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The Impact of Digital Economy on TFP of Industries: Empirical Analysis Based on the Extension of Schumpeterian Model to Complex Economic Systems

Jiaqi Liu [1], Yiyang Cheng [2], Yamei Fu [2,3,*] and Fei Xue [2]

1 School of Management, Xi'an University of Science and Technology, Xi'an 710054, China; vickyliu@xust.edu.cn
2 School of Economics and Management, Northwest University, Xi'an 710127, China; chengyiyang@stumail.nwu.edu.cn (Y.C.); 20230094@nwu.edu.cn (F.X.)
3 School of Statistics, Xi'an University of Finance and Economics, Xi'an 710100, China
* Correspondence: fuyamei@xaufe.edu.cn

Abstract: The digital economy (DE) is a new driver for enhancing total factor productivity (TFP). Using panel data from 30 provinces in China between 2011 and 2022, this study measures DE and TFP using the entropy-weighted TOPSIS method and the Global Malmquist–Luenberger method and further examines the impact of DE on the TFP of industries. The main findings are as follows: (1) DE can significantly improve TFP, though the extent of improvement varies. DE has the greatest impact on the TFP of the service industry, followed by the manufacturing industry, with the weakest effect on the agricultural industry. (2) The enhancement effect of DE on agriculture and the service industry is more pronounced in the central and western regions, while the improvement effect on manufacturing is more evident in the eastern region. (3) DE has facilitated the improvement of TFP in manufacturing industries such as textiles and special equipment manufacturing, as well as in service industries like wholesale and retail. However, it has not had a significant impact on the TFP of industries such as pharmaceutical manufacturing and real estate. This study has significant theoretical value and policy implications for China and other developing countries in exploring DE and achieving high-quality industrial development.

Keywords: digital economy; total factor productivity; agriculture industry; manufacturing industry; service industry

MSC: 91B44; 91B62

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1. Introduction

In recent years, the digital economy (DE) has expanded into new dimensions of economic development on a global scale. The G20 Digital Economy Development and Cooperation Initiative highlights the significant role of DE in promoting inclusive growth and sustainable development worldwide. According to data released by the China Academy of Information and Communications Technology (Figure 1), during the period from 2005 to 2022, the value added of China's DE escalated from 2616.1 billion to 50,200 billion, representing an increase of approximately 14 times. The proportion of DE in GDP ascended from 14.2% to 41.5%, amounting to an increase of 27.3 percentage points.

High-quality industrial development is an important approach for China to establish the new "dual circulation" paradigm. Essentially, achieving high-quality industrial development implies enhancing the total factor productivity (TFP) of industries [1,2]. As the driving force of the new round of industrial transformation, DE demonstrates distinct features and patterns in infrastructure, production factors, and production and service methods compared to the eras of agricultural and industrial economies. Its economic development paradigm relies on the evolution of technological revolutions to create an economic and social network of ubiquitous connectivity, drive the explosive growth of data factors, and promote disruptive innovations in social production and lifestyle, thereby providing new impetus for improving the TFP of industries. At present, major economic entities such as the United States, Germany, and Japan all highly value the development of DE and seize the commanding heights of the new economic development era by concentrating on cutting-edge technological innovation and facilitating the digital transformation of industries. The Chinese government also considers DE as a new impetus for economic development and puts forward the proposal of realizing high-quality development of industries with the help of digital technology.

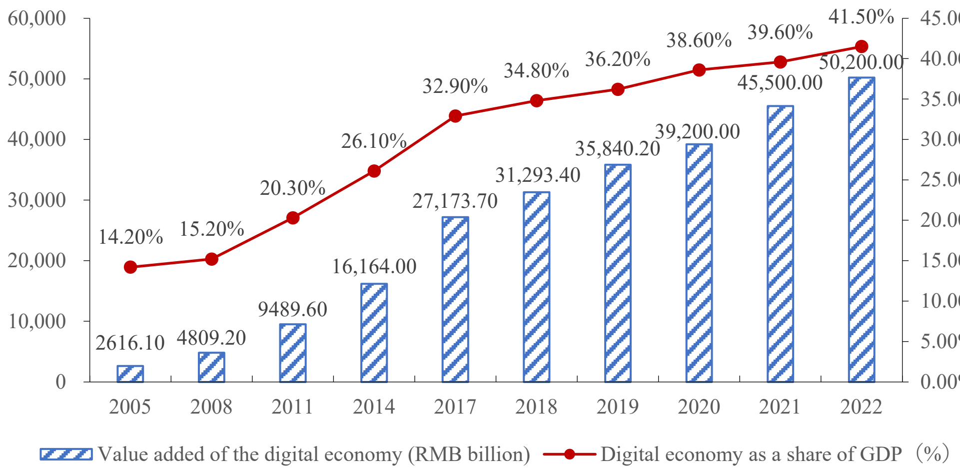

Figure 1. Value added of China's digital economy and its share of GDP, 2005–2022.

However, whether DE can indeed enhance the TFP of industries remains an unresolved research issue. In the late 1980s, the "Solow paradox" was proposed, depicting a paradoxical relationship between the vigorous expansion of investment in Information and Communication Technologies (ICT) in the United States and the low level of real productivity [3]. In the mid-1990s, the United States witnessed 118 months of high economic growth, high employment, and low inflation, co-existing with the phenomenon of the "new economy". Numerous studies have indicated that ICT was the driving force behind the emergence of the 'new economy' in the U.S. [4]. Nevertheless, some research has shown that the "Solow paradox" still exists and that the prosperity of the new economy stems from economic cycles and other factors [5]. With the extension of ICT technology to digital technology, the question of whether digital technology can enhance TFP and its mechanism of action has drawn continuous academic attention. Some scholars have discovered that DE can effectively enhance TFP [6–8]. Conversely, ref. [9], by combining the statistics of the United States, the United Kingdom, and Germany, pointed out that DE has not yet brought any improvement in the growth of TFP. Similarly, ref. [10] noted that DE has resulted in a much smaller increase in TFP than the electrification revolution.

Against this backdrop, this paper attempts to answer the following questions: Can DE break through the "productivity paradox" and promote the TFP of industries? Are there differences in the effects of DE on the TFP of agriculture, manufacturing, and service industries? Does the influence of DE on the TFP of industries exhibit regional heterogeneity and industrial heterogeneity? To address these questions, this paper first formulates a multi-sector Schumpeterian endogenous growth model to reveal the influence mechanism of DE on the TFP of industries within a complex economic system. Subsequently, it respectively computes the development level of the digital economy in Chinese provinces from 2011 to 2022, along with the TFP of agriculture, manufacturing, and service industries. Based on this, this paper establishes an econometric model, empirically examines the influence of DE on the TFP of industries, and elaborately dissects this influence from the perspectives of regional and industrial heterogeneity, providing policy support for the healthy and sustainable development of industries.

The contributions of this paper are as follows: First, considering the complexity of the economy, a multi-sector economic growth model is constructed from the perspective of efficiency-driven technological progress, providing a theoretical framework for analyzing the internal mechanism of DE's influence on the TFP of industries. Second, the provincial-industry TFP panel data for China's agriculture, manufacturing, and service industries are systematically calculated, revealing the effects, as well as regional and industrial heterogeneity, of DE on the TFP of different industries and providing empirical evidence for addressing the "Solow Paradox" of DE. Third, tools such as Python 3.11.4 and text analysis are utilized to measure the digital economy development index of each province in China by combining network and statistical data, which better reflects the overall impact of DE on the TFP of industries.

The rest of the paper is organized as follows: Section 2 provides a literature review. Section 3 establishes a theoretical model to define the relationship between DE and TFP in complex economic systems. Section 4 describes the measurement model configuration and data sources. Section 5 presents the empirical results and discussion. Section 6 summarizes the paper and offers policy recommendations and research limitations.

2. Literature Review

The empirical analysis of DE and the TFP of industries addresses three aspects: the connotation and measurement of DE, the connotation and measurement of TFP, and the influence of DE on the TFP of industries.

The concept of "digital economy" was first proposed by Don Tapscott in 1996. In the initial stage, when the concept was introduced, DE was essentially equivalent to the ICT industry [11]. With the advancement of digital technologies, the G20 Hangzhou Summit defined DE as "a series of economic activities that use digitalized knowledge and information as the key production factor, modern information networks as the important carrier, and the effective use of ICT as the crucial driving force for efficiency improvement and economic structure optimization" [12]. Based on this definition, scholars have conducted extensive discussions on statistical measurement, mainly including accessing the scale of DE [13] and measuring the development level of DE [14]. Among them, measuring the development level of DE provides a more comprehensive reflection of its connotation and is convenient for regional comparison [15].

The TFP of industries, as a crucial indicator for measuring the efficiency of industrial development, reflects the contribution of factors such as technological progress and improvements in organizational management, in addition to the input of elements like capital and labor, to the growth of output during the production process. Multiple studies have examined the measurement methods and influencing factors of the TFP of industries. Among them, the measurement methods include the Solow residual, Data Envelopment Analysis (DEA), and Stochastic Frontier Analysis (SFA) [16–18]. Among these methods, DEA, especially the Global Malmquist–Luenberger (GML) index method, can handle complex situations with multiple input and output factors and incorporate undesirable outputs, such as environmental pollution, into the analysis framework, thus reflecting the diversity and sustainability of the industrial production process more comprehensively [19]. Regarding the influencing factors, existing studies mostly focus on the effects of factors such as infrastructure investment, carbon emissions, and population aging [20–22]. In recent years, scholars have begun to pay attention to the impact of artificial intelligence (AI) and the Internet on the efficiency of different industries [23,24].

The study of the relationship between DE and the TFP of industries has a considerable history. Ever since the "Solow Paradox" was proposed, scholars have conducted extensive discussions on the impact of ICT on TFP and have formed two sharply contrasting viewpoints. One is the optimistic perspective. Some scholars have developed mathematical models from the perspective of task automation in their studies, suggesting that artificial intelligence will drive rapid growth in manufacturing productivity [25,26]. A study on TFP in different industries in Sweden found that although there was no significant correlation between ICT and TFP in the short term, there was a positive correlation after a lag of seven to eight years [27]. The other is the pessimistic perspective. Based on U.S. statistical data, ref. [28] argued that AI technology alone is insufficient to drive productivity growth. Ref. [29] proposed that excessive digitization leads to resource wastage and labor misallocation, which suppresses TFP growth.

In general, there are three aspects that require improvement in the existing studies. First, most studies rely on statistical data to reflect the development level of the DE. However, issues such as insufficient indicator coverage and poor data timeliness and availability make it difficult to objectively represent the overall impact of DE on the TFP of industries. Consequently, this paper constructs a multi-dimensional indicator system based on the connotation of DE and incorporates highly timely indicators, such as network indices, to more accurately depict the development level of China's DE, providing data support for researchers testing its impact on the TFP of industries. Second, previous research focuses on the impact of technical factors, such as ICT and AI, on the TFP of industries. However, as a new economic form, DE encompasses more than just technical characteristics. Currently, whether from a theoretical or empirical standpoint, research on the impact of DE on the TFP of industries remains relatively scarce. Therefore, this paper integrates DE and the TFP of industries into the same analytical framework for both theoretical analysis and empirical testing. Third, prior studies have analyzed the impact of DE on TFP within a single industry. Whether there are differences in the impact of DE on the TFP across different industries still needs validation. Therefore, this paper calculates the TFP of China's agriculture, manufacturing, and service industries, respectively, conducts comparisons using econometric regression, and performs extended analyses of regional and industry heterogeneity to enhance the understanding derived from existing studies.

3. Theoretical Model

To analyze the impact mechanism of DE on TFP, this paper incorporates DE into the firm's production activities based on the multi-sector Schumpeterian endogenous growth model constructed by [30]. Assume that an economy comprises three sectors: the general product sector, the industry product sector, and the research and development (R&D) sector. The role of the general products sector is to aggregate the final products produced by the n industry products sectors. The industry product sector operates under a perfect competition market. Each representative firm utilizes labor and intermediate goods as inputs for producing final products. The production of intermediate goods is carried out using optimal technological standards. Technological innovation in the economy originates from the R&D sector, which continuously generates new intermediate products for the economy through its R&D activities. This process facilitates technological progress within industries.

3.1. The Model

3.1.1. Firm Behavior in the General Product Sector

General products serve two functions: they are used for household consumption and firm investment. Assume that the production of general products is composed of final products from n sectors within the perfect competition market. The production function is specified as a Constant Elasticity of Substitution (CES) production function, which satisfies constant returns to scale, strict concavity, and the Inada conditions. The specific form is as follows:

$$Y_t = \left(\sum_{i=1}^{n} \varphi_i Y_{it}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, i = 1, 2, \cdots, n \quad (1)$$

where Y_t represents the quantity of general products, Y_{it} represents the quantity of final products from the i-th industry, and φ_i represents the importance of the i-th industry's final products in the general products. ε represents the elasticity of substitution between final product inputs across industries in production. When $0 < \varepsilon < 1$, there is complementarity between the final products of different industries, and when $\varepsilon > 1$, they are substitutable.

In a perfect competition market, producers of general products choose the optimal quantity Y_{it} of industry final products to maximize their profits, given the prices of industry final products P_{it} and the price of the general products P_t.

3.1.2. Firm Behavior in the Industry Product Sector

Assume that the economic system comprises n final product sectors, each characterized by perfect competition for both final products and factor markets, with each industry's final products produced by labor and specialized intermediate products distributed over the interval [0, 1]. The production function is specified as Equation (2):

$$Y_{it} = L_{it}^{1-\alpha} \int_0^1 A_{it}^{1-\alpha}(j) x_{it}^{\alpha}(j) dj \tag{2}$$

where L_{it} represents the labor input quantity used in producing final products of industry i, which ensures that the total labor across all industries equals the economy's endowment of labor. $x_{it}(j)$ represents the quantity of the j-th intermediate product used in the production process of final products in the industry i. $A_{it}(j)$ denotes the technological level of the j-th intermediate product in industry i; α represents the elasticity of specialized intermediate product output; $1 - \alpha$ represents the elasticity of labor output.

The production function of the industry's final products adheres to Harrod-neutral technological progress. In a perfect competitionmarket, firms producing final products in the industry i maximize profits by optimizing their inputs of intermediate product input $x_{it}(j)$ and labor input L_{it}, given predetermined prices for intermediate products $P_{it}(j)$ and wage rates W_{it}.

3.1.3. Firm Behavior in the R&D Sector

Assume that the R&D sector is composed of capitalists who produce a unique intermediate product. Their profit-driven behavior would incentivize them to enter industries with higher profitability. The production of intermediate products uses the industry's final products as inputs. Given the price P_{it} of the industry's final product, capitalists adjust the quantity and price of intermediate products to achieve profit maximization.

To sustain monopoly profits, capitalists rely on R&D activities to optimize production processes and enhance technological capabilities. Assume that the success probability of R&D activities is $\rho_{it}(j)$, and the technological level will increase from $A_{it}(j)$ to $\theta_i A_{it}(j)$, where $\theta_i > 1$. If R&D fails, the technological level of the intermediate product remains constant. Following the method proposed by [31], this paper expresses the probability of R&D success as a function of R&D input. The specific formulation is as follows:

$$\rho_{it}(j) = \lambda_i \left(\frac{R_{it}(j)}{L_{it} {A_{it}}^*(j)}\right)^{0.5} \tag{3}$$

where i represents industry, t represents time, j represents intermediate goods categories, $R_{it}(j)$ represents R&D inputs, ${A_{it}}^*(j)$ represents R&D objectives, and λ_i represents R&D efficiency.

According to the technological–economic paradigm characteristics of DE, innovation is the intrinsic force driving the development of digital economic paradigms. Digital technologies are universal and are capable of widespread application across multiple industries and domains, thereby empowering industry ecosystems and transforming enterprise business models and management practices, leading to disruptive innovation. Therefore, this paper incorporates digital technology into the innovation efficiency of the R&D sector.

Digital technologies contribute to the innovation efficiency of the R&D sector in two main aspects: First, by enhancing R&D efficiency through their pervasiveness and collaborative capabilities, thereby increasing the probability of R&D success. Second, by optimizing the combination of production factors through their use and thereby influencing the optimal innovation behavior of the R&D sector. This paper represents R&D efficiency as an increasing function of digital technology, which is denoted as digital, specifically as follows:

$$\lambda_i = \eta \times digital_{it}^{\beta} \tag{4}$$

where η represents the exogenous efficiency parameter, and β represents the efficiency parameter of digital technology.

3.2. Optimal Behavior Derivation Process

3.2.1. Optimal Behavior of Firms in the Industry Product Sector

The optimal behavior of firms in the industry's final product is defined as follows:

$$\max\left[P_{it}L_{it}^{1-\alpha}\int_0^1 A_{it}^{1-\alpha}(j)x_{it}^{a}(j)dj - W_{it}L_{it} - \int_0^1 P_{it}(j)x_{it}(j)dj\right] \tag{5}$$

Under conditions of perfect competition market in the labor and intermediate goods, the first-order partial derivatives of $x_{it}(j)$ in Equation (5) can be derived and set to zero yields. Then, $P_{it}(j)$ can be expressed as follows:

$$P_{it}(j) = \alpha P_{it}L_{it}^{1-\alpha}A_{it}^{1-\alpha}(j)x_{it}^{\alpha-1}(j) \tag{6}$$

Taking the first-order partial derivatives of L_{it} in Equation (5) and setting them to zero, we obtain Equation (7):

$$W_{it} = (1-\alpha)P_{it}L_{it}^{-\alpha}\int_0^1 A_{it}^{1-\alpha}(j)x_{it}^{\alpha}(j)dj \tag{7}$$

Given the demand for intermediate products, producers will determine the optimal price and quantity of intermediate products based on the principle of profit maximization. Assume that producing 1 unit of intermediate product requires consuming 1 unit of final product from the industry. The optimal behavior of intermediate product producers is represented by Equation (8):

$$\max[P_{it}(j)x_{it}(j) - P_{it}x_{it}(j)] \tag{8}$$

Combining Equations (6) and (8), the optimization behavior of intermediate product firms can be derived as follows:

$$\max\left[\alpha P_{it}A_{it}^{1-\alpha}(j)L_{it}^{1-\alpha}x_{it}^{\alpha}(j) - P_{it}x_{it}(j)\right] \tag{9}$$

By taking the first-order partial derivative of $x_{it}(j)$ in Equation (9) and setting it to zero, we obtain Equation (10):

$$x_{it}(j) = \alpha^{\frac{2}{1-\alpha}}A_{it}(j)L_{it} \tag{10}$$

According to Equations (6) and (10), $P_{it}(j)$ can be expressed as follows:

$$P_{it}(j) = \frac{P_{it}}{\alpha} \tag{11}$$

According to Equations (8), (10), and (11), a firm's profit from choosing to produce intermediate products is to be expressed as Equation (12).

$$\pi_{it}(j) = P_{it}(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}} A_{it}(j) L_{it} \tag{12}$$

This paper sets $\int_0^1 A_{it}(j)dj = A_{it}$ to achieve a simplified analysis. A_{it} represents the average level of technological progress in industry i. According to Equations (2) and (10), we obtain the optimal output of firms in industry i:

$$Y_{it} = \alpha^{\overline{1-\alpha}^{2\alpha}} L_{it} \int_0^1 A_{it}(j)dj = \alpha^{\overline{1-\alpha}^{2\alpha}} A_{it} L_{it} \tag{13}$$

Based on the preceding discussion, the success probability of intermediate product R&D activities depends solely on R&D efficiency. At equilibrium, the success probability of various types of intermediate product R&D activities in the industry is ρ_{it}. Therefore, the average level of technological progress A_{it} can be expressed as Equation (14):

$$A_{it} = \theta_i A_{i,t-1}\rho_{it} + A_{i,t-1}(1-\rho_{it}) \tag{14}$$

Based on Equation (14), the rate of technological progress growth for industry i is given by Equation (15).

$$g_{it} = \frac{A_{it} - A_{i,t-1}}{A_{i,t-1}} = \frac{\theta_i A_{i,t-1}\rho_{it} + A_{i,t-1}(1-\rho_{it}) - A_{i,t-1}}{A_{i,t-1}} = (\theta_i - 1)\rho_{it} \tag{15}$$

3.2.2. Optimal Innovation Behavior of the R&D Sector

The optimal behavior of the R&D sector is set as follows:

$$\max[\rho_{it}(j)\pi_{it}(j) - P_{it}R_{it}(j)] \tag{16}$$

From Equation (3), Equation (17) can be obtained as follows:

$$R_{it}(j) = L_{it}A^*_{it}(j)[\frac{\rho_{it}(j)}{\lambda_i}]^2 \tag{17}$$

From Equation (17), it can be observed that there is a positive correlation between $R_{it}(j)$ and $\rho_{it}(j)$. Therefore, the profit maximization of the R&D sector can be reformulated as the maximization of innovation probability. From Equations (12) and (17), Equation (16) can be expressed as follows:

$$max\left[\rho_{it}(j)P_{it}(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}} A^*_{it}(j)L_{it} - P_{it}L_{it}A^*_{it}(j)[\frac{\rho_{it}(j)}{\lambda_i}]^2\right] \tag{18}$$

Taking the first-order partial derivative of $\rho_{it}(j)$ in Equation (18) and setting it to zero yields:

$$\rho_{it}(j) = \frac{1}{2}(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}\lambda_i^2 \tag{19}$$

From Equation (19), it can be seen that $\rho_{it}(j)$ depends only on α and R&D efficiency λ_i. Therefore, in industry i, the probabilities of success in innovating various types of intermediate products are equal, which means $\rho_{it}(j) = \rho_{it}$. From Equations (4) and (19), Equation (15) can be expressed as follows:

$$g_{it} = (\theta_i - 1)\frac{1}{2}(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}\lambda_i^2 = \frac{1}{2}(\theta_i - 1)(1-\alpha)\alpha^{\frac{1+\alpha}{1-\alpha}}(\eta \times digital^{\beta}_{it})^2 \tag{20}$$

Equation (20) indicates that the rate of technological progress in industry i depends on parameters α, θ_i, η, β, and $digital_{it}$. It is evident that the development of DE can drive industry technological progress.

3.2.3. Optimal Behavior of the General Product Sector

According to Equation (1), the optimal behavior of the general product sector is as follows:

$$\max\left[P_t(\sum_{i=1}^{n}\phi_i Y_{it}^{\frac{1-\varepsilon}{\varepsilon}})^{\frac{\varepsilon}{1-\varepsilon}}-\sum_{i=1}^{n}P_{it}Y_{it}\right] \tag{21}$$

Taking the first-order partial derivative of Y_{it} in Equation (21) and setting it to zero yields, we obtain the following:

$$Y_{it}=\left(\frac{P_t\phi_i}{P_{it}}\right)^{\varepsilon}Y_t \tag{22}$$

3.3. Efficiency-Enhancing Effects of the Digital Economy

Based on the optimal behavior of firms in the general product sector, the output structure between any two industries, i and k, can be represented by the following:

$$\frac{Y_{it}}{Y_{kt}}=\frac{(P_t\phi_i/P_{it})^{\varepsilon}Y_t}{(P_t\phi_k/P_{kt})^{\varepsilon}Y_t}=(\frac{\phi_i P_{kt}}{\phi_k P_{it}})^{\varepsilon} \tag{23}$$

According to Equation (13), $\frac{Y_{it}}{Y_{kt}}$ can be expressed as follows:

$$\frac{Y_{it}}{Y_{kt}}=\frac{\alpha^{\frac{2\alpha}{1-\alpha}}A_{it}L_{it}}{\alpha^{\frac{2\alpha}{1-\alpha}}A_{kt}L_{kt}}=\frac{A_{it}L_{it}}{A_{kt}L_{kt}} \tag{24}$$

Assume that free mobility of labor across industry sectors, when the labor market reaches equilibrium, the wages in each industry sector are equal. According to Equation (7), we have the following:

$$1=\frac{W_{it}}{W_{kt}}=\frac{(1-\alpha)P_{it}L_{it}^{-\alpha}\int_0^1 A_{it}^{1-\alpha}(j)x_{it}^{\alpha}(j)dj}{(1-\alpha)P_{kt}L_{kt}^{-\alpha}\int_0^1 A_{kt}^{1-\alpha}(j)x_{kt}^{\alpha}(j)dj} \tag{25}$$

According to Equations (10) and (25), $\frac{P_{it}}{P_{kt}}$ can be expressed as follows:

$$\frac{P_{it}}{P_{kt}}=\frac{A_{kt}}{A_{it}} \tag{26}$$

Taking the natural logarithm of Equation (26) on both sides and differentiating with respect to time, we obtain Equation (27):

$$\frac{\dot{P}_{it}}{P_{it}}-\frac{\dot{P}_{kt}}{P_{kt}}=\frac{\dot{A}_{kt}}{A_{kt}}-\frac{\dot{A}_{it}}{A_{it}}=g_{kt}-g_{it} \tag{27}$$

Equation (27) indicates that the relative price changes between industry sectors depend on the rates of technological progress across those sectors. Sectors experiencing faster technological progress have lower rates of product price change compared to sectors with slower technological progress.

According to Equations (23), (24), and (26), $\frac{L_{it}}{L_{kt}}$ can be expressed as follows:

$$\frac{L_{it}}{L_{kt}}=(\frac{\phi_i}{\phi_k})^{\varepsilon}(\frac{A_{it}}{A_{kt}})^{\varepsilon-1} \tag{28}$$

Taking the natural logarithm of Equation (28) on both sides and differentiating with respect to time, and further substituting Equation (27), we obtain the following:

$$\frac{\dot{L}_{it}}{L_{it}} - \frac{\dot{L}_{kt}}{L_{kt}} = (\varepsilon - 1)(\frac{\dot{A}_{it}}{A_{it}} - \frac{\dot{A}_{kt}}{A_{kt}}) = (\varepsilon - 1)(g_{it} - g_{kt}) \tag{29}$$

where ε represents the elasticity of substitution in general product manufacturing. When $0 < \varepsilon < 1$, labor will move from sectors with higher rates of technological advancement to those with lower rates. When $\varepsilon - 1 < 0$, labor will move from sectors with lower rates of technological advancement to those with higher rates. According to Equations (1) and (13), Y_t can be expressed as follows:

$$Y_t = \left[\sum_{i=1}^{n} \phi_i (\alpha^{\frac{2\alpha}{1-\alpha}} A_{it} L_{it})^{\frac{\varepsilon - 1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon - 1}} \tag{30}$$

Let $L_t = \sum\limits_{i=1}^{n} L_{it}$, where L_t represents the aggregate labor force across industries. According to Equation (28), L_{it} can be expressed as follows:

$$L_{it} = \frac{A_{it}^{\varepsilon-1} \phi_i^{\varepsilon}}{\sum\limits_{i=1}^{n} A_{it}^{\varepsilon-1} \phi_i^{\varepsilon}} L_t \tag{31}$$

Let $d_{it} = \frac{L_{it}}{L_t}$, where d_{it} represents the share of labor force occupied by industry i, and then we obtain Equation (32):

$$d_{it} = \frac{L_{it}}{L_t} = \frac{A_{it}^{\varepsilon-1} \phi_i^{\varepsilon}}{\sum\limits_{i=1}^{n} A_{it}^{\varepsilon-1} \phi_i^{\varepsilon}} \tag{32}$$

Equation (30) can be rewritten as follows:

$$Y_t = \left(\sum_{i=1}^{n} {\phi_i}^{\varepsilon} {A_{it}}^{\varepsilon - 1} \right)^{\frac{1}{\varepsilon - 1}} \alpha^{\frac{2\alpha}{1-\alpha}} L_t \tag{33}$$

For simplifying, let $A_t = \left(\sum\limits_{i=1}^{n} {\phi_i}^{\varepsilon} {A_{it}}^{\varepsilon - 1} \right)^{\frac{1}{\varepsilon - 1}}$, where A_t represents the technological level of the general product sector. Then, per capita output can be expressed as Equation (34).

$$y_t = \frac{Y_t}{L_t} = \alpha^{\frac{2\alpha}{1-\alpha}} A_t \tag{34}$$

Taking the natural logarithm of $A_t = \left(\sum\limits_{i=1}^{n} {\phi_i}^{\varepsilon} {A_{it}}^{\varepsilon - 1} \right)^{\frac{1}{\varepsilon - 1}}$ on both sides and differentiating with respect to time gives the following equation:

$$\frac{\dot{A}_t}{A_t} = \frac{\sum\limits_{i=1}^{n} \phi_i^{\varepsilon} A_{it}^{\varepsilon-1} \frac{\dot{A}_{it}}{A_{it}}}{\sum\limits_{i=1}^{n} \phi_i^{\varepsilon} A_{it}^{\varepsilon-1}} \tag{35}$$

Based on $\frac{\dot{A}_{it}}{A_{it}} = g_{it}$, Equation (35) can be transformed into Equation (36).

$$\frac{\dot{A}_t}{A_t} = \frac{\sum\limits_{i=1}^{n} \phi_i^{\varepsilon} A_{it}^{\varepsilon-1} g_{it}}{\sum\limits_{i=1}^{n} \phi_i^{\varepsilon} A_{it}^{\varepsilon-1}} = \sum_{i=1}^{n} d_{it} g_{it} = \frac{1}{2} \sum_{i=1}^{n} d_{it} (\theta_i - 1)(1-\alpha) \alpha^{\frac{1+\alpha}{1-\alpha}} (\eta \times digital_{it}^{\beta})^2 \tag{36}$$

From Equation (36), it is evident that with the escalation of the digital economic development level, the rate of technological progress ascends concurrently. Generally speaking, the growth of technological progress is manifested as an augmentation in TFP. Consequently, the advancement of DE can propel the growth of TFP.

4. Materials and Methods

4.1. The Measurement of Digital Economy Development Index (DEDI)

The objective of this paper is to investigate the influence of DE on TFP. Hence, it is necessary to scientifically assess the development level of DE to uphold the reliability and accuracy of the empirical results. Scholars typically use statistical data to measure DEDI from the aspects of basic conditions, external environment, and integrated application of DE development. While this approach provides some reference value, it still faces issues such as inadequate coverage of DE indicators and limited timeliness and availability of data. This paper argues that DE signifies a novel economic form, with its main features displayed in three aspects: connectivity, data, and integration. Digital technology and infrastructure are fundamental in establishing interconnected networks. Data monetization underscores the economic value of data as a key component. Additionally, industrial digitalization and digital industrialization reflect the innovative application of digital technology in the real economy.

Based on existing research indicators, this paper develops a comprehensive DE measurement index system comprising five core indicators: digital technology, digital infrastructure, data monetization, digital industrialization, and industrial digitization, along with 21 underlying indicators, as illustrated in Table 1. In particular, network data such as the Baidu Index and the frequency of data-related words in government work reports are acquired using Python 3.11.4.

This paper evaluates China's DEDI using the entropy-weighted TOPSIS method. In contrast to the basic average method, the entropy-weighted TOPSIS method not only eliminates subjective biases, resulting in more objective and reliable weight calculations but also effectively demonstrates the significance of fundamental indicators in influencing DE metrics across various dimensions. The specific construction and measurement steps of DEDI are as follows:

1. Standardization Processing. To eliminate differences in dimensions and magnitudes among the various indicators, the range method is adopted to standardize each basic indicator in the measurement system. All the basic indicators selected in this paper are positive indicators, and the standardization formula is as follows:

$$Y_{ij} = \frac{X_{ij} - \min(X_{ij})}{\max X_{ij} - \min(X_{ij})} \tag{37}$$

   where X_{ij} and Y_{ij} represent the original and standardized basic indicators for measuring DEDI, respectively.
2. Calculate the Information Entropy. Calculate the information entropy E_j of each basic indicator Y_{ij}.

$$E_j = \ln \frac{1}{n} \sum_{i=1}^{n} \left[\left(Y_{ij} / \sum_{i=1}^{n} Y_{ij} \right) \ln \left(Y_{ij} / \sum_{i=1}^{n} Y_{ij} \right) \right] \tag{38}$$

3. Calculate the Weights. Calculate the weights W_j of each basic indicator Y_{ij}.

$$W_j = \left(1 - E_j\right) / \sum_{j=1}^{m} \left(1 - E_j\right) \tag{39}$$

4. Construct the Weighted Matrix. Construct the weighted matrix R of the measurement indicators for the development level of the digital economy.

$$R = \left(r_{ij}\right)_{n \times m} \tag{40}$$

where $r_{ij} = W_j \times Y_{ij}$.

5. Calculate the Euclidean Distance. Calculate the Euclidean distances d_i^+ and d_i^- between each measurement scheme and the optimal scheme Q_j^+ and the worst scheme Q_j^-:

$$\begin{aligned} d_i^+ &= \sqrt{\sum_{j=1}^{m} \left(Q_j^+ - r_{ij}\right)^2} \\ d_i^- &= \sqrt{\sum_{j=1}^{m} \left(Q_j^- - r_{ij}\right)^2} \end{aligned} \tag{41}$$

6. Calculate $DEDI_i$:

$$DEDI_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{42}$$

where the value of $DEDI_i$ ranges between 0 and 1.

Table 1. Evaluation index system of digital economy.

Primary Indicators	Secondary Indicators	Tertiary Indicators
Digital Economy	Digital Technology	Number of artificial intelligence patents (units)
		Number of industrial robot patents (units)
		Baidu index of digital technology
	Digital Infrastructure	Number of Internet broadband access ports (ten thousands)
		Number of web pages (ten thousands)
		Number of digital television users (ten thousands)
		Number of websites owned by every hundred enterprises (units)
		Fixed investment amount in the electronic information industry (billion CNY)
	Data Monetization	Number of data exchanges/data trading platforms (units)
		Number of enterprises ranking top 10 globally in cloud computing enterprises (units)
		The frequency of data-related words in government work reports
	Digital Industrialization	Output of mobile phones, integrated circuits, and microcomputer devices (ten thousands)
		Main business income of the manufacturing industry of communication equipment, computers, and other electronic equipment (billion CNY)
		Total volume of telecommunications services (billion CNY)
		Employees in the information transmission, software, and information technology service industry (ten thousand people)
		Software business revenue (billion CNY)
	Industrial Digitization	Number of rural broadband access users (ten thousand households)
		The proportion of villages with the Internet broadband service opened (%)
		Integration Development Index of Informatization and Industrialization
		Digital Finance Index
		E-commerce transaction volume (billion CNY)

4.2. The Measurement of Total Factor Productivity (TFP)

Referring to [32], this paper utilizes the GML index method to measure the TFP of agriculture (TFP_agri), the TFP of manufacturing (TFP_manu), and the TFP of services (TFP_serv) across 30 provinces in China. The calculation processes are shown in Appendix A. The input, desirable output, and undesirable output indicators used for calculating different industries are as follows:

1. Total Factor Productivity of Agriculture (TFP_agri). Input indicators include ① labor, quantified by the number of people employed in agriculture; ② land, measured by the sown area of crops; ③ machinery, measured by the total power of agricultural machinery; ④ fertilizer, measured by the amount of agricultural fertilizer applied; ⑤ pesticide, measured by the amount of pesticide utilized. Output indicators include ① desirable outputs, measured by agricultural value added and adjusted for inflation using 2011 constant prices; ② undesirable outputs, measured by the total amount of agricultural carbon emissions.
2. Total Factor Productivity of Manufacturing (TFP_manu). Input indicators include ① capital, measured by the capital stock; ② labor, represented by the average number of employees in manufacturing. Output indicators include ① desirable outputs, measured by the gross output value of manufacturing and its sub-sectors, adjusted using the producer price index of industrial products; ② undesirable outputs, measured by the weighted average of emissions from waste gas, wastewater, and solid waste.
3. Total Factor Productivity of Service (TFP_serv). Input indicators include ① labor, measured by the number of employed personnel at the end of the year in the service industry and its sub-sectors; ② capital, measured by the capital stock of the service industry. Output indicators include ① desirable output, measured by the value added of the service industry and its various sub-sectors; ② undesirable output, measured by pollution emissions.

4.3. The Estimation Model

In order to accurately identify the impact of DE on the TFP of industries, referring to [33], this paper constructs a panel regression model for analysis. The specific model setting is as follows:

$$TFP_{i,t} = \alpha_0 + \alpha_1 DEDI_{i,t} + \alpha_c CV_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{43}$$

where $TFP_{i,t}$ is the dependent variable, representing the TFP of industries in the i-th province and the t-th year. $DEDI_{i,t}$ is the independent variable, denoting the development level of DE. μ_i represents individual fixed effects, δ_t represents time fixed effects, and $\varepsilon_{i,t}$ represents random error terms that are independently and identically distributed.

This paper focuses on coefficient α_1 of the DEDI to determine whether it is significantly positive for testing the relationship between TFP and DE. To alleviate the estimation bias caused by omitted variables, this paper controls for other factors that may have an impact on the TFP of industries. These factors include the following: Per Capita Gross Domestic Product (Pgdp): The improvement in the level of economic development not only provides conditions for technological progress but also increases the demand for technological innovation, thereby promoting the enhancement of the TFP of industries. In this paper, the logarithm of Pgdp is selected to represent it. Fiscal Autonomy (FA): The influencing factors of the TFP of industries also comprise institutional factors. In regions with higher fiscal autonomy, the government has greater flexibility in adjusting fiscal expenditures, which benefits the flow of resources toward technological progress. In this paper, the ratio of general budgetary fiscal revenue to general budgetary fiscal expenditure is utilized to represent it. Foreign direct investment (FDI): Opening up to the outside world can drive the improvement of the TFP of industries by promoting employment growth in the industry, deepening material capital accumulation, and introducing advanced production technologies and management experiences. In this paper, the proportion of foreign direct investment in GDP is employed to measure it, and deflation and price conversion processing have been implemented.

4.4. Data Sources

The datasets utilized in this study are available from the China Statistical Yearbook, the China Fixed Assets Investment Statistical Yearbook, the China Rural Areas Statistical Yearbook, the China Industry Statistical Yearbook, the China Environment Statistical Yearbook, the DRCNET Database, and the Wind Database. The word frequency of the Baidu Index and government work reports is captured using Python 3.11.4. Missing data are imputed using the average growth rate. The study encompasses data from 30 provinces in China (excluding Hong Kong, Macao, Taiwan, and Tibet). The panel period is from 2011 to 2022, and 360 samples are obtained.

5. Results

5.1. The Baseline Regression Analysis

The specific regression results are presented in Table 2. The regression results of Models (1) to (6) demonstrate that, regardless of the inclusion of control variables, DE exerts a markedly positive influence on the TFP of agriculture, manufacturing, and service industries. Furthermore, by comparing Models (2), (4), and (6), it is evident that there are differences in the enhancing effect of DE on the TFP of different industries. The coefficients for TFP_agri, TFP_manu, and TFP_serv are 0.602, 0.942, and 1.865, respectively, all of which are significantly positive, at least at the 5% level. Evidently, DE is currently focusing its efforts primarily on the service industry. It has transcended the constraints of time and space, limited information, and precise dissemination. It is likely to disrupt the pattern that "the era of the service industry is an era of low growth." In traditional service industries, production and consumption must occur simultaneously in the same location and cannot be stored or transported. Nevertheless, DE has subverted these inherent features. Service commodities, such as artistic performances, education, and healthcare, can now be exchanged across time and space in the form of data via digital platforms, facilitating the trade of services and demands that were previously difficult to address. The advancement of digital technologies has also led to the emergence of business models like e-commerce and live streaming for selling goods. Economies of scale, economies of scope, and the long-tail effect in the service industry have progressively emerged and become prominent.

Table 2. The results of baseline regression.

	TFP_Agri		**TFP_Manu**		**TFP_Serv**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
DEDI	0.612 **	0.602 **	1.865 ***	0.942 **	4.753 ***	1.865 ***
	(0.304)	(0.289)	(0.549)	(0.410)	(1.188)	(0.491)
Ln pGDP		0.174 *		0.189 **		0.258 **
		(0.095)		(0.090)		(0.104)
FD		−0.212 *		−0.245 *		−0.220 **
		(0.125)		*(0.124)		(0.094)
Finance		0.174 *		0.010		0.241 **
		(0.099)		(0.008)		(0.121)
FDI		−0.078 *		0.367 ***		0.246 **
		(0.046)		(0.073)		(0.103)
Constant	0.929 ***	0.839 ***	0.599 ***	0.245 **	−0.342 ***	−0.243
	(0.111)	(0.137)	(0.145)	(0.103)	(0.090)	(0.203)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	360	360	360	360	360	360
R^2	0.736	0.835	0.843	0.746	0.805	0.824

Note: ***/**/* indicate statistical significance at 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

In conclusion, DE is capable of promoting the TFP of agriculture, manufacturing, and service industries in China, with variations in the enhancement effects across different industries. Specifically, the digital economy exerts the most substantial positive influence on the TFP of the service industry, followed by the manufacturing industry, while having the least impact on agriculture. This indicates that the effect of the digital economy on the TFP of the manufacturing and agricultural industries requires further enhancement. In the future, it is indispensable to accelerate the in-depth integration of DE with the manufacturing industry and facilitate the transformation from "Made in China" to "Intelligently Made in China". Additionally, it is of crucial significance to enhance the application of digital technologies in agriculture to achieve high-quality, efficient, and sustainable development in this sector.

5.2. The Endogenous Analysis

The baseline regression indicates a significant positive correlation between the development of DE and the enhancement of TFP in industries. Nevertheless, the baseline analysis merely utilized OLS regression. If there are latent endogenous issues in the model, the baseline estimation results might be inaccurate.

There are two main sources of potential endogeneity in this study. First, despite including control variables and accounting for both time-variant and invariant unobservable factors, some factors may still be difficult to capture, such as regional institutional differences and dynamic variations in industrial scale. Second, there is a two-way causality between DE and TFP. The technological level is a crucial driver of DE's development, and the TFP level, to some extent, reflects the strength of technological advancement. Therefore, the level of TFP may also influence the development of DE. To address this issue, this paper constructs a panel instrumental variable for DEDI (IV_DEDI) by multiplying the cross-sectional data of the number of fixed-line telephone subscribers at the end of 1998 in each province by the first-order lag of the Internet penetration rate [34].

As shown in Table 3, the Kleibergen–Paap rk LM statistic is significant at the 1% level, indicating that there are no issues with unidentifiable instrumental variables in the model. The Kleibergen–Paap rk Wald F statistic is also much larger than the critical value of 16.38 for the Stock–Yogo weak identification test at the 10% level, suggesting that the problem of weak instrumental variables can be excluded and that the selected instrumental variables are valid. The regression results from the first stage show a positive correlation between IV_DEDI and DEDI for agriculture, manufacturing, and service industries, at least at the 5% significance level. The second-stage regression results are 0.465, 0.646, and 1.746, respectively, and are significant at least at the 5% level. This implies that the positive effect of the digital economy on TFP across different industries remains robust even after accounting for endogeneity.

Table 3. The results of instrumental variable regression.

	TFP_Agri		TFP_Manu		TFP_Serv	
	First Stage	**Second Stage**	**First Stage**	**Second Stage**	**First Stage**	**Second Stage**
IV_DEDI	0.015 *** (0.004)		0.083 ** (0.038)		0.057 *** (0.011)	
DEDI		0.465 ** (0.194)		0.646 *** (0.092)		1.743 ** (0.814)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	360	360	360	360	360	360
R^2		0.952		0.913		0.945
F	77.53	2.67	74.24	18.35	76.35	44.82
Kleibergen–Paap rk LM	53.170 (0.0000)					
Cragg–Donald Wald F	1378.940					
Kleibergen–Paap rk Wald F	244.380					

Note: ***/** indicate statistical significance at 1%, 5% levels. Robust standard errors are reported in parentheses. *p*-values are reported in parentheses for Kleibergen–Paap rk LM.

5.3. The Robustness Test

To ensure the robustness of regression results, the following tests are conducted in this paper, as shown in Table 4:

1. Change the Empirical Model. In view of the temporal accumulation of TFP, the first-order lag term of the TFP, $TFP_{i,t-1}$ is added to Equation (37), and the first and second-order lag terms of DEDI are chosen as instrumental variables for the Generalized Method of Moments (GMM) estimation. Across different models, the results consistently show that the impact of DE on TFP remains positive;
2. Change the Independent Variable. In order to avoid the estimation bias caused by the estimation method, the vertical and horizontal scatter degree method is used to recalculate DEDI for robustness analysis, whose results robustly support the above conclusions;
3. Add the Control Variables. Additional control variables are incorporated, including levels of technological innovation, marketization, and infrastructure. The level of technological innovation typically contributes to the TFP of industries. A high degree of marketization confers a greater degree of innovation in industries, thereby facilitating the enhancement of the TFP. The upgrading of infrastructure levels, such as those of railways and highways, also expedites the flow of production factors and boosts industrial efficiency. The results reveal that the impact of DE on the TFP of industries is consistent with the baseline regression.

Table 4. The results of robustness test.

		TFP_Agri			**TFP_Manu**			**TFP_Serv**	
	Change the Independent Variable	**Change the Independent Variable**	**Add the Control Variables**	**Change the Independent Variable**	**Change the Independent Variable**	**Add the Control Variables**	**Change the Independent Variable**	**Change the Independent Variable**	**Add the Control Variables**
DEDI	0.465 ** (0.194)	0.576 *** (0.064)	0.432 *** (0.096)	0.886 ** (0.372)	0.986 * (0.557)	0.821 ** (0.345)	1.167 ** (0.558)	1.485 *** (0.160)	1.094 *** (0.168)
L.TFP_agri	1.197 *** (0.203)								
L.TFP_manu				0.985 *** (0.095)					
L.TFP_serv							0.814 *** (0.158)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR(1)	0.017			0.026			0.015		
AR(2)	0.793			0.868			0.754		
Sargan	0.989			0.993			0.996		

Note: ***/**/* indicate statistical significance at 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses. The p-values are in parentheses for AR(1), AR(2), and Sargan.

5.4. The Region Heterogeneity Analysis

Given the distinct spatial variance in the regional distribution of DEDI, this paper categorizes the samples into the eastern region, as well as central and western regions, for heterogeneity tests. Prior to conducting the sub-sample tests, this paper executed the between-group difference test. The outcomes demonstrated that the p-values of the SUR test all passed the significance test, suggesting that significant differences existed between the groups.

As shown in Table 5, DE exerts a significant facilitating effect on TFP_agri in the central and western regions, whereas its impact on TFP_agri in the eastern region is not notable. The possible reasons are as follows. The eastern region, driven by industrial construction and radiated by urban expansion, has manifested the feature of concentrated interests. The digital infrastructure in eastern cities is more advanced, and the level of human capital is higher as well. Thus, the marginal utility that the digital economy brings to industrial efficiency is relatively low. Under the traditional economic model, it has been difficult for agricultural development in the central and western regions to benefit from land value appreciation resulting from industrial agglomeration and infrastructure investment. Nevertheless, the strong diffusibility and high innovativeness of the digital economy have effectively broken the resource barriers between the eastern and the central and western regions and can optimize the allocation of resources such as capital and labor effectively. Especially, the implementation of the "E-commerce Assisting Farmers" program has offered a new channel for the sales of agricultural products in the central and western regions. Therefore, the digital economy is more conducive to promoting the enhancement of agricultural TFP in the central and western regions.

Table 5. The results of region heterogeneity analysis.

	TFP_Agri		TFP_Manu		TFP_Serv	
	East Region	**Central and Western Region**	**East Region**	**Central and Western Region**	**East Region**	**Central and Western Region**
DEDI	0.456	0.734 *	1.467 ***	0.835 ***	1.073 **	1.753 **
	(0.326)	(0.399)	(0.511)	(0.317)	(0.481)	(0.737)
Constant	0.942 **	0.991 *	−3.368 ***	−0.839	0.086	0.386 ***
	(0.410)	(0.583)	(0.812)	(0.742)	(0.261)	(0.102)
N	132	228	132	228	132	228
R^2	0.943	0.843	0.633	0.574	0.885	0.825
Chi^2	5.65 ***		6.35 **		5.38 ***	
p-value	0.005		0.014		0.001	

Note: ***/**/* indicate statistical significance at 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

In the manufacturing sector, DE's promoting effect on TFP_manu is more pronounced in the eastern region than in the central and western regions. The possible reasons are as follows: From the perspective of the foundation of economic development and resource endowment, the eastern region has a first-mover advantage in the manufacturing sector. Its industrial structure is relatively mature and diversified, having accumulated substantial physical capital and human capital in the early stages. This creates favorable conditions for the in-depth integration of the digital economy and manufacturing, enabling it to employ digital technologies more effectively to enhance production efficiency. From the perspective of technological innovation, the eastern region possesses dense research institutions, high-level universities, and innovative enterprise clusters, which can generate numerous technological innovation achievements and promptly apply them to manufacturing. This robust innovation ecosystem promotes the research, development, and promotion of digital technologies, further boosting the TFP of manufacturing in the eastern region. In contrast, the dominant industries in the central and western regions remain predominantly traditional manufacturing, and the integration of digital technologies in the manufacturing field is relatively lagging. Nevertheless, with the continuous reinforcement and improvement of the central and western regions in infrastructure construction, talent cultivation, policy support, and other aspects, the digital economy is anticipated to play a more significant role in the development of manufacturing in the central and western regions in the future.

Regarding the service industry, the impact of DE on TFP_serv in the central and western regions is greater than that in the eastern region. The possible reasons are as follows: Firstly, from the perspective of the spatial layout of industrial development, DE has optimized the industrial spatial organization pattern, giving rise to a virtual agglomeration mode that integrates online and offline services. Under this virtual agglomeration mode, the development, production, and sales of services can be accomplished via virtual platforms. For example, Taobao has enabled the virtual agglomeration of the wholesale and retail industry; Ctrip and Meituan have facilitated the virtual agglomeration of the accommodation and catering industry; DiDi has brought about the virtual agglomeration of the transportation industry; and the MOOC has realized the virtual agglomeration of the education industry. The service industries in the central and western regions have benefited from the “spatial spillover” dividend of this virtual agglomeration, leading to a more substantial improvement in productivity. In addition, in terms of cost and market access, service enterprises in the central and western regions, aided by the virtual agglomeration mode of the digital economy, can build online service platforms at a lower cost, break through geographical restrictions, rapidly expand their market scope, and lower market access thresholds. In contrast, due to the relatively complete offline service system in the eastern region, the transformation costs and resistance are relatively large.

5.5. The Manufacturing Industry Heterogeneity Analysis

The baseline regression results have considered the overall influence of DE on the TFP of industries. Whether there are disparities in the impact of DE on each subdivided industry awaits further validation. Based on data availability, the effect of DE on 21 subdivided manufacturing industries was examined and categorized into three types: low-skill manufacturing, medium-skill manufacturing, and high-skill manufacturing, based on the average education level of the employed personnel.

As shown in Table 6, it is evident that within the low-skill manufacturing industries, DE exerts a notably positive influence on the TFP of the agricultural and sideline food processing industry, food manufacturing, textile industry, textile and apparel industry, paper and paper products industry, and non-metallic mineral products industry. These industries are predominantly labor-intensive. The progressive attenuation of the demographic dividend and the escalating labor costs, among other factors, have compelled manufacturers to increase the utilization of intelligent equipment. It is precisely due to the initiative of “Replacing Humans with Machines” that the TFP of these industries has been elevated.

In the medium-skill manufacturing industries, with the exception of chemical raw materials and chemical manufacturing, DE has a remarkable enhancing impact on the TFP of other manufacturing industries. These industries are typically capital-intensive and possess the financial strength to support the transformation toward automation, digitalization, and intelligence. Nevertheless, the chemical raw materials and chemical products manufacturing industry lacks the necessary incentive mechanisms and management models for digital transformation and is more inclined to focus on the research and development of new materials. Consequently, it has dispersed its investments in digital development, resulting in an insignificant improvement in efficiency due to DE.

In high-skill manufacturing industries, DE has significantly elevated the TFP of general equipment manufacturing, special equipment manufacturing, and transportation equipment manufacturing industries. These industries are capital-intensive and have undergone a relatively high degree of digital transformation within enterprises. Nevertheless, DE has not exerted a significant impact on pharmaceutical manufacturing, as well as computer, communications, and other electronic equipment manufacturing. The potential reasons could be as follows: these industries are technology-intensive and demand a large number of highly skilled labor. However, at present, the application of DE in China’s manufacturing sector remains at the simplistic stage of “Replacing Humans with Machines”, lacking mastery of core digital technologies.

In conclusion, the impact of DE on the TFP of different industries in the manufacturing sector is heterogeneous. DE can significantly enhance the TFP of industries such as food manufacturing, rubber and plastic products industry, and special equipment manufacturing. However, it has no significant effect on the TFP of industries such as wine, beverage, and refined tea manufacturing. The possible reason is that these industries have high profit margins, and their production technologies are usually passed down through traditional craftsmanship, lacking the motivation for intelligent transformation. Furthermore, the digital economy can suppress the TFP of the tobacco industry, which may be due to the management model and distribution mechanism of state-owned enterprises in China.

Therefore, differentiated digital economy development strategies should be formulated for different industries.

Table 6. The results of manufacturing industry heterogeneity analysis.

	Low-Skill Manufacturing Industry						
	Agricultural and Sideline Food Processing Industry	**Food Manufacturing**	**Wine, Beverage, and Refined Tea Manufacturing**	**Textile Industry**	**Textile and Apparel Industry**	**Paper and Paper Products Industry**	**Non-metallic Mineral Products Industry**
DEDI	0.765 *	0.746 **	0.142	1.375 **	1.243 ***	0.943 **	0.915 ***
	(0.447)	(0.336)	(0.129)	(0.598)	(0.249)	(0.393)	(0.083)
R^2	0.835	0.924	0.975	0.825	0.856	0.867	0.817
	Medium-skill Manufacturing Industry						
	Chemical raw materials and chemical manufacturing	**Chemical Fiber Manufacturing**	**Rubber and plastic products industry**	**Ferrous Metal Smelting and Rolling Processing Industry**	**Non-ferrous Metal Smelting and Rolling Processing Industry**	**Metal Products Industry**	**Electrical Machinery and Equipment Manufacturing**
DEDI	0.675	0.745 **	0.798 *	0.636 ***	0.717 **	0.623 *	0.613 ***
	(0.681)	(0.339)	(0.424)	(0.091)	(0.306)	(0.565)	(0.102)
R^2	0.884	0.726	0.758	0.683	0.902	0.868	0.826
	High-skill manufacturing industry						
	Tobacco Industry	**Oil, Coal, and Other Fuel Processing Industries**	**Pharmaceutical Manufacturing**	**General Equipment Manufacturing**	**Special Equipment Manufacturing**	**Transportation Equipment Manufacturing Industry**	**Computer, Communications, and Other Electronic Equipment Manufacturing**
DEDI	−0.445 **	−0.356	0.754	0.785 *	0.926 **	0.757 ***	0.835
	(0.223)	(0.297)	(0.580)	(0.444)	(0.389)	(0.076)	(0.596)
R^2	0.913	0.698	0.801	0.984	0.635	0.703	0.755
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	360	360	360	360	360	360	360

Note: ***/**/* indicate statistical significance at 1%, 5%, and 10% levels. Robust standard errors are reported in parentheses.

5.6. The Service Industry Heterogeneity Analysis

To investigate the heterogeneity of DE's impact on the service industry, this paper examines its influence of DE on five subdivided service industries, as shown in Table 7.

DE exerts a significantly positive influence on the TFP of service industries, with the exception of the real estate industry. In the aspect of the wholesale and retail industry, the connectivity of DE has heightened the precision and efficacy of supply–demand matching, giving rise to business models such as business-to-customer and manufacturers to consumer. In the domain of transportation, warehousing, and postal services, the innovation of DE business models has generated considerable logistics demands. Furthermore, digital technologies have empowered processes like logistics transportation and goods distribution, effectively connecting and optimizing the reorganization of scattered transportation resources in the market and facilitating the standardization, large-scale operation, and intensification of logistics. In the financial industry, digital technologies enhance traditional banking, investment, and insurance, facilitating the optimization of business processes, user credit ratings, and investment risk assessments and consequently improving the efficiency of financial transactions.

Table 7. The results of service industry heterogeneity analysis.

	Wholesale and Retail Industry	Transportation, Warehousing, and Postal Services	Accommodation and Catering Industry	Financial Industry	Real Estate Industry
DEDI	1.356 **	1.325 ***	0.104 **	1.007 ***	0.843
	(0.565)	(0.189)	(0.043)	(0.168)	(0.766)
Constant	Yes	Yes	Yes	Yes	Yes
Control variable	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
N	360	360	360	360	360
R^2	0.3753	0.3435	0.3213	0.3865	0.3654

Note: ***/** indicate statistical significance at 1%, 5%levels. Robust standard errors are reported in parentheses.

In summary, the impact of DE on the TFP of different industries within the service sector also exhibits heterogeneity. At present, DE has a significantly positive effect on TFP in most industries, such as the wholesale and retail industries. However, it does not have a noticeable enhancing effect on the TFP of the real estate industry. The possible reasons are as follows: Currently, the real estate industry has a relatively low reliance on data elements, and the application of digital technologies in real estate development, construction, operation, and decoration is relatively weak. Although consumers can obtain property information through real estate trading platforms, actual transaction activities are significantly influenced by regional factors and market policies.

6. Conclusions

6.1. Conclusions and Policy Recommendations

In recent years, research on DE and TFP has witnessed a substantial increase. Nevertheless, empirical analysis at the industrial level remains relatively scarce in China. This paper utilizes panel data from 30 provinces in China, spanning from 2011 to 2022, to establish an econometric model examining the influence of DE on the total factor productivity of industries. In general, this paper provides empirical evidence at the industrial level for addressing the "Solow Paradox" and offers policy recommendations for the development of the digital economy in China. The main conclusions are as follows:

Firstly, DE can effectively promote the TFP of industries. The order of the enhancement effects in various industries is as follows: TFP of the service industry, TFP of the manufacturing industry, and TFP of agriculture. This conclusion remains valid after robustness tests and endogenous treatment. Secondly, compared with the central and western regions, DE has a stronger promoting effect on the TFP of manufacturing in the eastern region. However, DE has a more significant enhancing effect on the TFP of agriculture and services in the central and western regions than in the eastern region. Thirdly, the effect of DE on the TFP of industries presents industrial heterogeneity. In the manufacturing sector, DE can significantly enhance the TFP of traditional manufacturing industries such as agricultural and sideline food processing industry, but it has not yet shown a significant effect on the TFP of high-skill manufacturing industries such as computer, communications, and other electronic equipment manufacturing. In the service sector, the promoting effect of DE is more pronounced in industries such as wholesale and retail, while the real estate industry has not yet benefited from the dividends of DE.

Based on the above research and considering the current development status of DE, this paper presents the following suggestions:

Firstly, enhance the application of digital technologies in agriculture and fully leverage the role of technological progress in improving the TFP of agriculture. Strengthen the application of technologies such as the Internet of Things and artificial intelligence across all stages of agricultural production, processing, and sales. Accelerate the transformation and application of agricultural digital technology achievements, such as specialized sensors and agricultural robots, by holding exhibitions of these advancements and creating platforms for sharing, training, and promotion.

Secondly, formulate differentiated development strategies for manufacturing. For low-skill manufacturing, upgrading production equipment to be more intelligent, networked, and digital enables large-scale, customized, and flexible production. For medium-skill manufacturing, enhance connectivity among individuals, machines, objects, and systems. For high-skill manufacturing, focus not only on intelligent transformation, such as "replacing humans with machines", but also on emphasizing research, development, and the creation of advanced digital technologies.

Finally, there is a need to deepen the application of digital technology in productive service industries and leverage technological progress to enhance the TFP of these industries. The focus should be on facilitating the digital upgrading of productive service sectors. Technologies should be used to develop precise marketing and intelligent decision-making services. Additionally, focus on advancing scientific and technological innovation services, such as research and development and technological consultation, as well as services like green, inclusive, efficient, and secure digital finance. Avoid excessive allocation of resources, such as capital, talent, and R&D, to consumer service industries to prevent falling into the "dividend trap".

6.2. Limitations and Future Research

Given the constraints imposed by data availability and research methodologies, the article still has the following shortcomings: Firstly, although the paper provides empirical evidence of the digital economy's impact on improving the TFP of industries, the exploration of the underlying mechanism is insufficient. In the future, this issue should be addressed from a broader perspective to uncover the black box mechanism between the DE and TFP. Secondly, the paper focuses solely on the comprehensive indicator of TFP without examining the specific impacts of DE on individual production factors such as capital productivity and labor productivity. This lack of detail may obscure the differentiated effects of DE on various production factors. Therefore, subsequent research could delve into the independent impacts of DE on single-factor productivity, such as capital or labor, to construct a more comprehensive and detailed map of the influence pathways. Lastly, concerning research methodologies, the paper employs a traditional panel regression model for empirical analysis. With rapid advancements in big data and machine learning technologies, future research could incorporate these advanced techniques to validate and expand upon the conclusions. By leveraging modern data analysis tools, we can capture the intricate relationship between DE and TFP more precisely and provide policymakers with more scientific and reliable decision-making foundations, thus facilitating the sustainable and healthy development of DE.

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Appendix A. Process for Calculating Total Factor Productivity (TFP) of Industries

This paper employs the Global Malmquist–Luenberger (GML) index approach to measure the TFP of industries. This method not only resolves the multi-input and multi-output issues involving undesirable outputs but also overcomes the limitations of the Malmquist–Luenberger (ML) index model, and it possesses transitivity and cumulative multiplicability. The specific procedures are as follows:

1. Construct the Production Possibility Set. Suppose that there are K decision-making units (DMUs), each DMU having N inputs, $\mathbf{x} = (x_1, x_2, \cdots, x_N) \in R_+^N$, M desirable outputs, $\mathbf{y} = (y_1, y_2, \cdots y_M) \in R_+^M$, and J undesirable outputs, $\mathbf{b} = (b_1, b_2, \cdots, b_J) \in R_+^J$. The input, desirable output and undesirable output in each period t can be expressed as $x^{k,t}$, $y^{k,t}$, and $b^{k,t}$, respectively. On this basis, the current production possibility set $P^t(\mathbf{x}^t)$ is constructed.

$$P^t(\mathbf{x}^t) = \left\{ \begin{array}{l} \left(\mathbf{y}^t, \mathbf{b}^t\right) : \sum\limits_{k=1}^{K} z_k^t y_{km}^t \geq y_m^t, \quad m = 1, \cdots, M; \sum\limits_{k=1}^{K} z_k^t b_{kj}^t = b_j^t, \quad j = 1, \cdots, J; \\ \sum\limits_{k=1}^{K} z_k^t x_{kn}^t \leq x_n^t, \quad n = 1, \cdots, N; \sum\limits_{k=1}^{K} z_k^t = 1, z_k^t \geq 0, \quad k = 1, \cdots, K \end{array} \right\} \tag{A1}$$

where $P^t(\mathbf{x}^t)$ is a bounded closed convex set. The input and desirable output are highly disposable; that is, if $(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t) \in P^t(\mathbf{x}^t)$ and $\mathbf{x}'^t \geq \mathbf{x}^t$ or $\mathbf{y}'^t \leq \mathbf{y}^t$, then $(\mathbf{x}'^t, \mathbf{y}^t, \mathbf{b}^t) \in P^t(\mathbf{x}^t)$ or $(\mathbf{x}^t, \mathbf{y}'^t, \mathbf{b}^t) \in P^t(\mathbf{x}^t)$. In addition, two assumptions are required for dealing with undesirable outputs.

Axiom A1 (weak disposability axiom A1). *If $(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t) \in P^t(\mathbf{x}^t)$ and $0 \leq \theta \leq 1$, then $(\mathbf{x}^t, \theta\mathbf{y}^t, \theta\mathbf{b}^t) \in P^t(\mathbf{x}^t)$. This axiom means that if the undesirable output is to be reduced, the desirable output must be reduced at the same time, indicating that the improved environment and the pollution reduction are costly, so the idea of environmental regulation should be included in the analytical framework.*

Axiom A2 (zero combination axiom A2). *If $(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t) \in P^t(\mathbf{x}^t)$ and $\mathbf{b}^t = 0$, then $\mathbf{y}^t = 0$. This axiom means that if there is no undesirable output, then there is no desirable output. In other words, whenever a desirable output is produced, the undesirable output accompanies concurrently.*

In Equation (A1), z_k^t represents the weight of the cross-sectional data. If $z_k^t \geq 0$, then there are constant returns to scale; if $\sum\limits_{k=1}^{K} z_k^t = 1, z_k^t \geq 0$, then there are variable returns to scale. However, $P^t(\mathbf{x}^t)$ determines the current production frontier using current period data, which may lead to technological regress. For this reason, this paper constructs the global production possibility set, which enhances the comparability between the technical efficiencies of DMUs.

$$P^G(\mathbf{x}) = \left\{ \begin{array}{l} \left(\mathbf{y}^t, \mathbf{b}^t\right) : \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} z_k^t y_{km}^t \geq y_m^t, \quad m = 1, \cdots, M; \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} z_k^t b_{kj}^t = b_j^t, \quad j = 1, \cdots, J; \\ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} z_k^t x_{kn}^t \leq x_n^t, \quad n = 1, \cdots, N; \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} z_k^t = 1, \quad z_k^t \geq 0, \quad k = 1, \cdots, K \end{array} \right\} \tag{A2}$$

2. Calculate the Global Directional Distance Function. Taking period t as an example, the solution model of the DMU global directional distance function is shown in Equation (A3):

$$
\begin{aligned}
& D_0^G(\mathbf{x}^t,\mathbf{y}^t,\mathbf{b}^t;\mathbf{y}^t,-\mathbf{b}^t)=\max\beta \\
& s.t.\ \ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_m^{k,t} \geq (1+\beta) y_m^{r,t}, \quad m=1,\cdots,M \\
& \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_j^{k,t} = (1-\beta) b_j^{r,t}, \quad j=1,\cdots,J \\
& \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_n^{k,t} \leq (1-\beta) x_n^{r,t}, \quad n=1,\cdots,N \\
& z_k^t \geq 0, \qquad k=1,\cdots,K
\end{aligned} \tag{A3}
$$

3. Construct the GML Index. The global directional distance function is $\overset{\rightarrow G}{D_o}(x^\tau,y^\tau,b^\tau;g^\tau)=\max\{\beta:(y^\tau,b^\tau)+\beta g^\tau\in P^G(x^\tau)\}$, where $\tau=t,t+1$, $P^G(x^\tau)$ represents the global production possibility set and $g=(y,-b)$ is the directional vector. Under constant returns to scale, the GML can be expressed as follows:

$$
GML_t^{t+1}=\frac{1+\overset{\rightarrow G}{D_o}(x^t,y^t,b^t;y^t,-b^t)}{1+\overset{\rightarrow G}{D_o}(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})} \tag{A4}
$$

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