previous section, still focusing on the coefficients of the interaction term DID. The results in Columns (1) and (2) in **Table 8**, i.e., relative to the high degree of market competition, the positive effect of digital economy policies on TFP is more significant in the low market competition environment. The p-value of the Zou test result of the regression coefficient between groups is $0.000 < 0.1$, indicating that there is a significant difference in the interaction coefficient between the two groups. In a highly competitive market environment, firms face greater pressure to survive and more intense competition, which promotes high efficiency in the allocation of resources. However, such

efficiency may also lead to “over-competition”, whereby firms pursue market share in the short term to the detriment of long-term technological innovation and efficiency improvement. In contrast, a low-competition environment provides a relatively stable operating environment for enterprises, allowing them to devote more resources and energy to technological innovation and digital transformation, and thus to more effectively capitalize on the opportunities presented by digital economy policies.

Second, the heterogeneity of firms’ property rights. The results of the regressions grouped according to the ownership attributes of the firms are shown in Columns (1) and (2) in **Table 8**, which still focuses on the coefficient of the DID. The regression coefficient of digital economy development and TFP of state-owned enterprises shows a positive correlation at the level of 10%, and the regression coefficient for non-state-owned enterprises is significant at 1%.

It shows that the development of digital economy can not only promote the total factor productivity of state-owned and non-state-owned enterprises, but also this effect is more significant in non-state-owned firms. The p-value of the Zou test result of the regression coefficient between groups is $0.020 < 0.1$, which indicates that the coefficient of the interaction is significantly different between the two groups. This may be due to the fact that State-owned enterprises have distinct economic, political and social attributes and usually bear heavier policy burdens. These burdens include, but are not limited to, supporting major national strategic projects, stabilizing prices, safeguarding people’s livelihoods, etc., tasks that often require SOEs to invest large amounts of resources and sacrifice some of their economic interests in exchange for maximizing social benefits and the overall interests of the State.

Third, the heterogeneity of enterprise dynamic capabilities. According to the theory of dynamic capability, the heterogeneity among enterprises not only stems from the differences in static resources, but also lies in their ability to dynamically adjust resources and respond to environmental changes. In the context of the digital economy, the dynamic capabilities of firms are directly related to their ability to effectively absorb and apply digital technologies to increase total factor productivity of enterprises. Enterprises with different dynamic capabilities will show different levels of competitiveness and total factor productivity of enterprises in the digital economy. Therefore, this paper further explores the differential impact of digital economy development on the total factor productivity of enterprises with different levels of dynamic capabilities by dividing the sample into two groups of high and low dynamic capabilities based on the median dynamic capabilities of firms. The results are shown in Columns (5) and (6) in **Table 8**. For enterprises with different levels of dynamic capabilities, the development of digital economy can push the level of total factor productivity up, but the effect on enterprises with high dynamic capabilities is more significant. The p-value of the regression coefficient Zou test between groups is $0.000 < 0.1$, indicating that the interaction term coefficient is significantly different between the two groups. That is, in the context

of high dynamic capability enterprises, the development of the digital economy shows a more significant promotion effect on the total factor productivity of enterprises. For firms with high dynamic capabilities, they are able to quickly identify and seize the opportunities brought by digital economy policies. For enterprises with high dynamic capabilities, they can quickly recognize and seize the opportunities brought by digital economy policies, and they usually have strong technology absorption, innovation and adaptation capabilities, and can quickly integrate digital technologies into their production and management processes to improve production efficiency and resource allocation efficiency, thus increasing their total factor productivity. In contrast, enterprises with low dynamic capabilities may not be able to effectively utilize digital technologies in the face of digital economy policies due to insufficient technological absorptive capacity and difficulties in adjusting their strategies in a timely manner when the market environment is changing, thus missing out on good opportunities for development and constraining the improvement of their TFP.

Table 8. Results of heterogeneity analysis.

	TFP					
	column (1)	column (2)	column (3)	column (4)	column (5)	column (6)
	high market competition	low market competition	government owned	non-municipal	high dynamic capability	low dynamic capability
DID	0.1083*** (4.0101)	0.3073*** (4.1461)	0.0977* (1.8702)	0.1559*** (5.2545)	0.2155*** (4.9746)	0.1947*** (4.7302)
Employee	0.3711*** (19.8004)	0.2840*** (12.7431)	0.2863*** (11.7842)	0.3584*** (18.8831)	0.3047*** (14.7835)	0.3573*** (15.8463)
firmage	0.3163*** (3.2265)	0.0927 (0.8190)	0.1901 (1.5289)	0.1860* (1.7878)	0.1812* (1.7027)	0.3259** (2.5411)
Lev	0.6314*** (9.4795)	0.6450*** (8.8493)	0.7263*** (7.2613)	0.6274*** (9.6061)	0.6716*** (8.9773)	0.6718*** (8.3943)
ROA	2.4711*** (26.0027)	2.6096*** (22.8657)	3.2357*** (21.2143)	2.3716*** (26.0440)	2.5987*** (27.0436)	2.2809*** (16.8999)
Board	0.1311** (2.4558)	0.1174* (1.8389)	0.1356* (1.8539)	0.1213** (2.2716)	0.0694 (1.2359)	0.1273** (2.0314)
Indep	0.0009 (0.6469)	0.0023 (1.3928)	0.0013 (0.7118)	0.0021 (1.2639)	0.0016 (1.0770)	0.0006 (0.3411)
Dual	-0.0010 (-0.0688)	-0.0197 (-1.0951)	-0.0015 (-0.0669)	-0.0132 (-0.9231)	-0.0082 (-0.5029)	-0.0110 (-0.5790)
_cons	3.0289*** (8.8708)	4.7135*** (11.8832)	4.5076*** (9.5422)	3.6196*** (10.3082)	4.3691*** (11.5720)	3.3072*** (7.4737)
N	17882	17001	12305	21984	21542	13341

Continued

industry	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.5374	0.4143	0.4273	0.5077	0.3994	0.5420
r2_a	0.5365	0.4128	0.4252	0.5067	0.3982	0.5405

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusions and Recommendations

6.1. Findings

Taking all A-share listed companies in China from 2010 to 2022 as the research sample, this paper empirically analyzes the promotion effect of the development of the digital economy on the total factor productivity of enterprises as well as the mediating role of the level of data factor utilization, and also analyzes the effect of the influence of the external environment and the heterogeneity of the internal attributes to come up with the following three main conclusions: First, the development of digital economy can effectively promote the total factor productivity level of enterprises. This conclusion still holds after adding control variables, mediating variables and conducting a series of robustness tests such as parallel trend test and placebo test. Second, digital economic development can further enhance total factor productivity of enterprises by affecting the level of enterprise data factor utilization. Third, there is obvious heterogeneity in the positive impact effect of digital economy development on total factor productivity of enterprises, with the policy effect being more significant in regions with a lower degree of industry competition, and the total factor productivity of non-state-owned firms and firms with high dynamic capabilities being more affected by digital economy policies.

6.2. Policy Implications

First, the development of the digital economy should be stepped up. In the face of how to promote total factor productivity of enterprises, a problem that has long plagued government departments, traditional fiscal and tax policies, while they can alleviate the difficulties of enterprise financing and increase the enthusiasm of enterprises for innovation, have little impact on the issue of productivity. In view of the significant role of the development of the digital economy in this paper in promoting the total factor productivity of enterprises, government departments should further strengthen the construction of digital economy infrastructure and increase investment in this area, so as to give full play to the technological advantages of the digital economy and guide enterprises to shift to a high-quality and sustainable direction. Specifically, the government can formulate a targeted digital transformation road map for enterprises, helping them to clarify their transformation objectives and key tasks. It should also provide financial incentives for enterprises, such as tax breaks, investment subsidies and low-interest loans, to encourage them to increase their investment in digital infrastructure and data

talent training. At the same time, laws and regulations related to the digital economy should be improved, and the boundaries of rights and responsibilities in terms of data property rights and data security should be clarified, so as to provide convenience and regulatory protection for the digital transformation of enterprises. Section should be clarified, so as to facilitate and guarantee the digital transformation of enterprises.

Second, further strengthen the utilization of data elements. Effective utilization of data elements can not only help enterprises seize market opportunities, but also inject development momentum and build core competitiveness. In order to comply with the trend of digital economy, enterprises should quickly establish a sound information system and data management system, improve the collection, organization, analysis and utilization of data elements, integrate data into production activities as a key production factor, and make it synergistic with traditional production factors to create value together. The application of digital technologies and the effective use of data elements require a certain level of skills from employees. However, many employees may find it difficult to adapt to the changes in the digital economy due to inadequate skills or resistance to new technologies. Therefore, enterprises should strengthen the training and education of employees to improve their digital skill level and stimulate their interest and enthusiasm for digital technology, ensure that they are able to skillfully apply all kinds of data technology tools and methods, leverage mature digital platforms, and utilize digital technologies such as the internet, cloud computing, and big data to achieve digital transformation and empowerment, so as to achieve better utilization of data elements.

Third, formulating differentiated policies. When formulating policies, full consideration should be given to the impact of market structure and enterprise heterogeneity in order to better utilize the facilitating role of policies and promote enterprises to achieve high-quality development. As there are differences in the impact of digital economy policies on the total factor productivity of enterprises under different external environments and internal characteristics of enterprises, the government should take into full consideration the characteristics of different regions and different enterprises when formulating digital economy policies, and formulate differentiated policies to meet the innovation needs of different regions, industries and enterprises. In particular, for regions, industries and enterprises that are lagging behind in development, the government can take more targeted policy initiatives to stimulate innovation.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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