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Analysis of the Effect of Data Elements on the Total Factor Productivity of Enterprises in the Digital Economy

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Abstract: ***Total factor productivity is a path choice for achieving high-quality development. As data gradually becomes a new production factor, whether it can become an enabler to improve the total factor productivity of enterprises has become a widely discussed issue in the academic world. Using the data of A-share listed companies from 2001 to 2022, this paper constructs a two-way fixed-effects model to empirically test the impact of data factors on the total factor productivity of enterprises. The results show that data elements have a significant positive impact on enterprise total factor productivity, which remains significant after a series of robustness tests by replacing the explanatory variables, the core explanatory variable measurements, and introducing quasi-natural experiments. It further analyses its transmission mechanism and what different effects will be produced by enterprises in different regions and industries. Finally, combined with the above research, this paper puts forward the corresponding policy recommendations. Increase the cultivation of talents and the introduction of talents; achieve the issue of increasing total factor productivity in the context of high-quality development of the economy by fully leveraging the role of data elements; guide enterprises to make rational use of data elements; and balance the level of development of data elements.***

Keywords: Data factor, Total factor productivity, Two-way fixed effect, Digital economy**.**

1. Introduction

1.1 Research Background

Since the reform and opening up, China's economy has experienced a period of rapid development, with the average annual GDP growth rate reaching 9.5%, far higher than the world GDP growth rate of 2.9% during the same period. Even though affected by the epidemic, China's GDP level still ranks first in the world. But is it right for a country to only pursue high-speed development? Obviously that is not the case. In addition, China also exposed many problems in its early stages of development, such as serious environmental damage and lack of core innovation capabilities. With the development of the economy and the continuous changes in the international situation, my country's demographic dividend is about to disappear, the global influenza virus is fluctuating, and uncertainty has significantly increased. When faced with this series of problems, the Party Central Committee proposed in the report of the 19th National Congress of the Communist Party of China that "my country's economy has shifted from high-speed development to high-quality development", that is, my country's current development speed has shifted from high-speed growth to medium-high-speed growth, and the development goal is to shift from high-speed development to high-quality development. The path chosen for high-quality development is to focus on improving total factor productivity. Total factor productivity is the core variable that expresses the quality of economic development in the modern economic system. Improving total factor productivity is the driving force for high-quality development.

In Marxist political economics, the development of productivity is the fundamental driving force of economic progress. Science and technology are the primary productive forces. my country is currently undergoing a new round of scientific and technological revolution and industrial transformation. The scientific and technological revolution is developing rapidly. The innovation of digital technologies such as 5G technology, Internet of Things, artificial intelligence, and cloud computing marks the official arrival of the digital age. The synergistic integration of digital technology and related industries has formed the digital economy. The digital economy has developed rapidly in recent years, and its contribution to GDP growth has reached 67.7%. In the era of digital economy, data has become a new type of production factor added to the production activities of enterprises. The emergence of artificial intelligence has also profoundly changed the labor structure. Enterprises will reduce the demand for conventional low-skilled labor and increase the demand for unconventional high-skilled labor, thus achieving structural adjustment of the labor force (Yao Jiaquan, 2024). The digital economy has brought about profound changes in workers, labor factors, and labor materials. Production relations have also changed, giving rise to new productive forces and the emergence of new quality productive forces. The core hallmark of new quality productivity is a significant improvement in total factor productivity. In a sense, new quality productivity is to encourage innovation, drive the improvement of economic development quality with innovation, make full use of emerging factors and resources, break away from the original production mode, and achieve high-quality economic development. The external manifestation is a significant improvement in total factor productivity.

In the development of the digital economy, the importance of data has become increasingly prominent. The "14th Five-Year Plan for the Development of Digital Economy" promulgated in 2022 clearly pointed out that data will become the fifth largest production factor to participate in the production and manufacturing of enterprises. This undoubtedly raises the importance of data to a new level. Data is a concrete manifestation of networking, intelligence, and circulation, and has had a profound impact on the sales, logistics, management and other aspects of enterprises. It can be said that if an enterprise has as much data as possible, it will have as much market as possible. Data elements are expected to become a booster to promote the improvement of total factor productivity of enterprises, thereby accelerating the process of high-quality development in China and developing new quality productivity.

1.2 Research Significance

Total factor productivity is a measure of the level of economic growth brought about by other production factors other than labor and capital. It can be understood as the impact of technological progress on economic growth, and to some extent, it also shows the efficiency of resource allocation in the country or enterprise. Improving total factor productivity can promote the quality change, efficiency change and power change of my country's economic development (Cai Fang, 2017). Exploring the factors affecting my country's total factor productivity is the key to breaking the "Krugman curse". With the central government's "Opinions on Building a More Perfect System and Mechanism for Market-based Allocation of Factors" in 2020, which formally proposed for the first time in the world that data is a new type of production factor, local governments have also clarified measures to improve the market-based allocation of data factors. Exploring the relationship between data factors and total factor productivity is a reasonable question, which is of great significance to promoting my country's high-quality development and developing new quality productivity.

In 2015, the government was approved to establish the Guiyang Big Data Trading Platform, and the data factor market began to take shape. However, data is difficult to be recognized for accounting due to its characteristics such as uncertainty of income, updateability, and modifiability; data may involve personal privacy, sensitivity, and national security; there is no relevant system to regulate how to determine the property rights of data, and there are disputes over the right holders of data assets. The immaturity of data elements has also brought many difficulties to theoretical research. Foreign research generally constructs theoretical models and focuses on exploring the goals, objects, and difficulties of data factor market governance. Domestic research on data elements is more problem-oriented, focusing on the property rights legal bottlenecks and gray areas in China's current data factor market and proposing market governance countermeasures. However, there is a gap in the research on truly measuring data elements and explaining the impact of data elements on total factor productivity through empirical models. Therefore, this paper starts from the smallest unit of growth, the enterprise, to explore the construction of data elements and study the impact of data elements on the total factor productivity of enterprises, which has strong theoretical significance.

The marginal contribution of this paper may exist in the following aspects: starting from the perspective of the level of development of the urban digital economy, this paper analyzes the actual operation status of data elements under the digital economy from the perspective of micro-enterprises, and provides practical evidence for the development of the digital economy in cities; incorporating data elements into the analytical framework of enterprise productivity broadens the understanding of the factors affecting the total factor productivity of enterprises from a macro perspective, and enriches the existing research on enterprise productivity; through heterogeneity analysis, it can further identify whether there are differences in the impact of data elements on the productivity of enterprises in different regions and industries under the digital economy; there are few existing literatures that truly measure data elements and explain the impact of data elements on total factor productivity through empirical models. This paper is committed to exploring the impact of data elements on the total factor productivity of enterprises and providing practical evidence for micro-enterprises to achieve digital transformation.

2. Literature Review

2.1 Development Level of Digital Economy

The concept of digital economy is widely used in contemporary economic research and has many analytical angles, but the academic community still has not given a precise and complete definition of the true meaning of the specific concept of digital economy. Li Changjiang (2017) collected a large number of reasons for the emergence of digital economy from the perspective of the Internet, compared the relationship between digital economy and other related concepts, explored the origin and profound connotation of digital economy, and advocated that the essence of digital economy is the GDP level generated by a technology, and this technology happens to be digital technology. With the global economic slowdown in recent years, the road to recovery faces risks and challenges. The issue of digital economy was also raised at the G20 summit. Zuo Xiaodong (2016) proposed that modern information networks are becoming more and more a key place in economic activities, information and knowledge are gradually showing a trend of digitalization, and digital economy is also expected to optimize the economic structure. Based on their unique understanding of the current economic development of various countries in the world, Xu Qingyuan and Shan Zhiguang (2018) compared and evaluated the system formed by international and domestic indicators related to digital economy, and elaborated on the construction ideas and policy recommendations of my country's digital economy development level indicator system using comparative method. Today, the momentum of digital economy development is unstoppable. Pei Changhong, Ni Jiangfei, and Li Yue (2018) regard the digital economy as a high-end, sustainable economic form, and analyze it from the perspective of political economics. Its role in promoting all aspects of social economy is unprecedented and incomparable. Jing Wenjun and Sun Baowen (2019) respectively elaborated on the relationship between digital economy and economic growth and economic development from the perspective of macroeconomics, and finally concluded that the rapidly developing digital economy can provide a better mechanism for China to build a modern, advanced, and efficient economic system.

2.2 Development Level of Data Elements

As the fifth major production factor after labor, capital, land,

and technology, data conforms to the current digital economy and has attracted widespread attention from scholars at home and abroad. Regarding the connotation of data elements, the China Academy of Information and Communications Technology defines data as “statistical information displayed in binary based on pre-set coding.” Wu Zhigang (2021) believes from the perspective of political economics that data elements are projections of the real world portrayed in the human brain through consciousness; Wang Lei et al. (2021) elaborated that the scope of data elements includes raw data, processed and expanded data, and the inherent connection between data and data. Regarding the characteristics of data elements, Li Yongjian (2021) believes from the perspective of microeconomics that data elements have the characteristics of non-competitiveness and partial exclusivity. Domestic research on data elements focuses on problem-oriented, focusing on the problems existing in my country’s data element market and providing corresponding market governance methods. Liang Yu et al. (2021) analyzed the main difficulties facing my country’s data factor market, which are concentrated in the system and governance aspects. They proposed that on the one hand, we should support the development of data factors, and on the other hand, we should strengthen the government’s governance means, establish and improve relevant laws and regulations, and departmental regulations to promote the data factor market; Zhang Lixia and Sun Fangjiang (2021) judged the current situation of the data factor market from the perspective of competition, and proposed that the development of the data factor market should be shared but based on privacy considerations, and should take into account “exclusiveness” and efficiency and fairness. From the perspective of anti-monopoly, it is necessary to develop fairly and justly, and a unified market can be established to facilitate inter-regional supervision; Ren Baoping and Gao Fuping (2023) summarized the problems in my country’s data factor market, such as inadequate infrastructure protection system, inefficient market operation, and imperfect trading mechanism, and proposed specific solutions for data factor market governance.

2.3 Factors Affecting Total Factor Productivity

From the perspective of factors affecting enterprise production efficiency, there are many factors that affect the total factor productivity of enterprises. Existing literature has empirically verified these factors from multiple perspectives, which can generally be classified into macro factors and micro factors. On the one hand, enterprise productivity is inevitably significantly affected by the external environment, including but not limited to industrial policies, tax environment, and environmental regulations. Industrial policies, such as regional policy tools such as national economic development zones, as pointed out by Lin Yifu et al. (2018), as a tool for regional industrial policy, have a positive effect on promoting the total factor productivity of enterprises. However, as shown in Qian Xuesong’s (2018) research, when government intervention is too strong, such as implementing highly centralized industrial policies like the Ten Major Industrial Revitalization Plans, it may to some extent have a suppressive effect on the total factor productivity of enterprises. On the other hand, enterprise productivity is also deeply affected by internal factors. Factors such as a company’s innovation capabilities, financing constraints, and data management capabilities all affect the company’s production efficiency to varying degrees. In their study, Bauman and Kritikos (2016) paid special attention to the relationship between R&D, innovation and productivity of micro-SMEs. Through empirical analysis, they found that the R&D and innovation activities of micro-enterprises can effectively improve the productivity of enterprises, just like large enterprises. This finding emphasizes the importance of internal innovation activities in improving productivity.

2.4 Literature Review

At present, scholars at home and abroad have conducted extensive and in-depth research on the digital economy, but few have thought about a small entry point of the digital economy - data factors. At present, research on data factors mainly focuses on the interpretation of connotations and the identification of problems in the factor market. In the future, it is necessary to conduct more in-depth research on what operating mode data factors should adopt and how to measure them, so as to provide support for the orderly and efficient operation of the data factor market. Starting from data factors, this paper takes enterprises from a micro perspective as the research object, analyzes the impact of data factors on the total factor productivity of enterprises under the digital economy, expands the research boundaries of the digital economy, and forms an analytical framework for the total factor productivity effect of enterprises. Based on the empirical model of the impact of data factors on the total factor productivity of enterprises under the digital economy and the test of the mechanism of action, it proposes a specific optimization development path for enterprises to improve productivity from the perspective of improving resource allocation efficiency.

3. Mechanism Analysis and Research Hypothesis

In the context of the digital economy, data has become a new production factor for enterprises, running through all aspects of enterprise procurement, production, and sales. When combined with other digital products produced by the digital economy, it can effectively improve the production efficiency of enterprises. When combined with other traditional production factors, due to its own characteristics of strong penetration and zero marginal cost, it can effectively improve the level of enterprise resource allocation and improve the total factor productivity of enterprises. From the perspective of sales, online platforms can profile each consumer, judge the consumer’s hobbies and needs, and thus form a consumer database, accurately deliver to consumers, conduct targeted advertising, and customize sales services to increase enterprise output. At the same time, the digital economy era has also made sales channels diverse. The digital economy can use new computer technologies such as big data, artificial intelligence, and the Internet to break through the limitations of physical time and space, providing a realistic possibility for the real economy to “travel” all over the country without leaving home. Data elements have broken through the problems of “distance” and “inability to store”, and greatly improved the total factor productivity of enterprises through economies of scale and scope (Jiang Xiaojuan and Jin Jing, 2022). With the rapid development of the digital economy, as the credit target of small and medium-sized enterprises, banks have gradually developed and matured in digital operations, management, and data utilization capabilities. The application of digital technologies such as cloud computing and blockchain by banking institutions can improve banks' signal identification and risk prevention and control capabilities, which can reduce banks' rejection of small and medium-sized enterprise loans to a certain extent (Wang Jingxian, 2020); in addition, through the application of digital technologies in traditional industries, the optimization and reorganization of traditional production factors can be achieved, which can bring an increase in the number of units of production and an improvement in production efficiency to the real economy. The digital economy has become one of the driving forces of the real economy (Luo Qian, Wang Jun, and Zhu Jie, 2022).

Hypothesis 1: Data factors can improve the total factor productivity of enterprises.

Specifically, in terms of intelligent production and manufacturing, enterprises have complete record data for the entry and exit of inventory during the warehousing process. Enterprises can accurately grasp the characteristics of products by analyzing these data, reduce inventory for products with sluggish sales and stagnant sales, and increase the circulation speed of products that consumers like. Enterprises can share databases with suppliers and achieve collaborative development with suppliers. Intelligent storage can be achieved to reduce inventory, reduce warehousing costs and management expenses, and achieve flexible production, which can deliver on time without causing inventory accumulation and improve the level of resource allocation. A high-efficiency, low-inventory, and low-cost production model can be achieved to improve the total factor productivity of enterprises. Enterprises can integrate and analyze the data exported from the warehousing platform, grasp the degree of consumer preference for products and the market demand for products through the number of product outbound shipments, predict the life cycle stage of each product of the enterprise, and adjust the marketing methods of corresponding products in a timely manner. For example, for products with high market growth rates but low market share of the company's own products, it is necessary to give priority to providing corresponding resources to the company, seize the mainstream market hotspots, highlight product characteristics, and increase the market share of its own products. Therefore, the "storability" and "visualization" of data can enable the effective allocation of enterprise resources and improve enterprise productivity.

In terms of data information analysis capabilities, from a decision-making perspective, companies often set up cumbersome audit systems. The audit and approval system is on the one hand to avoid fraud risks, and on the other hand, because investment is risky, a project task needs to go through layers of selection before it can finally be put into trial. The uncertainty of reality also brings high decision-making costs to enterprises. Layered decision-making is an important reason for the decreasing returns to scale of enterprises. Data contains all the information generated by the economic activities of enterprises in the past. On the basis of a large amount of useful information accumulation, it can be transformed into the experience and knowledge of the enterprise itself, forming a personalized production model with its own characteristics. This is also an important manifestation of "learning by doing" in economics in the digital economy era. It is also possible to mine information through big data, and use machine learning algorithms to help enterprises better predict future economic activities, thereby reducing decision-making processes, reducing decision-making costs, reducing decision-making errors caused by limited knowledge reserves, effectively allocating existing resources of enterprises, and giving full play to the value of resources, thereby improving the total factor productivity of enterprises. From the perspective of production, data elements together with digital platforms can monitor the entire process of production and manufacturing, reduce the number of people in the management workshop, and reduce the management costs of enterprises. Global control of the entire production process of an enterprise can mobilize resources more effectively, monitor resource usage, promptly identify resource mismatch risks, and improve resource allocation efficiency.

In terms of factor utilization and factor integration, data factors are different from traditional factors such as labor, land, and capital. The non-competitiveness and zero marginal cost characteristics of data factors can directly bring about increasing returns to scale, and enterprises can also continue to expand their production scale, directly leading to improved enterprise productivity. In addition, data factors can also drive the digital transformation of other production factors. They themselves have strong penetration and high innovation capabilities, and can improve the utilization efficiency of traditional production factors in the production process. Based on data visualization, enterprises can more effectively utilize labor, capital, etc. in the production process, so that other production factors can be recombined more efficiently and innovative development of production factors can be achieved. Therefore, the deeper the integration of data with other production factors, the greater the effect on total output and the greater the increase in enterprise productivity.

Based on the above analysis, we can find that: whether in terms of intelligent manufacturing, data information analysis capabilities, or factor utilization and factor integration, data factors in enterprises improve the total factor productivity of enterprises by better allocating resources.

Hypothesis 2: Data factors can improve the total factor productivity of enterprises by improving the efficiency of resource allocation.

4. Research Design

4.1 Data Sources

This paper selects A-share listed companies in Shanghai and Shenzhen from 2001 to 2022 as research samples to explore the impact of data elements on total factor productivity. On this basis, in order to ensure the validity of the data, financial companies and companies with ST, *ST, and PT during the sample period were excluded. After screening and eliminating missing values, 34,581 observations were finally obtained. In order to avoid the interference of outliers, all data were winsorized by 1%. The data in this article comes from the

Guotai An CSMAR database.

4.2 Variable Description

4.2.1 Explained variable

This paper uses total factor productivity (TFP) as the explained variable. Total factor productivity is not only related to technological progress, but also reflects factors such as the knowledge level, management skills, institutional environment and calculation errors of material production (Lu Xiaodong and Lian Yujun, 2012). It can better measure the productivity effect of data elements. The calculation of total factor productivity is estimated based on the Cobb-Douglas production function:

$$Y_{it} = A_{it} L_{it}^{\alpha} K_{it}^{\beta} \tag{1}$$

Among them, Y, L and K represent the output, labor input and capital input of the enterprise respectively, and A is the total factor productivity of the enterprise. By taking the logarithm of model (1), the model can be transformed into the following linear model (2):

$$y_{it} = \alpha l_{it} + \beta K_{it} + u_{it} \tag{2}$$

Among them, y, l and k are the logarithmic forms of Y, L and K respectively, and the residual term contains the logarithmic information of the enterprise's total factor productivity A. Due to the simultaneity bias of the traditional OLS method for calculating total factor productivity In order to solve the problems of sample selectivity and attrition bias, this paper refers to Xie Qian et al. (2021) and uses the method of Oli and Parks (1996) to calculate the total factor productivity of listed companies. In terms of indicator selection, enterprise output, labor force and capital input are measured by the natural logarithm of enterprise operating income, number of employees and net value of fixed assets plus 1. The method of Oli and Parks (1996) also involves the intermediate input indicator of enterprises, which is measured by the natural logarithm of cash paid by enterprises for the purchase and construction of fixed assets, intangible assets and other long-term assets plus 1.

4.2.2 Explanatory variables

Data elements. Data elementization is the process of cleaning, processing and organizing data, making it "machine-readable", ready for production and use, and entering socialized mass production through circulation. According to the evolution of data elementization and the logic of "input-transformation- output" in economics, the development level of data elements is constructed from three dimensions: "data collection-data transformation-data realization". Data collection can be measured by the level of big data technology and cloud computing technology, data transformation can be measured by the application of data technology, and data realization can be measured by the level of artificial intelligence technology and blockchain technology. Therefore, the number of disclosures of the sub-indicators of the five indicators of big data technology, cloud computing technology, data technology application, artificial intelligence technology and blockchain technology in the annual financial report of the enterprise is counted, and the level of data element input is measured by summing the number of disclosures of all indicators. The higher the frequency of the five indicators appearing in the financial report, the higher the level of data element utilization of the enterprise.

4.2.3 Control variables

In the study of total factor productivity of enterprises, the size, financial status and external evaluation level of enterprises will affect the impact of data elements on total factor productivity of enterprises. Therefore, referring to the research of Yao Jiaquan et al. (2024), the following variables are selected as control variables: enterprise size (size), debt-to-asset ratio (lev), profitability (roa), and market value of enterprises (TobinQ). The calculation method of the main variables in the regression model is shown in Table 1 below.

Table 1: Variable definition

Variable Types	Variable Name	Variable Symbols	Variable Description
Core explanatory variables	Data element level	Shujuyaosu	Frequency of occurrence of data element related indicators in financial reports
		digital	Frequency of "application of digital technology" appearing in financial reports
Explained variable	Total Factor Productivity	TFP	OP method
			LP Method
			GMM Method
Control variables	Enterprise scale	size	Natural logarithm of total assets per year
	Debt-to-asset ratio	lev	Total liabilities at the end of the year/Total assets at the end of the year
	Profitability	roa	Net profit/average balance of total assets
	Enterprise market value	TobinQ	(Market value of tradable shares + Number of non-tradable shares * Net asset value per share + Book value of liabilities) / Total assets

5. Empirical Analysis

5.1 Model Construction

In order to examine the impact of data factors on the total factor productivity of enterprises, this paper establishes the following regression model (3):

$$TFP_{it} = \alpha + \beta \text{shujuyaosu}_{it} + \gamma \text{controls}_{it} + \lambda_i + year_t + \varepsilon_{it} \tag{3}$$

Among them, i and t represent the company and year, respectively, TFP_{it} is the total factor productivity of the enterprise, $\text{shujuyaosu}_{\text{it}}$ is the level of the company's data elements, $\text{controls}_{\text{it}}$ and are the relevant levels of enterprise size, debt-to-asset ratio, profitability, and enterprise market value, respectively. What we are concerned about is β the value of and whether the results of this variable are significant. λ_i and $year_t$ are the individual fixed effects and year fixed effects, respectively, ε_{it} and is the random error term.

5.2 Descriptive Statistics

The descriptive statistical results are shown in Tables 2 and 3. Panel A describes the sample size, mean, and other related information disclosed in the annual reports of enterprises on big data technology, cloud computing technology, digital technology application, artificial intelligence technology, and blockchain technology. It can be seen that the total number of disclosed samples is 34,581 enterprises. Most enterprises have actively responded to the call of the digital economy era and actively cultivated and formed data elements. Among them, the mean of digital technology application is 4.88 and the maximum is 433, indicating that the application of data technology accounts for the largest proportion in the measurement level of data elements. As shown in Panel B, the mean of total factor productivity (TFP) calculated in this paper is 6.638, which is similar to the calculation results of Xie Qian (2021). The mean of data elements is 11.8, the standard deviation is 32.6, and the difference between the maximum and minimum values is 547, indicating that there are obvious differences in the utilization level of data elements among enterprises.

Table 2: Descriptive Statistics Panel A

variable	Number of samples	Mean	Standard Deviation	Minimum	Maximum
Big Data Technology	34,581	2.541	10.95	0	334
Cloud computing technology	34,581	2.670	10.95	0	248
Application of digital technology	34,581	4.879	15.29	0	433
Artificial Intelligence Technology	34,581	1.477	8.721	0	432
Blockchain Technology	34,581	0.245	2.315	0	119

Table 3: Descriptive Statistics Panel B

variable	Number of samples	Mean	Standard Deviation	Minimum	Maximum
id	34,581	315,383	273,453	2	872,925
year	34,581	2,015	5.628	2,001	2,022
TFP_OP	34,581	6.638	0.912	3.363	11.42
Shujuyaosu	34,581	11.8	32.6	0	547
size	34,581	22.14	1.311	19.01	28.64
lev	34,581	0.418	0.193	0.00708	0.994
roa	34,520	0.0452	0.0664	-0.931	1.285
TobinQ	34,179	1.962	1.327	0.641	31.40

5.3 Benchmark Regression

Table 4: Benchmark regression results

variable	(1) TFP_OP	(2) TFP_OP	(3) TFP_OP	(4) TFP_OP
Shujuyaosu	1.516*** (12.327)	1.781*** (13.75)	0.488*** (4.80)	0.519*** (4.64)
size			0.404*** (97.82)	0.391*** (79.06)
lev			0.515*** (26.24)	0.443*** (21.46)
roa			1.823*** (49.01)	1.783*** (46.95)
TobinQ			0.016*** (6.00)	0.015*** (6.78)
Constant	5.136*** (229.234)	5.348*** (287.81)	-3.219*** (-38.73)	-2.925*** (-29.01)
Observations	34,581	34,581	34,118	34,118
R-squared	0.0629	0.0623	0.5377	0.609
Symbol FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 4 examines the impact of data factors on the total factor productivity of enterprises. The difference between columns (1) and (2) and columns (3) and (4) is that columns (1) and (3) only fix the year, while columns (2) and (4) fix both the year and the individual. Column (2) shows that the regression coefficient of the data element is 1.781, which is significant at the 1% level. Column (4) shows that after adding relevant control variables, the coefficient of the data factor is still significantly positive. In economic terms, after controlling for other factors, every 1% increase in the level of enterprise data factors will lead to a 0.52% increase in total factor productivity TFP, which is also statistically significant. The above results show that, when other conditions remain constant, data factors can significantly improve the total factor productivity of enterprises, and Hypothesis 1 is verified. As for other control variables, the results are also reasonable. The larger the scale, the higher the debt-to-asset ratio, the stronger the profitability, and the higher the corporate value, the higher the total factor productivity of the enterprise.

5.4 Robustness Test

5.4.1 Replace the measurement method of the explained variable

5.4.1.1 LP measures total factor productivity

The semiparametric method proposed by Levinsohn and Petrin (2003) has been widely used by many scholars. The OP method requires that the real investment of enterprises must be greater than 0, which may result in the loss of data of many enterprise samples. The LP method solves the sample loss problem by replacing variables on the basis of the OP method. Therefore, this paper uses the LP method as a robustness test to run the benchmark regression of equation (3). Columns (1) and (2) of Table 5 report the regression results of using the LP method to measure enterprise total factor productivity as the explained variable. It can be found that regardless of whether control variables are added or the measurement method of the explained variable is changed, the results remain significant.

5.4.1.2 GMM measures total factor productivity

Table 5: The impact of data elements on enterprise total factor productivity under LP and GMM methods

variable	(1) TFP_LP	(2) TFP_LP	(3) TFP_GMM	(4) TFP_GMM
shujuyaosu	2.641*** (19.24)	0.912*** (8.44)	1.684*** (13.12)	0.715*** (6.17)
size		0.528*** (110.38)		0.308*** (59.98)
lev		0.500*** (25.06)		0.432*** (20.20)
roa		1.811*** (49.34)		1.883*** (47.84)
TobinQ		0.019*** (9.22)		0.014*** (6.13)
Constant	6.893*** (349.93)	-4.211*** (-43.20)	4.399*** (238.67)	-2.163*** (-20.71)
Observations	34,581	34,118	34,581	34,118
R-squared	0.049	0.650	0.0669	0.4143
Symbol FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: *** p<0.01, ** p<0.05, * p<0.1

Blundell and Bond (1998) proposed a generalized method of moments. The basic idea of this method is to solve the endogeneity problem in the model by adding instrumental variables. As a robustness test, this paper uses the GMM method to measure total factor productivity and runs the benchmark regression of equation (3). Columns (3) and (4) of Table 5 report the regression results of the enterprise total factor productivity calculated using the GMM method as the explained variable. It can be found that regardless of whether control variables are added or the measurement method of the explained variable is changed, the results remain significant. This fully demonstrates that the data factor has a significant and robust effect in promoting the total factor productivity of enterprises.

5.4.2 Replace the core explanatory variable measurement method

In the descriptive statistics, we can find that when measuring data element indicators, “application of digital technology” has the largest mean and maximum values, indicating that in a statistical sense, the application of data technology indicates that the data element is representative to a certain extent. Therefore, we change the measurement method of the core explanatory variable and use the frequency of “application of digital technology” in the annual report of the enterprise to represent the level of the enterprise data element as a way of robustness test, and run the benchmark regression of equation (3). Table 6 reports the results of the impact of data elements on the total factor productivity of enterprises when digital technology is used to reflect the level of enterprise data elements. It can be found that regardless of whether control variables are added or the measurement method of core explanatory variables is changed, the results are still significant.

Table 6: The impact of data elements (application of digital technology) on total factor productivity of enterprises

variable	(1) TFP_OP	(2) TFP_OP
digital	4.752*** (17.28)	1.844*** (7.77)
Constant	5.347*** (288.25)	-2.892*** (-28.73)
Observations	34,581	34,118
R-squared	0.066	0.535
Controls	NO	YES
Symbol FE	YES	YES
Year FE	YES	YES

Note: *** p<0.01, ** p<0.05, * p<0.1

5.4.3 DID Method

In the past few years, most industrialized countries in the world have successively introduced relevant policies for big data pilot zones. In 2015, the State Council issued the “Action Outline for Promoting the Development of Big Data” (hereinafter referred to as the “Outline”). The “Outline” pointed out that “regional pilot projects should be carried out to promote the construction of big data comprehensive pilot zones such as Guizhou”. In September of that year, Guizhou Province launched the construction of the first national big data comprehensive pilot zone. The following year, the second batch of provinces approved to build national big data comprehensive pilot zones were released, including Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Henan, Shanghai, Chongqing and Guangdong. The main task of the big data comprehensive pilot zone is to promote the development of the regional big data industry, including data resource management integration and sharing and opening, data center integration, data resource application, data element circulation, and big data industry agglomeration. Therefore, researchers often measure the level of data element development and circulation in the region by whether the region has established a big data comprehensive pilot zone (Qiu Zixun and Zhou Yahong, 2021). This policy has promoted the digital transformation of enterprises and provided strategic support and guarantee for their affiliated enterprises. The DID model is as follows (4):

$$TFP_{it} = \beta_0 + \beta_{did} DID_{it} + \gamma controls_{it} + year_t + \varepsilon_{it} \quad (4)$$

This paper further adopts the construction of a comprehensive big data pilot zone proposed in the Outline as a quasi-natural experiment. The province where enterprise i is located has been approved to build a national comprehensive big data pilot zone in the Outline in year t and is classified as the experimental group, with DID defined as 1. The enterprises that are not on the approved list in that year are regarded as the control group, with DID defined as 0. The setting of control variables controls is consistent with the above. Fixed effects are used for regression analysis, and cluster-robust standard errors are used to correct the heteroskedasticity problem. The regression results are shown in Table 7. It can be seen that after adding the control variables, the coefficient is 0.059 and is still significant. This shows that when the province where the enterprise is located establishes a big data pilot zone, the enterprise’s total factor productivity increases by 0.06 units compared to when no big data pilot zone is set up. This result is significantly positive, indicating that the research conclusion that data factors improve the total factor productivity of enterprises remains robust after alleviating the endogeneity problem.

Table 7: The impact of the establishment of a national big data comprehensive experimental zone on the total factor productivity of enterprises

variable	(1) DID	(2) DID
DID	0.179*** (46.65)	0.059*** (21.99)
size		0.426*** (624.50)
lev		0.879*** (167.86)
roa		1.988*** (129.38)
TobinQ		0.009*** (15.89)
Constant	6.622*** (5651.85)	-3.280*** (-232.29)
Observations	750214	740140
R-squared	0.914	0.629
Year FE	YES	YES

Note: *** p<0.01, ** p<0.05, * p<0.1

6. Further research

6.1 Mechanism Analysis

The above research shows that data factors have a promoting effect on the total factor productivity of enterprises. So, what is the transmission mechanism of this factor affecting the total factor productivity of enterprises? Since total factor productivity is a concept of Solow residual value, it is easy to decompose the resource allocation aspect. The theoretical analysis in the previous article also explained that data factors may improve the total factor productivity of enterprises by improving the efficiency of resource allocation. This article draws on the measurement method of Richardson (2006) and uses the absolute value of the residual calculated by the model to measure Ineff. The larger the value, the worse the efficiency of enterprise resource allocation. The specific model of mechanism analysis is as follows:

$$Ineff_{it} = \theta + \beta_2 shujuyaosu_{it} + \gamma controls_{it} + \lambda_i + year_t + \mathcal{E}_{it} \quad (5)$$

As shown in Table 8, when no control variables are added, the coefficient of data factors on resource allocation efficiency is −0.163, which is significant at two stars. When control variables are added, the significance of data elements on resource allocation efficiency increases. Ineff is an inverse variable. The larger the value, the worse the efficiency of enterprise resource allocation. It is reasonable for the coefficient to be negative. The coefficient of TobinQ is negative, but only one star of this coefficient is significant. This indicates that the value is statistically insignificant.

Yang Rudai (2015) calculated that China's total factor productivity growth rate is between 2% and 6%, mainly relying on the improvement of resource allocation efficiency and the new growth model. Gong Guan and Hu Guanliang (2013) also pointed out: China's total factor productivity in the manufacturing industry will increase by 57.1% in 1998 and 30.1% in 2007. In these 10 years, the improvement of capital allocation efficiency has promoted the increase of total factor productivity by 10.1%. Yang Wanping and Li Dong (2023) discussed in detail the impact of resource allocation structure efficiency on total factor productivity. Resource allocation structure efficiency aims to promote the continuous improvement of the output, structure, technology and welfare of the entire economy by promoting the coordinated optimization and systematic development of the allocation structure of multiple production factors among economic entities. Yu Liangchun and Wang Yujia (2016) took the automobile industry as an example and showed that fixed asset investment in the automobile industry will promote the growth of its total factor productivity. This shows that through the guidance of industrial policies and the optimization of resource allocation, the improvement of enterprise total factor productivity can be promoted. There are also many existing literatures that have confirmed that resource allocation efficiency can indeed improve the total factor productivity of enterprises.

In summary, it has been effectively proven that data elements can improve the total factor productivity of enterprises by improving the efficiency of enterprise resource allocation.

Table 8: Mechanism analysis regression results

variable	(1) Ineff	(2) Ineffi
Shujuyaosu	-0.163** (-2.33)	-0.275*** (-3.88)
size		0.034*** (11.10)
lev		0.035*** (2.67)
roa		0.171*** (7.34)
TobinQ		-0.002* (-1.92)
Constant	0.137*** (13.31)	-0.585*** (-9.22)
Observations	31087	30709
R-squared	0.0083	0.01
Symbol FE	YES	YES
Year FE	YES	YES

Note: *** p<0.01, ** p<0.05, * p<0.1

6.2 Heterogeneity Analysis

Although this paper has demonstrated the authenticity of data elements in improving the total factor productivity of enterprises, is there a certain difference in the sensitivity of enterprises in different regions and of different natures to data elements? Research on this issue helps to have a deeper understanding of the boundary conditions of data elements. Therefore, this paper discusses the heterogeneity of data elements on the total factor productivity of enterprises from two aspects: the different regions where enterprises are located and the nature of the enterprises themselves.

6.2.1 Regional heterogeneity

This paper studies whether the region where the enterprise is located affects the effect of data elements on the total factor productivity of the enterprise. Table 9 lists the regression results of the three groups of samples. Columns (1), (2), and (3) report the estimated values of the enterprise subsamples in the eastern, central, and western regions respectively. We can find that all of them remain robust in terms of treatment effects, and the estimated coefficients in the western region are greater than those in the eastern and central regions. This shows that among enterprises in the western region, the level of data elements of the enterprise can better promote the improvement of the total factor productivity of the enterprise.

The above heterogeneity may be attributed to the following reasons: First, the special attributes of data elements are consistent with the economic characteristics of the western region: data elements have the characteristics of non-competitiveness, externality, low replication cost, and immediacy, which enable data elements to play a greater role in the western region. Compared with the eastern and central regions, the western region has certain differences in resource endowment, industrial structure, etc., and the special attributes of data elements are conducive to the realization of high-quality economic development in the western region. Through the mining, analysis and utilization of data elements, the western region can reduce information interaction bias and factor transaction costs, and promote the flow of innovation factors to enterprises and industries with high production efficiency and high marginal output. This helps to break the "information island" and "data barrier", realize the efficient allocation of factors, and improve the total factor productivity of enterprises. Secondly, the attention and support of data elements at the national level also provides good development opportunities for the western region. For example, the "Data Elements ×" Three-Year Action Plan (2024-2026) jointly issued by the National Bureau of Statistics and 17 other departments clearly puts forward typical scenarios for the value of data elements and measures to promote the activation of the potential of data elements. This will provide more policy support and market opportunities for enterprises in the western region, and stimulate data factors to play a greater role in promoting the improvement of total factor productivity of enterprises. Therefore, data factors in the western region can better promote the improvement of total factor productivity of enterprises, mainly due to the special attributes of data factors and the support of national policies.

Table 9: Regional heterogeneity regression results

variable	(1) Eastern TFP_OP	(2) Central TFP_OP	(3) Western China TFP_OP
Shujuyaosu	0.436***	0.593***	1.386***
	(6.37)	(2.72)	(4.05)
Constant	-4.400***	-5.614***	-5.617***
	(-88.15)	(-55.10)	(-43.89)
Observations	62016	11799	8365
R-squared	0.508	0.505	0.574
Controls	YES	YES	YES
Symbol FE	YES	YES	YES
Year FE	YES	YES	YES

Note: *** p<0.01, ** p<0.05, * p<0.1

6.2.2 Industry heterogeneity

This paper studies whether the characteristics of an enterprise itself will affect the effect of data factors on the total factor productivity of the enterprise. Referring to the method of Peng Hongxing and Mao Xinshu (2017), according to the classification guidelines for listed companies in my country issued by the China Securities Regulatory Commission in 2012, companies with classification codes of C25-C29, C31-C32, C34-C41, I63-I65 and M73 are defined as high-tech industry companies. On this basis, regression analysis is conducted and the results are shown in columns (1) and (2) of Table 10. It can be seen that for high-tech enterprises, the role of data factors in promoting the overall productivity of the enterprise is not significant, while for non-high-tech industries, the role of data factors in promoting the overall productivity of the enterprise is significantly positive.

Referring to the method of Yin Meiqun, Sheng Lei, and Li Wenbo (2018), enterprises are specifically subdivided into labor-intensive, capital-intensive, and technology-intensive industries in accordance with the “2012 CSRC Guidelines on Industry Classification of Listed Companies”. The group regression was performed according to formula (3) and the results are shown in columns (3), (4) and (5) of Table 10. Similar to high-tech enterprises and non-high-tech enterprises, for labor-intensive and capital-intensive enterprises, data factors can significantly improve the total factor productivity of enterprises, but the promoting effect on technology-intensive enterprises is not significant.

Table 10: Industry heterogeneity regression results

variable	(1) High Technology TFP_OP	(2) Non-high-tech TFP_OP	(3) Labor intensive TFP_OP	(4) Capital Intensive TFP_OP	(5) Technology intensive TFP_OP
shujuyaosu	0.144	1.288***	1.269***	2.717***	0.104
	(1.16)	(5.57)	(3.86)	(4.46)	(0.89)
Constant	-4.478***	-5.57***	-5.124***	-5.129***	-4.769***
	(-46.43)	(-61.49)	(-40.00)	(-32.95)	(-53.88)
Observations	14384	19734	11324	6042	15870
R-squared	0.523	0.511	0.452	0.551	0.606
Controls	YES	YES	YES	YES	YES
Symbol FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: *** p<0.01, ** p<0.05, * p<0.1

The reason for the above heterogeneous results may be that high-tech industries such as information transmission, software and information technology, or so-called technology-intensive industries, are closely related to big data, and the impact of data element levels on such industries is different from that on other industries. Therefore, many scholars will exclude listed companies in the information transmission, software and information technology service industries from the benchmark regression for research (Shi Qingchun, Niu Yue, Xu Hui, 2023). However, in this study, the relevant listed companies were not excluded during data processing, but this was explained in the heterogeneity analysis.

7. Conclusion and Policy Recommendations

Faced with China’s current high-quality economic growth model and the emergence of new quality productivity, improving total factor productivity is not only a source of power to promote my country’s development, but also an integral part of my country’s reform efforts. With the vigorous development of the digital economy, data factors have become the fifth largest production factor of enterprises. Whether data factors can become a booster to improve the total factor productivity of enterprises has become a widely discussed issue in academia. This paper uses the data of A-share listed companies from 2001 to 2022 to construct a two-way fixed effects model and empirically examines the impact of data factors on the total factor productivity of enterprises. The results show that data factors have a significant positive impact on the total factor productivity of enterprises. After replacing the explained variables, the measurement method of the core explanatory variables, and introducing a series of robustness tests such as quasi-natural experiments, the results are still significant. Further analysis found that the improvement of enterprise total factor productivity can be achieved by improving resource allocation efficiency. Heterogeneity analysis shows that the western region is more sensitive to data elements than the central and eastern regions. High-tech enterprises and technology-intensive enterprises are closely related to the digital economy, so they have other economic development models. This article is dedicated to studying the impact of data elements on the total factor productivity of enterprises under the digital economy and exploring the mechanism behind it. This is of great significance for achieving high-quality development, and also provides a certain reference for how enterprises can carry out reforms in the context of the Internet. Based on this, the policy implications of this article are as follows:

First, increase efforts in talent cultivation and talent introduction. The formation and development of enterprise data elements requires talents, and talents are the first resource. There are too few cross-disciplinary talents in my country. To give full play to the role of data elements in promoting the total factor productivity of enterprises, we need compound talents who are both proficient in digital technology and master the company's development model. However, there are few academic talents in this field in China, and the training of such talents in universities has not attracted enough attention. Therefore, the Ministry of Education should first strive to cultivate cross-disciplinary talents in data science and corporate governance. Only when talents are effectively cultivated can the development of data elements and the role of data elements in promoting my country's economy be guaranteed. Listed companies should also take the initiative to find college students, cooperate with local key digital economy universities, and conduct campus recruitment in various colleges and universities during the job search season. Relevant enterprises can provide talent subsidies for outstanding graduates, master's students, and doctoral students to attract outstanding graduates to work in real economy enterprises, bring excellent digital technology talents to the development of Chinese listed companies, and inject more new vitality into the traditional economy. The two play a role of mutual selection and mutual promotion.

Second, in order to improve total factor productivity in the context of high-quality economic development, we must make full use of the role of data factors. This article empirically proves that the current data factor has a significant promoting effect on the total factor productivity of enterprises. Enterprises should seize the dividends of the times, actively promote the digital transformation of enterprises, transform data into assets owned and controlled by themselves, guide enterprises to firmly determine the direction of digital strategic transformation, and reasonably use cutting-edge technologies in the digital economy era, such as cloud computing and the Internet of Things, to improve their own productivity.

Third, guide enterprises to make rational use of data elements. In the mechanism analysis, we can conclude that data elements improve the total factor productivity of enterprises by improving the efficiency of enterprise resource allocation. Data elements are also integrated into all aspects of enterprise production and construction. The characteristics of data elements such as reproducibility and transferability mean that data elements are easy to use. Enterprises need to fully tap the utilization potential of data elements. In terms of intelligent manufacturing, data information analysis capabilities, or factor utilization and factor integration, data elements can enable better resource allocation in enterprises. At the same time, the circulation and exchange of data elements involve issues such as personal privacy and state secrets. Therefore, while making full use of the role of data elements in promoting total factor productivity, we must also pay attention to the ethics and ownership of data dissemination. The characteristics of data elements are reproducible and modifiable, which greatly increases the possibility of stealing data elements. If the legitimate interests of data asset owners cannot be protected, there will be fewer and fewer innovative activities in society.

Fourth, balance the development level of data elements in the east, middle and west. In the heterogeneity analysis, we can see that data elements have a greater boosting effect on listed companies in the west. This shows that the characteristics of data elements can be more integrated with the development level of the western region. By mining and utilizing data elements, the western region can accelerate the transformation and application of scientific research results and promote the digital transformation and intelligent upgrading of traditional industries. The national level's attention and support for western data elements will also provide good development opportunities for the western region and promote data elements to play a greater role in promoting the improvement of total factor productivity of enterprises. In the construction of the next national big data test platform, more attention should be paid to the development of data elements in the western region, and the country's investment in the development of data elements in the east, middle and west should be balanced. Even the construction of data elements in the western region should be strengthened.

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