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Research on the impact of digital economy on industrial green total factor productivity—analysis based on Chinese provinces

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ABSTRACT

Against the background of booming digital economy growth and the perspective of industrial green transformation, this article empirically evaluates the impact of digital economy on industrial green total factor productivity (GTFP) based on provincial-level panel data in China from 2010 to 2020. First, this article calculates the digital economy index (DEI) and industrial GTFP, analyzes the regional development characteristics of the two, and finds that the growth of digital economy and industrial GTFP is unbalanced, basically showing the east high and west low distribution. Then, empirically examines the impact of digital economy on industrial GTFP and finds that digital economy can significantly improve industrial GTFP, with obvious regional variability. Finally, the threshold model regression reveals that this promotion effect has a threshold effect, which gradually weakened as the DEI value crosses the corresponding threshold value.

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1. Introduction

China, the world's largest consumer of resources, has yet to break free from its severe reliance on the environment and energy. With China's economic development entering a new stage, increased environmental pollution, tightening factor endowment, declining labor dividends, and declining capital gains render the rough-and-tumble approach unsustainable. Indeed, many of today's vexing structural issues stem from the previous rough development's distorted allocation of resources and factors. Therefore, changing the method of economic growth, speeding up the conversion of old and new kinetic energy, and increasing resource allocation efficiency are required as a crucial first step to achieving the goals. In this setting, several scholars have concentrated on ways to improve industrial green total factor productivity (GTFP). Simultaneously, with continual digital technology update and iteration, as well as

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continuous strong involvement in the social economy, the growth of digital economy has progressively grown into a huge historical opportunity to drive the evolution of replacing old growth drivers with new ones. Scholars have become increasingly interested in whether the expansion of digital economy will assist enhance China's industrial GTFP and achieve the "double carbon" goal. A variety of economic operations that employ digital technology to improve economic structure and efficiency are referred to as being part of the "digital economy". Existing studies have indicated that digital economy growth benefits enterprises, industries (Li et al., 2019). Digital economy can improve industrial structure, increase economic organization efficiency and allocation, reduce pollution emissions, and encourage the transformation of the green economy due to its broad range of impacts and numerous levels.

To significantly increase industrial GTFP, the organic fusion of digital economy and green development has become a must for achieving industrial transformation and upgrading in the future. So, can digital economy boost industrial GTFP? What is the inherent mechanism of action if the conclusion is correct? Given the disparities across geographical locations, is there any heterogeneity in the digital economy on GTFP? The investigation of these topics is crucial for boosting the environmentally friendly value of digital economy, enhancing resource allocation, expanding industrial GTFP, and encouraging green development. On that basis, this article aims to explore the relationship between digital economy with industrial GTFP, as well as whether there are differences between the two in their respective characteristics and spatial distribution, and to propose countermeasures from the standpoint of industrial green transformation. The following are the key marginal contributions: although there have been more studies on industrial transformation, few have explored the coupling of digital economy growth and industrial GTFP. This paper fills a void by investigating comprehensively the digital economy's influence mechanism on industrial GTFP. It is critical for practical purposes to thoroughly examine the impact of digital economic growth on industrial GTFP. Therefore, this article develops a complete evaluation system, characterizes regional digital economy status systematically, and empirically evaluated the influence of digital economy on industrial GTFP.

2. Literature review

Regarding the topics of digital economy, GTFP, and industrial green transformation discussed in this article, the current related research focuses on the following three areas.

First, digital economy-related literature. Some academics argue that digital economy is a particularly unique economic structure, through the virtual way to complete the transaction of goods and services, and that its development is intimately tied to the growth of information and communication technology (ICT). Miller and Wilsdon (2001) believe that digital economy is a technological revolution based on the Internet with rich innovative connotations, which realizes the driving innovation of the economy. Due to the rapid expansion of the Internet and ICT, the application of digital economy has invaded many spheres of daily life and production, offering the necessary basic safeguards for modernizing business operations, and enhancing efficiency (Beomsoo et al., 2002; Thomas, 2006). The flourish and emerge of e-commerce are one of the most prominent features, which further promotes the setting up of information and communication infrastructure, which will accelerate the economic growth (Ivus & Boland, 2015; Jorgenson & Vu, 2016). The progress of ICT and digital technology is the essential component of digital economy, and this advancement will hasten the emergence of new business models with specific green attributes, like the sharing economy and platform economics (Bukht & Heeks, 2018). Based on the heterogeneity of the development in different nations and areas, there is no international standard for the selection of indicators and measurement of digital economy indicators, nor is there a unified indicator system for the quantitative analysis of the digital economy's development level. Pan et al. (2021) built a four-dimensional indicator system: digital economic infrastructure, digital industrialization, industrial digitalization, and digital governance.

Second, GTFP-related literature. Enhancing GTFP is an important manifestation of underlining the significance of enhancing economic growth quality, fostering the construction of a green development pattern, and leading the new normal of economic development. Ahmed (2012) believes that GTFP is a comprehensive index that considers both economic growth and ecological balance. Chung et al. (1997) was the first in GTFP measurement research to add pollutant emissions into the TFP measurement framework by establishing the directional distance function (DDF) and calculating the Malmquist-Luenberger (ML) productivity based on it. Fukuyama and Weber (2009) improved relevant indexes based on data enveloping analysis (DEA) and constructed a new model, slack based measure (SBM)-DDF based on relaxation variables. This method can avoid the unreasonableness of pollution variables entering the production function and solve the problem of input-output variable measurement bias. Yuan (2015) proposed a GTFP measurement index based on the SBM-DDF function with a dynamic time series effect. The conventional development mode of China's manufacturing industry, as the driving force of the economy and society, is difficult to sustain, and all sectors of society are yearning for high-quality manufacturing industry development mode. Therefore, green growth, green innovation, and green development have become the primary criteria for assessing the transformation and upgrading (Shi & Li, 2019). Previous research has found that industrial structure, government intervention, FDI, environmental regulation, innovative human capital, and other factors influence GTFP and that these factors influence GTFP (Ana et al., 2018; Li et al., 2019; Ouyang et al., 2020; Pucci et al., 2020), through both direct and indirect pathways (Huang et al., 2019; Zhou et al., 2008).

Third, the connection between the digital economy and industrial GTFP literature. Following Solow's 1987 proposal of the "productivity paradox", the academic community began extensive research on ICT, productivity improvement, and output growth (Kraemer & Dedrick, 1994). Digital economy expands the dimensions and complexity of economic transformation and green development. At the enterprise level, digital economy can empower each end of the industrial and supply chains, improve enterprise innovation and production efficiency, and promote green economic development (Li & Tao, 2012). By integrating and innovating with traditional agriculture, industry, and services, digital economy can integrate digital technologies into all stages of production and distribution, driving the upgrade of industrial structures.

Meanwhile, digital economy lowers the cost of gathering and integrating technological resources, while the optimization of business processes and improved performance of information systems represent a qualitative leap in information technology that can be capable of improving enterprise information analysis ability and management decision-making greatly (Dedrick et al., 2013). At the industrial level, 4.0 Industrial revolution has arrived, and the transformation and growth of digital technology has promoted the enterprises digital transformation to better cope with potential risks and challenges in the future (Borangiu et al., 2019; Shi et al., 2018). Digital technology, which benefited from digital economy, as a kind of universal technology, can be applied during the process of optimizing and upgrading, boosting industrial organization upgrading, digitizing, and promoting green transformation (Li et al., 2019). At the macroeconomic level, digital economy provides technical assistance to government regulation. By establishing an environmental supervision system, it can strengthen the targeted tracking management of heavily polluting industries and enterprises by collecting and integrating social environmental monitoring data in real-time, efficiently, and openly. On the other hand, the integration of traditional production factors with digital economy allows for the transfer of production factors from primary to secondary and tertiary industries. Capital and factor allocation is constantly refined, and ultimately flows to high-efficiency industries, effectively reducing economic growth's reliance on energy, as well as realizing the transformation and upgrading of the industrial structure towards digitization, rationalization and greening (Kohli & Melville, 2019).

In addition, some research has focused on the impact of digital economy on GTFP and revealed that through the innovation, informationization level, talent and financial agglomeration, and capital allocation, digital economy can affect technical efficiency and technological advancement, all of which boost GTFP. According to Cheng and Qian (2021), digital economy has a nonlinear effect on industrial GTFP. Lu et al. (2022) argue that the Internet promotes industrial GTFP and that there is a nonlinear relationship between the two. The ability of the enterprise to innovate, the cost of the enterprise, the level of industrial structure, and external supervision are all important ways to promote improvement. Through literature review, it is found that in the context of sustainable development, there is few research on the impact of digital economy as a new production factor on GTFP in China. The present literature is insufficiently precise to investigate the direct and indirect effects of digital economy on industrial GTFP. To address the issues, this research provides the following theoretical analysis framework (shown in Figure 1) that aims to investigate the enhancement mechanism of digital economy on industrial GTFP in China. Then it constructs a digital economy indicator system, empirically studies the impact of digital economy on industrial GTFP and evaluates the direct and indirect impacts basing the regional heterogeneity.

3. Mechanism and status analysis

3.1. Mechanism analysis

This article examines the influence mechanism of digital economy on industrial GTFP from the following three perspectives. First, digital economy has the potential to be a

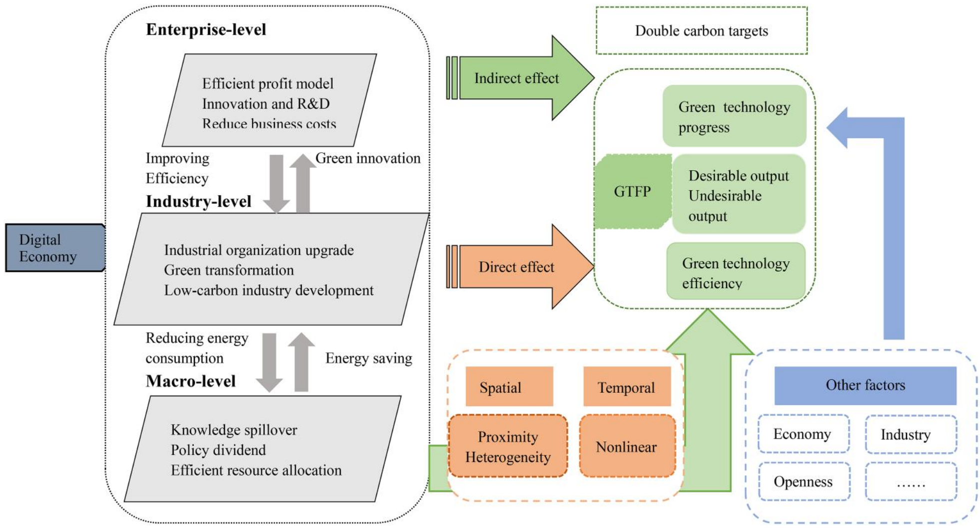


Figure 1. Mechanistic of digital economy on GTFP.
Source: Compiled by the author.

technological trailblazer because to the technology spillover effect. The Industrial Internet of Things, cloud computing, big data, blockchain, and other emerging digital technologies are continually evolving, rapidly infiltrating numerous industrial domains, and redesigning the industrial production system (Cai & Wang, 2012; Zhou et al., 2021). Blockchain technology attracts a diverse set of investors to create a decentralized financing platform for green infrastructure, ensuring that new industrial infrastructure meets carbon emission reduction goals. The accuracy and depth of knowledge of information captured by big data is at the heart of big data. Use big data to connect the entire process from production to consumption, monitor industrial production in real-time with the help of a big data platform, accurately predict input and output using data collection, transform the industry's previous high input and high consumption production mode into a data economy mode, form a scientific monitoring system, and upgrade to high-end intelligence. In the intelligent manufacturing trend, industrial enterprises continue to improve manufacturing equipment, production processes tend to be green, the existing production model continues to improve and upgrade, a green production system gradually takes shape, and high-pollution product technology will be replaced by green and efficient production technology. Pollutant verification and diagnosis are accomplished through environmental pollutant emission systems and carbon emission management systems, which aid in the optimization of targeted energy savings and emission reductions (shown in Figure 2). Advanced digital technology has considerably promoted industrial green technology evolution in infinite iteration and innovation, generating a benign model of digital technology innovation and green technology innovation development. As a result, industrial and green production processes are constantly being improved, and GTFP is significantly increased (Yang et al., 2022; Zhou et al., 2021).

Second, digital economy can encourage further industrial structure optimization. According to the transformation and upgrading theory, innovation theory, and

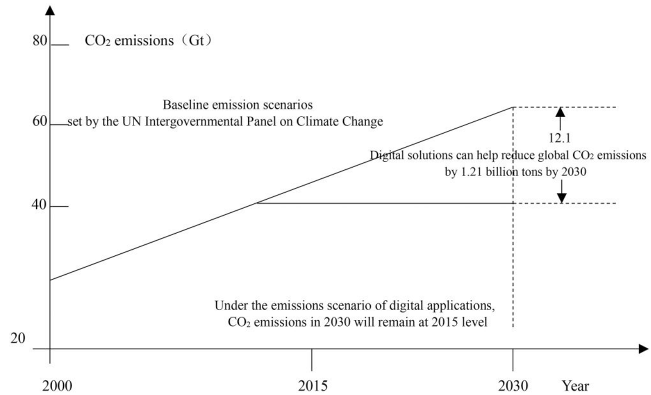


Figure 2. Emission scenarios for digital applications.
Data source: World Bank.

technology-economy mode theory, digital economy can promote a specific industry to highly integrate and extend its own product production chain, supply chain, and value chain through digital transformation, improve production cooperation ability within the supply chain, affect the economic activities of other industries, and form the "correlation effect" of digital economy. In terms of industry, it is mainly manifested in facilitating industrial digital transformation and promotes industrial green development. Intelligent production mode and visualized industrial organization mode are the main forms of industrial digital transformation. Digital technology combined with industrial software in the industrial production process to achieve the production of complex structural components, change the original industry output structure and output efficiency, improve production and management and other work, reduce raw material waste while constantly optimizing product performance, and improve the flow rate and matching rate of production factors. Industrial robots have increased labor productivity and facilitated the transition from energy-intensive and labor-intensive to knowledge- and technology-intensive. With more transparent, parallel networked organizations to make precise strategic decisions, digital technology has dramatically changed the organizational structure and had an "enabling effect" on industrial upgrading and production improvement.

Third, digital economy can reduce resource mismatch and thus improve resource allocation efficiency, as well as contribute to energy savings in industrial energy consumption and pollution reduction. Factor allocation is a key factor affecting TFP, and therefore GTFP (Zhou et al., 2021). The market distortion caused by factor mismatch will result in the loss of TFP and total production. On the one hand, new digital technology, intelligent technology, can supply the new green industrial enterprise production factors, large data to analyze huge amounts of data, and optimize industrial enterprise daily operation process, improve the elements of supply and demand matching accuracy, improve resource allocation structure, reduce resource waste, and the deadweight loss to industrial production output is close to capacity. Provide platform and technical support for enterprises' green production, as well as promote the improvement of industrial green production efficiency. On the other hand, digital technology application may effectively improve resource collecting efficiency, stimulate the creation of high-end resource products, and raise product added value. It encourages the increase of the pollutant treatment in the process of energy consumption by firms, as well as fully utilizing allowing the digital economy to fully realize its role in energy consumption, energy savings, and pollution reduction. As a result, the digital economy improves energy efficiency, reduces pollution, and raises industrial GTFP.

3.2. Status analysis

Digital economy is quickly emerging in the post-epidemic period, so for conventional sectors, digitalization has become a guide for industrial transformation and upgrading, as well as a major critical trend for sustainable and steady development. In 2020, the scale of digital economy in China has reached $39.2 trillion, accounting for 38.6% of GDP and growing at a 9.7% annual rate against the backdrop of sluggish global economic growth or even recession, becoming one of the primary drivers of national economic recovery and growth. Between 2005 and 2020, the proportion of China's digital economy to GDP increased from 14.2% to 38.6%, a 2.4 percentage point increase year on year. The added value of digital economy of China's service industry, industry, and agriculture accounted for 40.7%, 21.0%, and 8.9% respectively in 2020, demonstrating that the industry's digital revolution is accelerating and meanwhile integration is deepening. As illustrated in Figures 3–6.

In the future, ICT integration in industry will be a primary focus. The convergence of digital economy is currently concentrated primarily in the tertiary industry. Digital economy is suffering reverse penetration, and there is insufficient integration between digital technology and industry. Unlike traditional industrialization, which is based on resources and the endowment of production factors, the core competitiveness of the new industrial economy based on ICT capital is based on technological innovation. China has generally entered the middle and late stage of industrialization to promote the transformation of old and new dynamic energy (as shown in Figure 7), and promote the transformation of traditional industries into high-end, low-carbon and intelligent. As a result, China should establish an independent innovation system that supports industrial digital transformation as soon as possible, as well as a complete innovation chain of advanced industries.

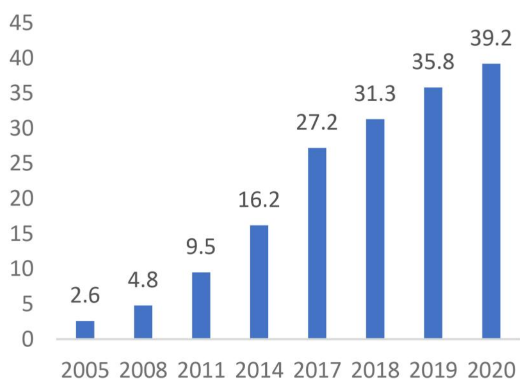


Figure 3. China's digital economy (trillion yuan).
Source: China Academy of Information and Communications Technology.

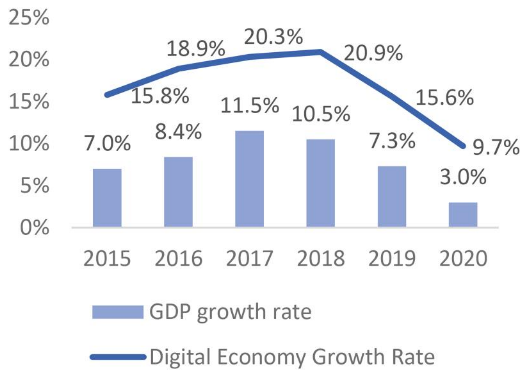


Figure 4. Digital economy and GDP growth rate.
Source: China Academy of Information and Communications Technology.

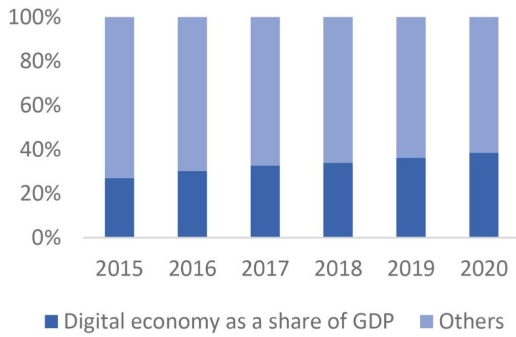


Figure 5. China's digital economy as a share of GDP.
Data source: China Academy of Information and Communications.
Source: China Academy of Information and Communications Technology.

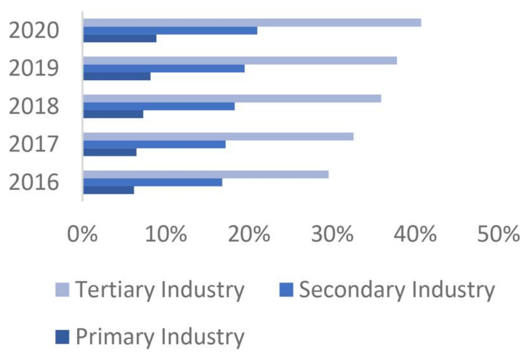


Figure 6. China's digital economy penetration rate.
Source: China Academy of Information and Communications Technology.

4. Methodology

4.1. GTFP measurement method

Referring to the practices of Chen (2016) and Chung et al. (1997), based on the DDF model, the ML productivity index is constructed to measure industrial GTFP. The

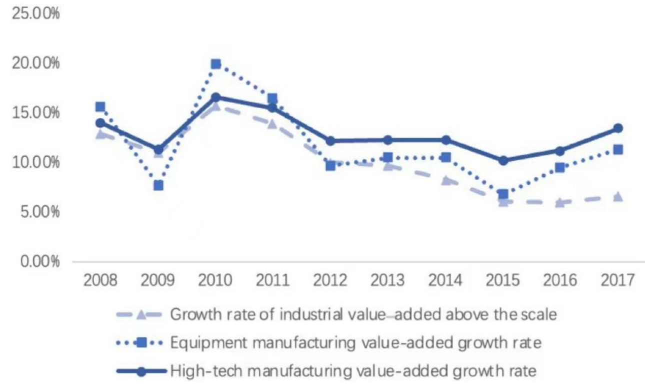


Figure 7. China's industrial new and old dynamic energy trends.
Source: China Academy of Information and Communications Technology.

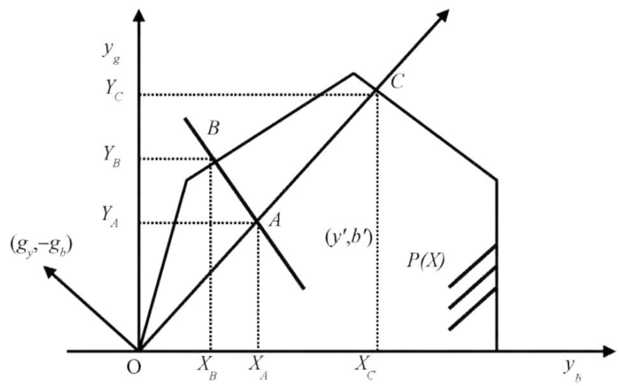


Figure 8. Production possibility frontier and distance function.
Source: Chambers et al. (1996).

first step is to define the environmental technology model. The outputs include the desirable output vector y and undesirable output vector b. x is the production factors vector of the input. The set of outputs is shown below.

$$p(x) = \{(y, b) : \max\ y(x, b)\}, x \in R_N^+ \tag{1}$$

where $p(x)$ denotes the set of production possibilities for the "good" and "bad" outputs produced by the input $x \in R_N^+$. The environmental technology model is subject to three premises: first, that undesirable outputs are jointly weakly disposable, second, that desirable and undesirable outputs are "zero-sum", and third, that inputs x and desirable outputs y are strongly disposable. Then, the production possibilities frontier of the environmental technology model can be constructed. $p(x)$ outlines the production possibility bounds for two outputs (y, b) under a given input x (shown in Figure 8).

The set of production possibility set provided by environmental technology is the basis for quantifying industrial GTFP. As a result, industry may be viewed as a unit of production decision-making, thus it is possible to calculate the relative effectiveness of each decision-making unit.

$$\overrightarrow{D_0}(x,y,b;g) = sup\{\beta : (y,b) + \beta g \in Y(x)\} \tag{2}$$

where, g is the direction vector, reflecting the preference for desirable output and undesirable output. g is set as $g = (y - b)$ to represent the direction vector of outputs increase or decrease. Thus, DDF denotes the maximum multiple that can be expanded along with the direction vector g, output vector $(y - b)$ when the input vector x is certain.

If the undesirable output is not considered, the desirable and undesirable outputs will increase at the same time, that is, point A will be projected to point C in equal proportion (shown in Figure 8). When considering the undesirable output, point A expands along the direction vector g to point B on the production possibility boundary (shown in Figure 8), meaning that the total industrial output value is maximized, and pollution emissions are minimized. The problem can be resolved when there are more than two outputs by building a linear program with the following formula.

$$\overrightarrow{D_0^t}\left(x^t, y^t, b^t; y^t, -b^t\right) = \max \overrightarrow{D_0^t}(x,y,b;g) = \max\beta \tag{3}$$

$$\begin{gathered} s.t.\ \sum_{k=1}^{k} \lambda_k^t y_{ks}^t \geq (1+\beta) y_{ks}^t,\ \sum_{k=1}^{k} \lambda_k^t b_{km}^t \geq (1+\beta) b_{ks}^t,\ \sum_{k=1}^{k} \lambda_k^t y_{kn}^t \geq x_{kn}^t,\ \lambda_k^t \geq 0 \\ s = 1,2 \ldots S; m = 1,2 \ldots M;\ n = 1,2 \ldots N; K = 1,2 \ldots K \end{gathered} \tag{4}$$

N, S, and M respectively stand for different types of input factors, as well as desirable and undesirable outputs. And $x = (x_1, x_2, \ldots, x_N) \in R_N^+$, $y = (y_1, y_2, \ldots, y_N) \in R_S^+$, $b = (b_1, b_2, \ldots, b_N) \in R_M^+$; $k = 1, 2, \ldots$, K denotes the decision units; $t = 1, 2, \ldots$, T and $\lambda_{\mathrm{k}}^{\mathrm{t}}$ stand for the period and weight of each cross-sectional observation respectively. The ML productivity index for is then as follows.

$$ML_t^{t+1} = \left\{ \frac{1 + D_0^t\left(x^t, y^t, b^t; g^t\right)}{1 + D_0^t\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)} \times \frac{1 + D_0^{t+1}\left(x^t, y^t, b^t; g^t\right)}{1 + D_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)} \right\}^{\frac{1}{2}} \tag{5}$$

The ML index can be further decomposed into technical efficiency change (EFFCH) and technological progress change (TECH). Among them, EFFCH represents the output growth caused by the change of internal efficiency of producers, which mainly comes from the change of pure technical efficiency and the change of production scale efficiency, while TECH represents the output growth caused by technological progress.

$$EFFCH_t^{t+1} = \frac{1 + D_0^{t+1}\left(x^t, y^t, b^t; g^t\right)}{1 + D_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)} \tag{6}$$

$$TECH_t^{t+1} = \left\{ \frac{\left[1 + D_0^{t+1}\left(x^t, y^t, b^t; g^t\right)\right]}{\left[1 + D_0^t\left(x^t, y^t, b^t; g^t\right)\right]} \times \frac{\left[1 + D_0^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)\right]}{1 + D_0^t\left(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1}\right)} \right\}^{\frac{1}{2}} \tag{7}$$

When ML $>$ 0, it indicates that GTFP is rising. EFFCH $>$ 0 indicates the growth of industrial output caused by changes in technology and production scale. TECH $>$ 0 indicates that technological progress leads to the growth of industrial output.

4.2. Digital economy index

Currently, there is no unified standard for measuring the digital economy development index. Based on basic concepts and data availability (Yang & Jiang, 2021; Zhao et al., 2019), this article constructs a digital economy index system as shown in Table 1.

When multiple indicators exist in an evaluation system, integrating them can be difficult due to different magnitudes and orders of magnitude. The entropy method has the advantage of objective assignment, which is reflected in the data analysis after the standardization of the original data, and then the entropy method is used to objectively assign each index to obtain the weight matrix (Pei, 2020). Finally, the weights of each indicator are multiplied by the standardized values and added together to calculate each city's high-quality development index, as shown below.

4.2.1. Data standardization

Set DEI of each province as x_{ij} and its standardized value as y_{ij}, then the positive index is:

$$y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}, i = 1, 2, \ldots, m, \;\; j = 1, 2, \ldots, n \tag{8}$$

and the inverse index is:

$$y_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})}, i = 1, 2, \ldots, m, \;\; j = 1, 2, \ldots, n \tag{9}$$

Table 1. Digital economy index.

Primary indicators	Secondary indicators	Tertiary indicators	Properties
Digital Economy Development Composite Index	Internet penetration rate	Internet users per 100 people	+
	Number of Internet-related employees	Computer services and software as a percentage of the number of employees	+
	Internet-related outputs	Total telecom services per capita	+
	Number of mobile Internet users	Number of cell phone subscribers per 100 people	+
	Digital Financial Inclusion Development	China Digital Inclusive Finance Index	+

Source: China Statistical Yearbook.

4.2.2. Indicators weight

The proportion of the evaluation index p_{ij} of the i-th evaluation object in j is calculated:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, i = 1, 2, \ldots, m, \ j = 1, 2, \ldots, n \tag{10}$$

The entropy value E_{ij} of the jth evaluation index is calculated as follows:

$$E_{ij} = -\frac{1}{lnm} \sum_{i=1}^{m} p_{ij} ln(p_{ij}), \ j = 1, 2, \ldots, n \tag{11}$$

The weight w_j of the jth evaluation indicator is calculated as:

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)}, j = 1, 2, \ldots, n \tag{12}$$

4.2.3. Score calculation

$$Z_i = \sum_{j=1}^{m} w_j y_{ij}, j = 1, 2, \ldots, m, \tag{13}$$

The equation produces a score ranging from 0 to 1. The indicator's value will be normalized to 1 or 0 if it exactly equals the maximum or minimum value. To facilitate comparison, this paper introduces the concept of efficacy coefficient to transform the standardized value of the index, replacing the coefficient with a percentage and specifying that $Y_{ij} = 60$ when $X_{ij} = \max(X_{ij})$ and $Y_{ij} = 100$ when $X_{ij} = \min(X_{ij})$. The standardized value of the improved index is $Y_{ij} \times 40 + 60$, and the mean value of each index is between 60 and 100.

4.3. Dagum Gini coefficient

To analyze the spatial differences of our digital economy, the Dagum Gini coefficient method will be used in this paper. According to Dagum's method 1997, the Gini coefficient of digital trade can be defined using the following formula, which is decomposed by subgroups.

$$G = \sum_{j=1}^{k} \sum_{h=1}^{k} \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} \frac{\sum_{j=1}^{k} \sum_{h=1}^{k} \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} \left| y_{ji} - y_{hr} \right|}{2n^2 \overline{y}} \tag{14}$$

The digital economy Gini coefficient G, which represents the overall variation, can be further decomposed into a fraction G_w contributed by intra-regional variation, a fraction G_{nb} contributed by inter-regional net differences and a hyper-variance density G_t. The relationship between them satisfies.

$$G = G_w + G_{nb} + G_t \tag{15}$$

Among them, the hyper-variance density reflects the differences brought by the cross-over parts of different regions (subgroups). According to the Gini coefficient decomposition method proposed by Dagum, the overall variance can be further decomposed and represented by the following equations.

$$G_{ji} = \frac{\frac{1}{2\overline{Y}_j}\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left|\mathrm{y}_{\mathrm{ji}} - \mathrm{y}_{\mathrm{hr}}\right|}{n_j^2} \tag{16}$$

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j \tag{17}$$

$$G_{jh} = \sum_{i=1}^{n_j}\sum_{r=1}^{n_j} \frac{\left|\mathrm{y}_{\mathrm{ji}} - \mathrm{y}_{\mathrm{hr}}\right|}{n_j \mathrm{n_h}\left(\overline{Y}_j + \overline{Y}_h\right)} \tag{18}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j) D_{jh} \tag{19}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j)(1 - D_{jh}) \tag{20}$$

Where $p_j = n_j\overline{Y}$, $s_j = n_j\overline{Y}_j/n\overline{Y}$, $j = 1, 2, 3, \ldots, $ k. In addition, G_{jh} is the interaction between indicators in region j and region h. d_{jh} is the difference in digital economy between these two regions, which is mathematical expectation of summing all the sample values of $\mathrm{y_{jh}} - \mathrm{y_{ji}} > 0$ in j and h-th subgroups. Similarly, p_{jh} is mathematical expectation of summing all the sample values of $\mathrm{y_{hr}} - \mathrm{y_{ji}} > 00$ in j and h-th subgroups.

The defining equations of G_{jh}, d_{jh} and p_{jh} are given by Eqs. (21) (22), and (23), respectively.

$$D_{jh} = \frac{\left(d_{jh} - p_{jh}\right)}{\left(d_{jh} + p_{jh}\right)} \tag{21}$$

$$d_{jh} = \int_0^{\infty} dF_j(y) \int_0^{y} (y - x) dF_h(x) \tag{22}$$

$$p_{jh} = \int_0^{\infty} dF_h(y) \int_0^{y} (y - x) dF_j(x) \tag{23}$$

4.4. Econometric model

The following baseline model is built to examine the influence of digital economy on industrial GTFP. The full-text data description is shown in Table 2.

$$\mathrm{gtfp}_{\mathrm{it}} = \delta_0 + \delta_1 \mathrm{dei}_{\mathrm{it}} + \delta_2 \mathrm{Z}_{\mathrm{it}} + \mu_{\mathrm{i}} + \mathrm{v}_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \tag{24}$$

where subscripts i and t represent cities and years in turn, *gtfp* denotes industrial GTFP, *dei* denotes digital economy development, and Z is the control variable; v is the time fixed effect; ε is the potential random error term.

5. Empirical result analysis

5.1. Digital economy

This part analyses the regional development level of China's digital economy in recent years, and divides China into three regions according to geographical location: east, central, and west (shown in Figures 9–12). In absolute terms, the growth of digital economy in the nationwide increased year by year. However, there is a substantial imbalance in the spatial distribution, and the "digital divide" is mostly expressed in the following characteristics: eastern region > nationwide > western region > central region. In changing trends terms, the growth in the nationwide and east, central, and west have demonstrated an upward trend. In the East, however, the increasing tendency is more significant. It can be seen from the regional characteristics of digital economy development that digital economy development is roughly consistent with the level of regional economic development, and the higher the level of regional economic development, the higher the level of digital economy development. This is since the growth of digital economy requires good Internet, logistics, and other infrastructures, which are more widely spread in regions with higher level of economic growth, giving a firm foundation for the healthy and rapid growth of digital economy.

Table 3 displays the DEI Gini coefficient. The overall Gini coefficient is dropping year by year and the nationwide Gini coefficient is 0.1951 in 2011, 0.0639 in 2020. The regional differences are gradually narrowing.

Figure 13a depicts the evolution of the DEI Gini coefficient. Overall, there is still a disparity in the growth of digital economy, although it is closing year by year. The maximum Gini coefficient value is 0.1951 in 2011, and the minimum value is 0.0639 in 2020, representing an 85.28% drop. This pattern implies that as China's digital

Table 2. Full-Text variable description.

Variable	Name	Symbols
Explained variables	Green Total Factor Productivity	GTFP
Explanatory variables	Digital Economy	DEI
Control variables	Economic Development Level	GDP
	Infrastructure	INF
	Level of Urbanization	URBAN
	Level of financial development	FINANCE
	Research and Development	R&D

Source: China Statistical Yearbook

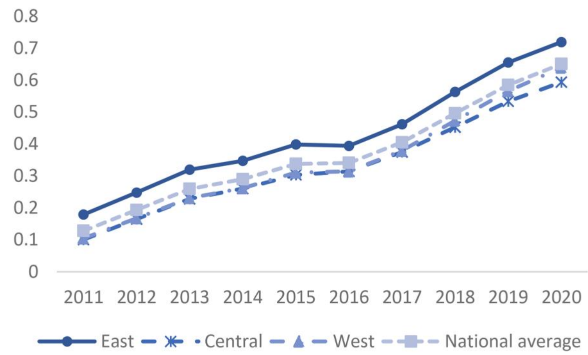


Figure 9. DEI Development trend.
Source: Calculated by the author.

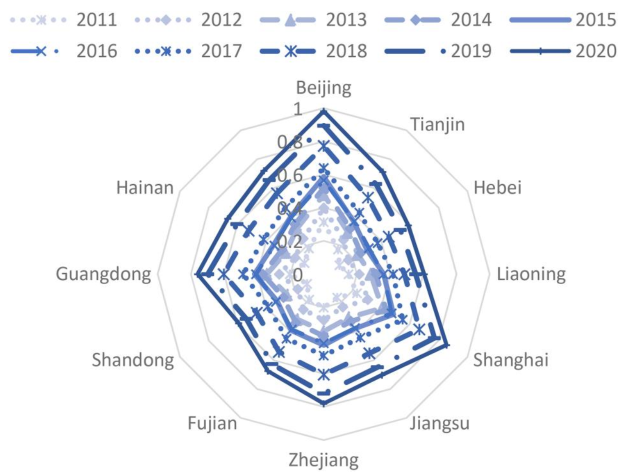


Figure 10. DEI in East.
Source: Calculated by the author.

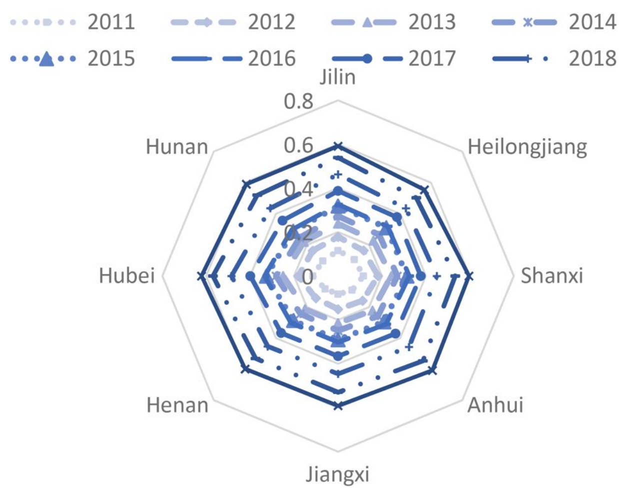


Figure 11. DEI in Central.
Source: Calculated by the author.

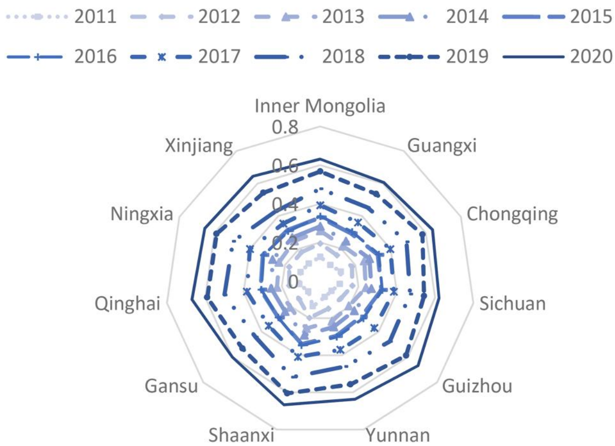


Figure 12. DEI in West.
Source: Calculated by the author.

Table 3. Dagum Gini coefficient.

		Inter-regional differences			Intra-regional variation			Contribution rate (%)		
Year	Nation-wide	East	Central	West	East-Central	East-West	Central-West	Gw	Gnb	Gt
2011	0.1951	0.1675	0.0740	0.0941	0.2815	0.2669	0.0885	0.2305	0.7060	0.0636
2012	0.1397	0.1336	0.0464	0.0639	0.2022	0.1965	0.0574	0.2345	0.6962	0.0692
2013	0.1139	0.1147	0.0315	0.0498	0.1671	0.1627	0.0435	0.2334	0.7032	0.0635
2014	0.0997	0.1094	0.0286	0.0396	0.1449	0.1435	0.0353	0.2409	0.6872	0.0719
2015	0.0912	0.1020	0.0266	0.0336	0.1379	0.1282	0.0326	0.2393	0.7013	0.0594
2016	0.0793	0.0897	0.0225	0.0323	0.1143	0.1151	0.0284	0.2430	0.6801	0.0769
2017	0.0711	0.0837	0.0189	0.0278	0.1053	0.1014	0.0251	0.2450	0.6892	0.0658
2018	0.0719	0.0859	0.0178	0.0307	0.1098	0.0944	0.0321	0.2509	0.6891	0.0599
2019	0.0676	0.0870	0.0183	0.0245	0.1043	0.0851	0.0332	0.2562	0.6778	0.0661
2020	0.0639	0.0866	0.0151	0.0203	0.0983	0.0767	0.0380	0.2562	0.6542	0.0896

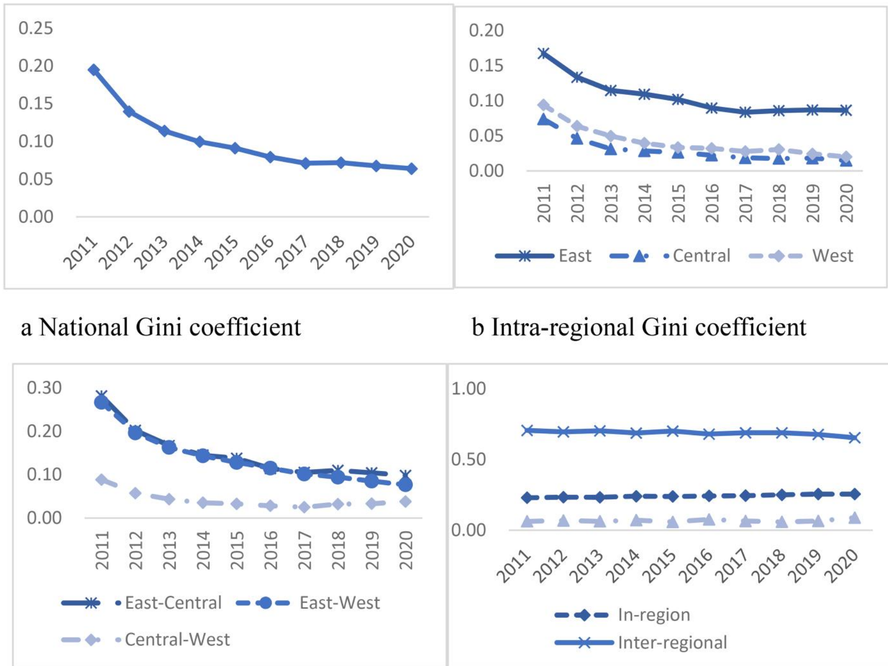
Note: Overall G represents the nationwide Gini coefficient, reflecting the overall difference; “East-Central” refers to the difference between the east and central, and so forth; Gw is the intra-group difference, Gnb is the inter-group difference, and Gt is the super-variable density difference.
Source: Calculated by the author.

economy expands and extends, the gap in digital economic growth between regions is gradually closing, which is consistent with reality.

Figure 13b shows the dynamic trend of the Gini coefficient within the three major regions. The three regions’ Gini coefficients all show a downward trend, showing that the gap difference among the digital economy growth in each province is gradually closing. The central region has experienced the smallest change in DEI Gini coefficient, followed by the western region, while the eastern region has experienced the most change. This disparity, however, has significantly shrunk over time, showing that the overall trend is going toward balanced development.

Figure 13c depicts the distinctions between the three major regions: east, central, and west. The Gini coefficient value is dropping year by year, showing that the degree of irregularity in the growth of digital economy across areas is reducing. In terms of digital economic development, the central and west have the smallest variations.

Figure 13d depicts the source of the disparity. There are three components to the difference in digital economy growth: inter-regional differences, intra-regional differences, and super-variable density disparities. Overall, intraregional differences have long been



a National Gini coefficient

b Intra-regional Gini coefficient

c Inter-regional Gini coefficient.

d Differential source contribution ratio

Figure 13. DEI Dagum Gini coefficient.
Source: Calculated by the author.

bigger than interregional differences, indicating a significant imbalance in the expansion of the region's digital economy and the need for robust steps to encourage coordinated intra-regional digital economy development.

5.2. Industrial GTFP

To ensure the data consistency and availability, observations from 30 provinces and cities (excluding Tibet, Hong Kong, Macao, and Taiwan) in China are chosen from 2011 to 2020, accounting for administrative divisions and missing data. All data comes from the China Urban Statistical Yearbook, the China Environmental Statistical Yearbook, province and municipal statistical yearbooks, and a communique. The following are detailed descriptions of input-output indicators (shown in Table 4).

5.2.1. Input factors

Labor input and capital input, respectively, are the average annual number of industrial employees above the size of each province in China and the balance of industrial net fixed assets to measure. To eliminate the effect of price fluctuations, the fixed asset price index based on 2012 is used. Due to a severe lack of coal, oil, gas, and other energy consumption data, this paper chooses the industrial electricity consumption of the entire society to approximate the energy input status for the sake of data availability and parallelism.

Table 4. Input-Output variables.

Variable Type	Variable Name	Instructions
Inputs	Labor	Average annual number of industrial employees (10,000)
	Capital	Actual capital stock (billion yuan)
	Energy	Total industrial energy consumption (million tons of standard coal)
Desirable outputs	Industrial value added	Use price index deflator (billion yuan)
Undesirable outputs	Industrial SO_2 emissions	(tons)
	Industrial dust	(tons)
	Total ammonia nitrogen emissions	(tons)

Source: China Statistical Yearbook.

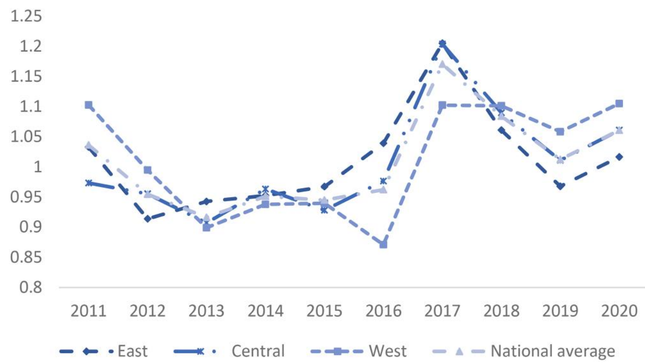


Figure 14. Dynamics of industrial GTFP.
Source: Calculated by the author.

5.2.2. Desirable output

The desirable output is represented by the added value of industrial enterprises larger than the designated size, and the ex-factory price index of industrial products in 2012 is used as the base period for the reduction.

5.2.3. Undesirable output

Industrial smoke (dust), industrial sulfur dioxide emissions, and total ammonia nitrogen emissions are used as undesirable outputs.

Figure 14 shows the industrial GTFP measured using the SBM-ML index and multiplied cumulatively year by year from 2011 to 2020. From the national level, industrial GTFP shows a rising trend year by year. The development of industrial GTFP follows a "W"-shaped ascending trend of "down -up-down-up", and the level of green development fluctuates but remains high. This reflects that in recent years, China's industry has been focusing on technological innovation, meeting the production goals of energy saving and consumption reduction, and implementing industrial green development while achieving economic benefits.

5.3. Baseline regression analysis

Table 5 shows the baseline regression results. Column (1) displays the simple ordinary least squares (OLS) regression results, which reveal that the DEI coefficient is significantly positive, implying that digital economy growth greatly contributes to the increase of industrial GTFP. Column (2) displays the random effects regression results, and column (3) adjusts for year and regional effects. Regardless of whether fixed effects are considered, the DEI coefficients are positive and statistically significant, demonstrating that digital economy development contributes significantly to promote GTFP. As evidenced by the regression results in column (3), after controlling for a range of variables, the DEI coefficient is 1.6816, which passes the 1% significance level test, indicating that digital economy growth is positively related to GTFP.

5.4. Regional heterogeneity analysis

The above analysis is mainly based on the average impact effect. However, given China's wide territory and numerous resources, it remains to be analyzed whether different regional development characteristics affect the relation between the two. As a result, this section will further investigate the regional heterogeneity, with the goal of revealing the impact of digital economy on regional GTFP and providing a reference for different regions to formulate relevant policies that are appropriate for different places. Consistent with the preceding, the entire region is geographically separated into eastern, central, and western regions. Table 6 reports the results. According to column (1) to (3), the growth of digital economy produces a significant positive effect on the enhancement of GTFP in the east and west. Among them, the effect in the west is the most significant, with a coefficient of 2.7964, which passes the 10% significance level test. The DEI coefficient in the east is 2.4539, passing the 5% significance level test. The DEI coefficient in the central is 0.5096, which fails to pass the significance test, indicating that the enhancement of digital economy on industrial GTFP improvement is not significant.

5.5. Robustness and endogeneity analysis

To further verify the robustness of the baseline regression results, the following methods are used for robustness tests: (1) Sample years. Considering that China's industrial development was in a trough period in 2015 and was greatly affected by the global economic downturn. In addition, the trend of integration between the Internet and

Table 5. Baseline regression results.

Variables	OLS (1)	Random effects (2)	Fixed effects (3)
DEI	0.1985** (2.19)	0.2091** (2.22)	1.6816*** (2.71)
GDP	−0.0364 (−0.49)	−0.0572 (−0.69)	−0.3569 (−2.24)
INF	−0.0087 (−0.34)	−0.0068 (−0.23)	0.0952 (0.62)
URBAN	0.2983 (1.22)	0.4006 (1.45)	2.0897*** (3.05)
FINANCE	0.0019 (0.11)	−0.0009 (−0.02)	−0.0445 (−0.90)
RD	−3.0535 (−1.61)	−3.3549 (−1.55)	−10.1645 (−1.53)
Cons	1.2076* (1.74)	1.3786* (1.80)	3.6440** (2.23)
Year-fixed	No	No	Yes
Province-fixed	No	No	Yes

Note: Regression estimates in the table control for temporal biofixes effects and control variables; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively. The same below.
Source: Calculated by the author.

Table 6. Regional heterogeneity analysis.

Variables	East (1)	Central (2)	West (3)
DEI	2.4539** (2.45)	0.5096 (0.31)	2.7964* (1.73)
GDP	−0.4460 (-1.60)	−0.2227 (-0.64)	−0.6702 (-1.66)
INF	0.2523 (0.74)	−0.0945 (-0.48)	0.0666 (0.20)
URBAN	2.5857** (2.27)	4.3766** (2.31)	5.9853 (1.63)
FINANCE	0.0122 (0.15)	−0.0273 (-0.22)	−0.2294* (-1.98)
RD	−12.6806 (-1.19)	−9.3710 (-0.74)	−35.8019* (-1.88)
Cons	3.7200 (1.15)	1.3489 (0.37)	5.8905* (1.73)
Year-fixed	Yes	Yes	Yes
Province-fixed	Yes	Yes	Yes

Source: Calculated by the author.

Table 7. Robustness and endogeneity test.

Variables	(1)	(2)	(3)	(4)
DEI	1.9483* (1.98)	1.4529* (1.85)	1.7451*** (2.72)	2.2616*** (3.14)
GDP	−0.6803** (-2.01)	−0.4783** (-2.43)	−0.3669** (-2.05)	−0.3183* (-1.96)
INF	−0.4046 (-1.37)	0.1499 (0.74)	0.1358 (0.86)	−0.0278 (-0.18)
URBAN	6.6053*** (3.00)	3.4626*** (2.87)	2.6416*** (3.07)	2.7318*** (3.82)
FINANCE	−0.1523 (-1.46)	−0.0792 (-1.28)	−0.0478 (-0.91)	−0.0423 (-0.83)
RD	−21.5475 (-1.65)	−7.5694 (-0.96)	−12.1349* (-1.76)	−15.2827** (-2.21)
OPEN			−0.2058 (-0.98)	
GOVERNMENT			0.3675 (0.55)	
Cons	5.0088 (1.26)	4.3074** (2.29)	3.4286* (1.85)	2.9235* (1.70)
Year-fixed	YES	YES	YES	YES
Province-fixed	YES	YES	YES	YES

Source: Calculated by the author.

traditional industries became more evident from 2015 to 2020, and digital infrastructure investment also changed. Therefore, column (1) presents the regression results for the period from 2016 to 2020. (2) Sample cities. Given that the political, economic, and cultural policies of municipalities in China differ from those of other provinces, which may have an impact on the regression results, hence samples excluding municipalities are utilized for regression. Column (2) reports the regression results after excluding the data of Beijing, Shanghai, Tianjin, and Chongqing. (3) Adding control variables. The baseline regression model may have the possibility of omitted variables. Considering this possibility, this study added two control variables, government regulation level and trade openness, to the regression model and repeated the regression as before. The relevant results are reported in column (3). (4) Lag effect. Given the latency in the impact of digital economy, the industrial GTFP of the current period may be influenced by the digital economy of the previous period, so the core explanatory variable in column (4) is changed to the DEI with a one-period lag. Table 7 reports the model regression results, and the explanatory variable, DEI coefficients in column (1)-(4) remain significantly positive, which is largely consistent with the previous baseline regression results in Table 5, indicating that the robustness of the baseline regression.

5.6. Threshold effect analysis

Table 8 shows the F statistics and *p*value calculated through the Bootstrap method. Firstly, a single threshold test is performed on the national sample, yielding an F-value of 35.44 and *p*value of 0.0000, representing that there exists a single threshold effect.

Table 8. Threshold effect test.

Region	Threshold Model	F-value	P-value	Threshold value 10%	5%	1%
Nationwide	Single threshold	35.44***	0.0000	15.7928	18.3391	25.9715
	Double threshold	7.01	0.4750	14.6331	17.6827	23.5164
	Triple threshold	7.96	0.5190	16.2071	20.5405	29.5855
East	Single threshold	6.31	0.5410	16.5359	24.0504	45.0105
	Double threshold	6.70	0.3500	10.8744	13.3064	18.9728
	Triple threshold	6.39	0.5330	15.9075	19.3449	26.9926
West	Single threshold	8.97	0.2250	12.1516	14.4996	21.3646
	Double threshold	3.18	0.7770	15.3696	19.0170	28.0371
	Triple threshold	5.14	0.3820	10.6277	12.8703	19.8922

Source: Calculated by the author.

Table 9. Estimated threshold values.

Region	Threshold value	Estimated value	95% confidence interval
Nationwide	Single threshold	0.3463	(0.3319, 0.3534)

Source: Calculated by the author.

Secondly, this regression is tested for the presence of a double threshold effect, with corresponding F-value of 7.01 and *p*value of 0.4750, which are not significant in a statistical sense. Therefore, it is assumed that there exists only the single threshold. Furthermore, heterogeneity threshold model is further evaluated to eliminate the regional heterogeneity interference. Based on the heterogeneous estimation results of the east and west, it is found that the threshold variables in both regions did not pass the single threshold test. The above analysis has demonstrated that based only on the nationwide there exists a single threshold effect. Furthermore, the DEI coefficient changes before and after passing the threshold value are investigated using threshold regression.

Table 9 reports the threshold value and the corresponding 95% confidence interval and shows that the nationwide threshold value is 0.3463. Next, a consistency test is conducted between the threshold estimation value and the actual value. Based on the results in Table 9, the likelihood ratio function chart is plotted. When DEI is employed as the threshold variable, Figure 15 depicts a trend plot of the likelihood ratio series LR as a function of the threshold value. The horizontal axis shows the threshold value, the vertical axis represents the probability function value. The dashed line represents the critical value at the 95% confidence level. According to the likelihood ratio test formula proposed by Hansen, the null hypothesis is rejected when $LR_n(\gamma) > c(\alpha)$. When $\alpha = 5\%$, the critical value of the LR statistic is 7.35. The red dashed line in the figure represents the critical value of the likelihood ratio at the 95% confidence level, which is 7.35.

Table 10 shows the threshold regression results. It has been discovered that digital economy growth has a considerable positive correlation with industrial GTFP, implying that digital economy development enhances industrial GTFP. Furthermore, this study divides different regions based on the threshold value. Specifically, when DEI value is lower than the threshold value ?1 (0.3463), the DEI coefficient is 0.6174, which is significant at the 10% level. When DEI value is greater than the threshold value ?1 (0.3463), DEI coefficient is 0.1398, significant at the 10% level. It is obvious that the intensity of the enhancement obviously differs in intervals, exhibiting

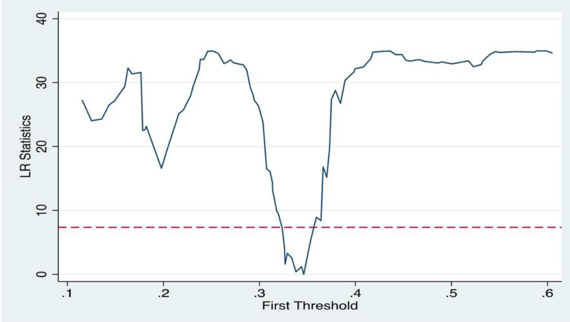


Figure 15. Estimated values and confidence intervals.
Source: Calculated by the author.

Table 10. Model estimation results.

Variables	Nationwide
DEI (DEI≤0.3463)	0.6174* (2.00)
DEI (DEI>0.3463)	0.1398* (1.98)
GDP	−0.0828 (−0.30)
INF	−0.0542 (−0.65)
URBAN	1.6590 (1.68)
FINANCE	−0.0173 (−0.22)
RD	−10.5117 (−1.46)
Cons	1.3222 (0.49)
Year-fixed	YES
Province-fixed	YES

Source: Calculated by the author.

threshold effect characteristics As DEI crosses the corresponding threshold, the enhancement on industrial GTFP growth gradually diminishes.

6. Conclusions and implications

Given that digital economy is increasingly becoming a new driving force for high-quality economic growth, this article focuses on the green value of digital economy and empirically tests the enhancement of digital economy on industrial GTFP using provincial-level panel data in China from 2010 to 2020. The research shows that: First, digital economy and industrial green development typically exhibit a pattern of fluctuation and rise, but the overall level is relatively low, and the difference between provinces is clear, with a distribution trend of high east and low west. Second, digital economy has an overall favorable impact on industrial GTFP. The regional heterogeneity analysis reveals that digital economy has a considerable impact on industrial GTFP growth in the east and west, but not in the central. Third, the threshold regression demonstrates that the promotion impact has a single-threshold effect, and when the DEI value reaches the appropriate threshold value, the promotion gradually diminishes.

Based on the above empirical results, some implications are proposed as follows: First, upgrade green technology with digital economy and promoting the digital and industrial economy integration. Strengthen digital infrastructures such as 5 G base stations, industrial Internet, big data centers, regional digital economy industry docking, data center, and platform construction, and build regional and national integrated big data center national hub nodes. Build a national data network system of "East data and West calculation", realize the interconnection of new infrastructure and information sharing, so that developed areas can motivate backward regions to share the "digital dividend" and promote industry's green transformation. Second, implement regional synergetic development strategy. To avoid blind expansion and "digital divide", it is vital to adjust development to local conditions, give scientific direction, implement synergetic development strategy, and steadily promote the digital economy growth. Digital economy has the potential to break the constraints of time and space and effectively address the uneven spatial development of economic activities, thereby providing critical support for the optimal allocation of regional spatial resources and coordinated green development of regional industries. Therefore, it is vital to support the coordinated and linked development of diverse regions to accomplish the holistic, balanced, and structured development of industrial green transformation. Third, implement regional differentiation strategy and take targeted measures in different regions. At present, there are major variations between regions and regions in China regarding the uneven degree of the digital economy growth and industry green development. Each region should put more resources into digital integrated development based on its own actual layout planning, local dominant industries, and the commanding heights of development. Focus on the regional landmark green industrial chain, cultivate and support leading enterprises to build industrial chain and industrial Internet platform, actively carry out digital and green transformation.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

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