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Research Article

The Impact of Digital Economy on Industrial Carbon Emission Efficiency: Evidence from Chinese Provincial Data

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Digital economy has become an important driving force for green economic growth in China. Based on the province-level data of China from 2003 to 2018, this paper constructed the Total-factor Nonradial Directional Distance Function (TNDDF) model to measure the carbon emission efficiency of industrial sector and discussed the impact of digital economy on carbon emission efficiency. Empirical analysis shows that the carbon emission efficiency of China's industrial sector is low, and there is obvious regional heterogeneity where the carbon emission efficiency of eastern China is higher than that of central and western China. Areas with high level of digital economy development have higher carbon emission efficiency, and digital economy is conducive to promoting energy conservation and pollution reduction in China's industrial sector. The optimal threshold interval of digital economy for promoting carbon emission efficiency is explored by means of threshold model. In view of this, the Chinese government should vigorously develop the digital economy, promote industrial enterprises to networking and digital evolution, and improve the efficiency of carbon emission as well.

1. Introduction

The continuous increasement of industrial carbon emissions has led to extreme climate problems such as global sea level rise, and it has become a consensus all over the world to improve carbon emission efficiency of industrial sector and reduce industrial greenhouse gas emissions [1, 2]. Since reform and opening-up, China's economy has maintained a medium-high growth rate, with its GDP reaching more than 10 trillion yuan in 2020. China's industrialization process and its rapid development of industrial economy have provided important impetus for the miracle of China's sustained economic growth. At the same time, resource exhaustion and environmental problems caused by excessive energy consumption have become a major problem facing China's economic development. In 2016, the Chinese government put forward its voluntary emission reduction commitment in the Paris Agreement, striving to achieve peak carbon dioxide emissions in 2030, of which the carbon emission intensity is reduced by 60% to 65% compared with 2005. Furthermore, the 14th Five-Year Plan promulgated by China proposed the idea of ‘spurring green development and promoting harmonious coexistence between man and nature, which stresses that industrial transformation can promote green economic growth. Following the plan, by 2035, green production lifestyles will be widely formed, and carbon emissions will be steadily dropped after the peak, thereby striving to achieve the goal of building a beautiful China and a deep integration of digital and real economy. At the same time, relying on the rapid development of digital technologies such as big data and the Internet, China's digital economy has penetrated into all aspects of enterprise production and residents living. It also shows great potential in improving the production efficiency of industrial enterprises, optimizing the industrial structure, and improving the misallocation of resources [3]. Based on the total factor efficiency theory, carbon emission efficiency of industrial sector reflects the maximum economic output and minimum undesirable output like carbon emissions that can be obtained by industrial enterprises in terms of given capital, labor, and energy input. The higher the carbon emission efficiency of industrial sector is, the more conducive it is to promoting the green development of the industry. Therefore, it is of great practical significance to study the impact of digital economy on the carbon emission efficiency of China's industrial sector.

In the present context of global low-carbon and ecological civilization construction, digital economy has become an important force to promote sustainable economic and social development, making it attract great attention from governments around the world [4]. And as an economic power, China has also entered the era of digital economy. According to the "Digital Economy Report 2021" released by the United Nations Conference on Trade and Development (UNCTAD), China and the United States are the best positioned to participate in and benefit from the digital economy. In accordance with the "White Paper on China's Digital Development (2021)" released by China Academy of Information and Communications Technology, the scale of China's digital economy has increased from 11 trillion yuan at the beginning of the 13th Five-Year Plan to 39.2 trillion yuan in 2020, accounting for 38.6% of GDP. Digital economy has become the core growth engine of the national economy. The global order is entering a new phase of adjustment, with digital technology deeply integrated with production and life, and the COVID-19 pandemic promoting the full penetration of the digital economy. China's 14th Five-Year Plan emphasizes the needs to continue to develop digital economy and promote digital industrialization and industrial digitalization, so as to realize the deep integration of digital economy and real economy. It can be said that digital economy has become an important driving force for China's green economic growth.

As a big energy consumer, Is a high level of digital economy able to promote carbon efficiency in the industrial sector? At what level of development can the digital economy be most conducive to promoting the carbon efficiency in the industrial sector? This paper is mainly focusing on the above problems and contributing to the existing research mainly from the following aspects. Firstly, the TNDDF model is used to calculate the carbon emission efficiency. Secondly, it discusses the green transformation of China's industrial sector from the perspective of digital economy. The development of digital economy has become an important channel for energy conservation and emission reduction, which is conducive to opening the black box of realizing green economic growth. Finally, in order to investigate the dynamic impact of digital economy on the carbon emission efficiency of industrial sector in a more comprehensive and in-depth way, the optimal intensity range of digital economy to stimulate the carbon emission efficiency of industrial sector is sought through nonlinear test with digital economy as the threshold variable.

The remaining parts of this paper are arranged as follows: the second part reviews the existing literature from the perspectives of the impact of digital economy on economic growth and green development. The third part calculates the carbon emission efficiency by selecting the carbon emission index and using the Total-factor Nonradial Directional Distance Function (TNDDF) model. The fourth part is the construction of threshold effect model and introduction to the relevant variables and data sources. The fifth part analyzes the empirical results, mainly from the basic, regional heterogeneity and threshold. The sixth part is to draw conclusions based on empirical analysis and put forward corresponding countermeasures and suggestions.

2. Literature Review

There are few literatures that directly analyze digital economy and carbon emission efficiency. This paper sorts out the existing literature from the perspectives of the impact of digital economy on economic growth and green development.

In the study of the influence of digital economy on economic growth, some scholars point out that digital economy has a positive role in promoting economic growth. Wu et al. [5] believe that digital economy is becoming a new driving force for global economic growth, and enterprises are increasingly relying on the Internet for production, operation, and sales. The Internet combines internal business processes with external business activities, reducing the cost of internal communication and information exchange through external communication [4, 6]. Perez and Lacalle [7] argue that the emergence of the Internet has changed the ability of global information sharing, while the knowledge and innovation it is releasing have a significant positive impact on economic growth, especially in developing countries. Jorgenson and Khuuong [8] pointed out that the notable feature of digital economy is the rapid development of e-commerce, which further promotes the construction of infrastructure such as information and communication, thereby accelerating the economic growth of a country. Wu et al. [9] analyzed the provincial panel data of China from 2006 to 2017 by using the dynamic spatial Dubin model, mediation effect model, and dynamic threshold panel model and pointed out that information and communication technology supported by the Internet has become an important driving force to promote the intelligent development of environmental governance in China. Deng and Zhang [10] used nonradial distance function (NDDF) to measure energy and carbon emission performance based on Chinese provincial data from 2006 to 2017. The bidirectional fixed effect model is constructed, and it is concluded that the development of Internet mainly improves energy and carbon emission efficiency by promoting industrial structure upgrading and technology diffusion. Wang et al. [11], based on OECD data, KPWW method, and multipanel regression, discusses the impact of digital technology innovation and technology spillover on domestic carbon emission intensity and its mechanism and points out that the information industry has become a 'new engine' to drive world economic growth. However, there is little research on the negative impact of the Internet on economic growth. Steffen et al. [12] believe that the influence of digitalization on energy consumption mainly includes inhibition effect and growth effect. The inhibition effect is mainly reflected in the fact that digitalization can reduce energy intensity by improving energy use efficiency and optimizing industrial structure [13]. The mechanism of growth effect is mainly manifested in two aspects: the energy consumption directly increased by the production, use, and disposal of digital technology; and the energy demand indirectly caused by the economic development empowered by digital technology [5, 14].

The research on the relationship between digital economy and green development is also one of the hottest issues in academic circles in recent years [3, 15, 16]. Whether digital economy can promote green development is controversial at present, with most scholars believing that digital economy promotes green development. Wu and Zhang [17] found that China's technological Internet and platform Internet have significantly improved the green total factor productivity of forestry in the short term. As the Chinese government speeds up the 'Internet+' development plan, the integrative development of energy and Internet has become a new way of green urban development. Li et al. [18] evaluated the environmental effects of the Energy Internet demonstration project implemented by the Chinese government and found that the measure was improving the air quality of the pilot city and surrounding cities. Shahnazi and Shabani [19] found that there is a spatial spillover effect between the progress of Internet technology and environmental pollution. From the perspective of environmental detection, the development of Internet technology plays a significant role in reducing environmental pollution. Koomey et al. [20] pointed out that when digital technology spills over to the agricultural sector, manufacturing sector, and housing construction sector, it is also conducive to eliminating carbon emission levels. Ismagilova et al. [21] believe that the information system (IS) method promotes the intelligent use of information and communication technology (ICT), thereby providing optimized and advanced services for individuals as well as affecting their quality of life and the sustainable management of natural resources. Singh and Sahu [22] argue that green information technology and related innovations mainly make use of the contribution of technology to emission reductions, while ICT replaces the physical world. Ishida [23] estimated the long-term and short-term relationship between ICT and energy consumption in Japan from 1980 to 2010. The study found that ICT investments contribute to modest reductions in energy consumption in the long and short term. Schulte et al. [24], with the industrial panel data of OECD countries, and Khuntia et al. [25], with the cross-sectional data of Internet investment and energy consumption in India's manufacturing industry, believe that the development of internet can reduce energy consumption. Saidi et al. [26] studied the panel data of 67 countries in the world and found that the higher the ICT development level represented by the amount of Internet access and the number of mobile phone users, the higher the power consumption level. Salahuddin and Gow [27] studied the relationship between Internet development and energy consumption in Australia and found that there was no significant correlation between Internet development and carbon emissions in the short and long term. Lange and Pohl [12] found that the hope of digitalization to reduce energy consumption had not been proved, and digitalization did not save energy, while it increased energy consumption instead. Existing studies did not directly point out that the digital economy will hinder environmental pollution. On the contrary, some scholars believe that the Internet has not played a positive role in energy efficiency and energy consumption. Salahuddin and Alam [28] studied the long-term and short-term impacts of Internet information technology on electricity consumption by using OECD panel data from 1985 to 2012, but it shows that OECD countries have not yet achieved improvements in energy efficiency through the adoption of Internet information technology.

Above all, the review of the literature indicates that many scholars have made use of all kinds of analysis method to examine the impact of the digital economy on economic growth and economic development from different perspectives, and China's industrial sector currently has problems such as low-carbon emission efficiency, high pollution, and high energy consumption in industrial development [29–31]. These provide an important reference for the research of this paper. But there are still some deficiencies that need to be further improved. First of all, most scholars have conducted detailed studies on the relationship between digital economy and economic growth but have not incorporated digital economy and carbon emission efficiency into a unified research framework. Secondly, digital economy is an important driving factor of technological innovation, but the existing research has not considered the spatial spillover and nonlinear impact of digital economy on the efficiency of energy saving and emission reduction. Finally, few studies have taken China's industrial sector as the research object to analyze the impact of digital economy on the carbon emission efficiency of China's industrial sector. Therefore, our study helps clarify the relationship between digital economy and carbon emission efficiency and then provides pertinent suggestions for further promoting the development strategy of digital economy and helping China achieve green economic transformation.

3. Measuring Carbon Emission Efficiency of China's Industrial Sector

3.1. TNDDF Model. Since Chambers et al. [32] proposed a Directional Distance Function (DDF) that maximizes the expected output while minimizing the undesirable output based on the Data Envelopment Analysis (DEA) method, a large number of studies apply the directional distance function to seek the best combination of economic development and energy conservation and emission reduction. Based on the practice of China's green economy development, Zhang et al. [33] proposed the Total-factor Nonradial Directional Distance Function (TNDDF), which has the advantage of not only avoiding the problem of no solution in linear programming, but also achieving the comparability of intertemporal efficiency. Therefore, this paper will use the TNDDF function proposed by Zhang et al. [33] to measure the carbon emission efficiency of China's industrial sector.

Suppose that there are j decision-making units (DMUs), and each DMU uses the input factor $x \in R_+^m$ to obtain the desirable output $y \in R_+^n$ and undesirable output $b \in R_+^k$.

Then, according to the definition of Färe et al. [34], the environmental technology function $P(x)$ is

$$P(x)=\left\{\left(x^t,y^t,b^t\right):\ \sum_{j=1}^{J} z_j^t y_{jn}^t \le y_n^t, \sum_{j=1}^{J} z_j^t b_{jk}^t = b_k^t, z_j^t \ge 0,\quad \forall j,m,n,k,\right. \tag{1}$$

where z_j^t is the intensity variable, which assigns weights to each observation unit. The equal sign in the constraints means that the environmental technology function has weak disposability of output as well as zero binding characteristics. Then, according to Zhang et al. [33], the TNDDF function can be defined as

$$\overrightarrow{N\ D}\left(x,y,b;g_x,g_y,g_b\right)=\sup\left\{\omega^T\beta:\ \left(x-\beta_x g_x, y+\beta_y g_y, b-\beta_b g_b\right)\in P(x),\right. \tag{2}$$

where $\omega^T = (\omega^x, \omega^y, \omega^b)^T$ is the weight vector. According to the setting of Zhang et al. [33], the weights of inputs and desirable and undesirable outputs are all 1/3. In this study, the input factors include capital (K), labor (L), and energy (E), while the desirable output is the industrial added value (Y) of each province, and the undesirable output is the total carbon dioxide emissions of each city (S). Therefore, the weight vector in this study can be set as $\omega^T = (1/9, 1/9, 1/9, 1/3, 1/3)^T$, the slack variable as $\beta = (\beta_K, \beta_L, \beta_E, \beta_Y, \beta_S)^T \ge 0$, and the direction vector as $g = (-K, -L, -E, Y, -S)$.

Then, the TNDDF function can be solved as follows:

$$\begin{aligned}
\overrightarrow{N\ D}^G\left(x^t,y^t,b^t;g_x,g_y,g_b\right) &= \mathrm{Max}\,\omega_K\beta_K^{Gt}+\omega_L\beta_L^{Gt}+\omega_E\beta_E^{Gt}+\omega_Y\beta_Y^{Gt}+\omega_S\beta_S^{Gt},\\
s.t \sum_{j=1}^{J}\sum_{t=1}^{T} z_j^t Y_j^t &\ge \left(1+\beta_Y^{Gt}\right)Y_j^t, \sum_{j=1}^{J}\sum_{t=1}^{T} z_j^t K_j^t \le \left(1-\beta_K^{Gt}\right)K_j^t, \sum_{j=1}^{J}\sum_{t=1}^{T} z_j^t L_j^t \ge \left(1+\beta_L^{Gt}\right)L_j^t,\\
\sum_{j=1}^{J}\sum_{t=1}^{T} z_j^t E_j^t &\le \left(1-\beta_E^{Gt}\right)E_j^t, \sum_{j=1}^{J}\sum_{t=1}^{T} z_j^t S_j^t \ge \left(1+\beta_S^{Gt}\right)S_j^t,\\
z_j \ge 0, j=1,2,\ldots J;\ &\beta_K^{Gt}\ge 0, \beta_L^{Gt} \ge 0, \beta_E^{Gt}\ge 0, \beta_Y^{Gt}\ge 0, \beta_S^{Gt}\ge 0.
\end{aligned} \tag{3}$$

According to Lin and Zhu [35], carbon emission efficiency (CEE) can be defined as

$$CCE_{i,t} = \frac{1/2\left(1-\beta_{E,\mathrm{it}}^*\right)+1/2\left(1-\beta_{S,\mathrm{it}}^*\right)}{1-\beta_{Y,\mathrm{it}}^*}, \tag{4}$$

where $\beta^* = (\beta_L^*, \beta_K^*, \beta_E^*, \beta_Y^*, \beta_S^*)$ is the optimal solution for the slack variable in equation (4).

3.2. Indicators' Selection. This study takes 30 provinces in China as the research object and uses Matlab software to measure the carbon emission efficiency of the industrial sector from 2004 to 2017. The input factors in the TNDDF function are capital, labor, and energy. Drawing on the research of Jin and Shen [36], this paper uses the perpetual inventory method to estimate the capital stock of each province in China. The relevant data required for capital stock calculation are all from the China Statistical Yearbook (2004–2019) and transformed into constant prices with a base period of year 2000. The energy input and labor input data of the industrial sector in each province are from the China Industrial Statistical Yearbook (2004–2019).

Desirable output is measured by using the value added of the industrial sector in each province. The original data are from the China Industrial Statistical Yearbook (2004–2019) and converted to constant prices by taking year 2000 as the base period. According to the research of Guo and Yuan [37], the undesirable output is measured by using the total emissions of carbon dioxide, and the original data come from the China Environmental Statistics Yearbook (2004–2019).

3.3. Results of Carbon Emission Efficiency. Figures 1 and 2 show the CEE distribution in China in 2008 and 2017, respectively. It can be seen that the spatial distribution of CEE in China has strong regional regularity. The provinces with the highest CEE values are mainly concentrated in the eastern part of China and gradually distributed to the periphery. Further, Figure 3 depicts the change of CEE in terms of time trend.

As shown in Figure 3, during the whole observation period, the average carbon emission efficiency index in China was greater than 0.50, except in 2003 (SARS broke out in China in 2003, the secondary industry with industry as the main body increased significantly; especially the high-carbon manufacturing industry led to the decline of carbon emission efficiency), the average over the sample period was 0.603. And carbon emission efficiency is showing a growing trend, with an average annual growth rate of 2.6%. This is consistent with the general background of China's recent mandatory restrictions on reducing carbon emission intensity, increasing intensity of energy conservation and emission reduction, and economic development gradually entering a new normal. The Chinese government has issued a series of environmental policies focusing on carbon emission reduction. In 2011, the year 2011 carbon intensity target was officially included in China's 12th Five-Year Plan. In 2014, the Chinese government officially proposed that carbon emission could peak by around 2030. And in 2015, China set a target of reducing carbon emission intensity by 60% to 65% compared with 2005 by 2030. In the report of the 19th National Congress of the Communist Party of China, it is proposed to promote efficiency reform, improve total factor productivity, reduce carbon emissions, and improve carbon emission efficiency to achieve sustainable development.

From the regional perspective, there are great differences in the values of carbon emission efficiency index among the three regions of eastern, central, and western China in different periods. As can be seen from Figure 1, the eastern coastal area has the highest carbon emission efficiency value with a high of 0.980, mainly due to the rapid economic growth, energy structure, and technological progress in the

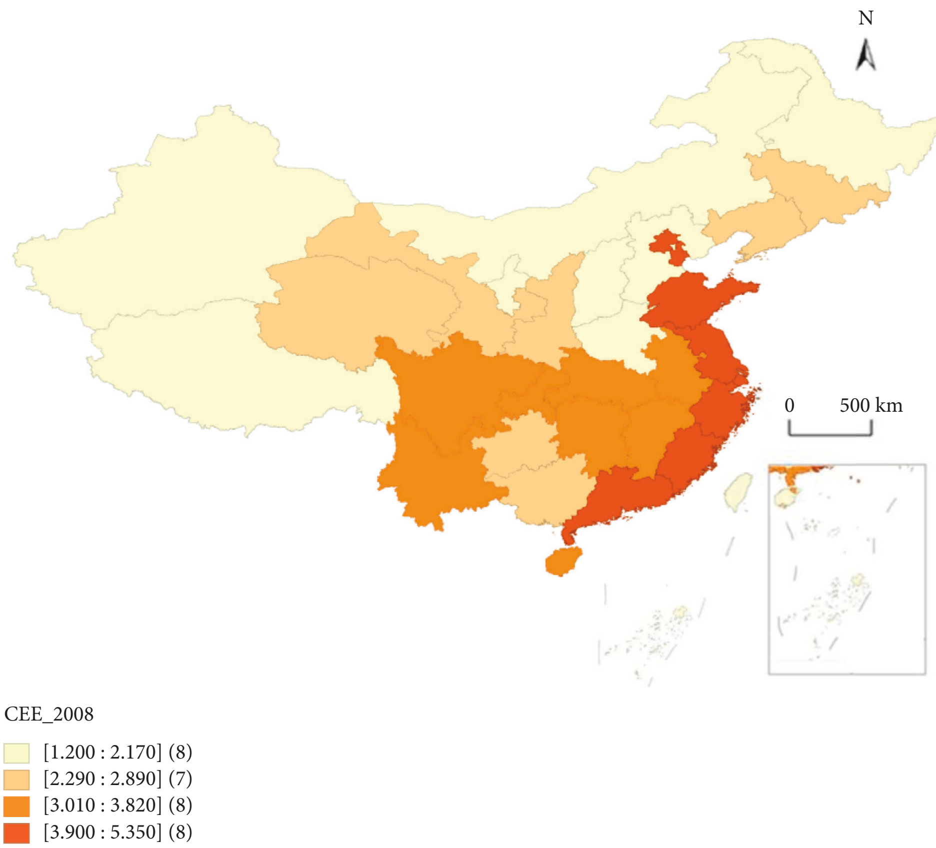

Figure 1: CEE of China in 2008.

eastern region. In particular, technological progress can reduce energy intensity and improve carbon emission efficiency to a certain extent. Meanwhile, part of the industrial gradient in the eastern region is transferred to the central and western regions. After 2010, the gap between the carbon emission efficiency of the central and western regions and that of the eastern regions has gradually increased; especially the carbon emission efficiency in western region began to decrease in 2011. This is largely related to the transfer of 'high-carbon' industries from the eastern regions to the central and western regions since 2010. The central and western regions mainly undertake the industrial transfer of high-polluting and high-energy-consuming industries from the eastern region. Although it is beneficial to improve the level of industrial development in the short term, such rapid economic development in the short term comes at the cost of environmental pollution, so the carbon emission efficiency gradually decreased in the long term. Therefore, the government agencies of central and western provinces should establish and improve the long-term mechanism of industrial carbon emission efficiency growth in practice and maintain the steady growth of carbon emission efficiency by means of continuously improving technological level.

In addition, this paper remeasures the carbon emission efficiency of China's industrial sector using the Data Envelopment Analysis (DEA) model that does not consider undesired outputs. According to Figure 4, it is not difficult to observe that the variation trend of industrial carbon emission efficiency in Eastern, Central, and Western China is consistent with the TNDDF model. However, it is worth noting that, before 2013, the carbon emission efficiency of western China was significantly higher than that of the central region, which is obviously contrary to the fact that western China has undertaken the transfer of a large number of pollution-intensive industries. Furthermore, the carbon emission efficiency results calculated by the DEA model are obviously high, which indicates that the results of the DEA model calculation without considering the undesirable output are deviation biased. This is also in line with the research conclusions by some scholars that the traditional carbon emission efficiency is higher than that considering the undesirable output. It shows that choosing the TNDDF model to measure the carbon emission efficiency of China's industrial sector is more scientific and robust.

4. Empirical Model and Variables

4.1. A Dynamic Panel Model. One of the core issues to be explored in this paper is the impact of digital economy on carbon emission efficiency of industrial sectors. Based on the theoretical analysis above, this paper constructs the following dynamic econometric model:

$$\begin{aligned} \ln \mathrm{CEE}_{i,t} = {} & \alpha_0 + \beta_1 \ln \mathrm{CEE}_{i,t-1} + \beta_2 \ln \mathrm{Digital}_{i,t} \\ & + \sum \delta \ln X_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

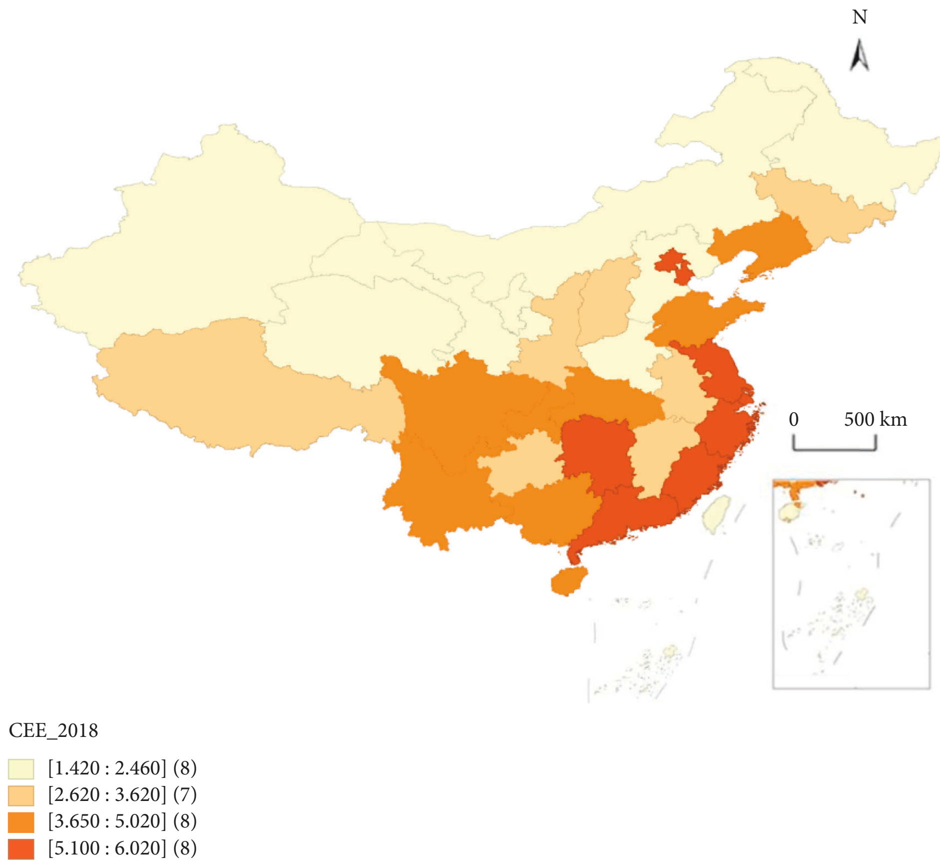

Figure 2: CEE of China in 2018.

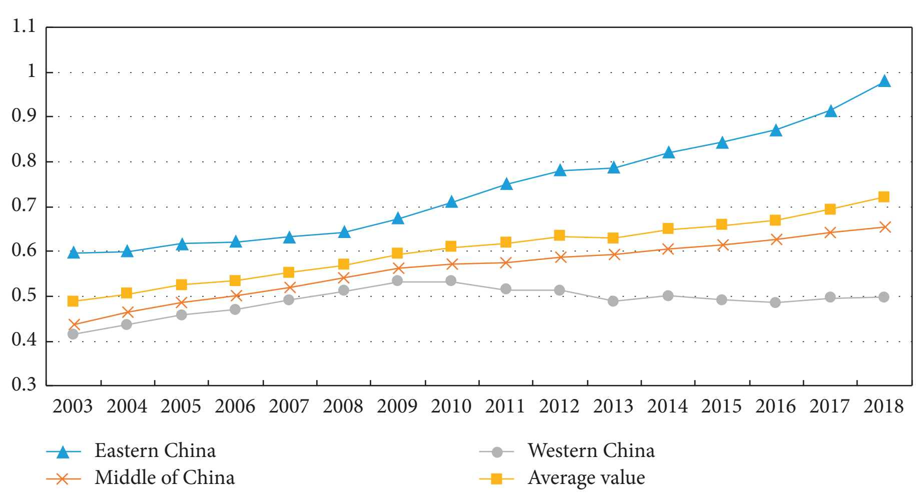

Figure 3: Trend of CEE of the three economic zones in China.

where i denotes the region, and t denotes the year. CEE represents carbon emission efficiency of China's industrial sector. Digital represents the Digital economy development index. X represents the control variable selected based on existing literature: specifically, foreign direct investment (FDI), capital deepening (Inv), export trade (Ex), gross domestic product (GDP), and government size (Gov). ε represents the error term, and ln represents taking the natural log.

The existing studies have not reached a consensus on the view that China's digital economy can improve the carbon emission efficiency of some industries, indicating that digital economy may have a nonlinear impact on the carbon emission efficiency of China's industrial sector. Therefore, in order to investigate the dynamic impact of digital economy on carbon emission efficiency of industrial sector in a more comprehensive and in-depth manner, especially to examine the optimal intensity range of the carbon emission efficiency

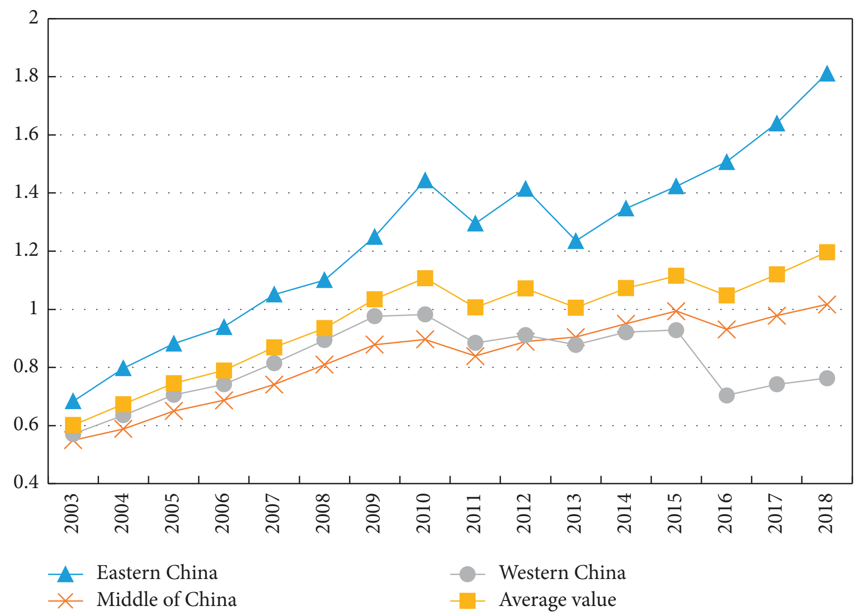

FIGURE 4: CEE trend of China's three economic zones measured by DEA model.

of the industrial sector where the digital economy stimulates environmental regulation and high-quality economic effects, this paper further takes the digital economy as the threshold variable and adopts the method of Hansen [38] to test the threshold effect. The specific model is set as follows:

$$\begin{aligned} \ln CEE_{i,t} &= \alpha_0 + \beta_1 \ln CEE_{i,t-1} + \theta_1 \ln \text{Digital}_{i,t} \times I\left(\ln \text{Digital}_{i,t} \le s_1\right) + \\ \theta_2 \ln \text{Digital}_{i,t} &\times I\left(s_1 \le \ln \text{Digital}_{i,t} \le s_2\right) + \ldots + \theta_n \ln \text{Digital}_{i,t} \times I\left(\ln \text{Digital}_{i,t} \ge s_n\right) + \\ &+ \sum \delta \ln X_{i,t} + \varepsilon_{i,t}, \\ \text{In}CEE_{i,t} &= a_0 + \beta_1 \text{In}CEE_{i,t-1} + \theta_1 \text{InDigital}_{i,t} \times I\left(\text{InDigital}_{i,t} \le s_1\right) + \theta_2 \text{InDigital}_{i,t} \times I\left(s_1 < \text{InDigital}_{i,t} \le s_2\right) + \\ &\ldots + \theta_n \text{InDigital}_{i,t} \times I\left(\text{InDigital}_{i,t} \ge s_n\right) + \sum .\delta \text{In} X_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

where $I(\cdot)$ is indicator function, and X is the set of control variables in the above baseline regression.

4.2. Variable and Data Source. At present, there are two main categories for measuring the development level of digital economy: single index measurement method and comprehensive index measurement method. The disadvantage of single index measurement method is that the research results may be biased due to the subjectivity of index selection or fail to fully reflect the development level of Internet in various regions due to the one-sidedness of index selection. In view of this, this paper draws on the research methods of Han et al. [39] to construct a comprehensive index of digital economy development by using the number of fixed broadband Internet users, mobile phone users, and general Internet users per 100 people. The specific measurement method of the comprehensive index of digital economy development is as follows:

$$\text{Digital}_{\text{it}} = \left(\text{net}_{\text{it},1} \times \text{net}_{\text{it},2} \times \text{net}_{\text{it},3}\right)^{1/3}, \tag{7}$$

where $\text{net}_{it,\ 1}$, $\text{net}_{it,\ 2}$, $\text{net}_{it,\ 3}$ successively represent the number of fixed broadband Internet users per 100 people, the number of mobile phone users per 100 people, and the number of general Internet users per 100 people in region i during period t. After geometric weighted average of the three indicators, the comprehensive index Digital of Digital economy development can be obtained.

There are 5 control variables in this study. First, regarding the foreign direct investment (FDI), this paper chooses the ratio of foreign direct investment to regional GDP to measure it; second, regarding the capital deepening (Inv), it is measured by the ratio of the net fixed assets of each region to its GDP; third, regarding the export trade (Ex), it is measured by the proportion of the total import and export volume of each region to the region's GDP; fourth, regarding the government size (Gov), it is measured by the ratio of government consumption to GDP of each region; finally,

Table 1: Summary statistics of main variables.

Variables	Mean	Sd	Min	Max
EQ	0.5681	0.0927	0.4933	0.8694
Digital	0.4323	0.0708	0.3990	0.7202
Tech	6.1222	0.0633	5.2037	7.0166
Allocation	0.1653	0.7112	0.0033	0.2191
FDI	69.7877	2.6604	45.5537	89.1336
Inv	2.8352	0.0273	0.7899	4.5385
Ex	9.1754	0.1644	2.1082	14.7367
Gov	0.1081	0.0097	0.0042	0.1691
GDP	11.8736	0.8566	2.1083	14.8766

Table 2: Dynamic panel data regression results.

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Cons_	1.051^{***} (0.035)	1.052^{***} (0.034)	1.051^{***} (0.035)	1.054^{**} (0.032)	1.057^{*} (0.031)	1.150^{***} (0.039)
LnDigital_{it}	0.114^{***} (0.005)	0.145^{***} (0.004)	0.145^{***} (0.004)	0.117^{***} (0.003)	0.120^{***} (0.001)	0.205^{***} (0.002)
Lnfdi_{it}		0.012^{**} (0.000)	0.014 (0.001)	0.012^{***} (0.003)	0.015^{*} (0.000)	0.011^{***} (0.004)
LnInv_{it}			0.052^{***} (0.115)	0.054^{***} (0.107)	0.055 (0.110)	-0.056^{**} (0.111)
LnEx_{it}				-0.094^{**} (0.051)	-0.095^{*} (0.051)	-0.101^{***} (0.050)
Lngdp_{it}					0.135^{**} (0.005)	0.139^{*} (0.005)
LnGov_{it}						0.022^{***} (0.054)
AR(1)	0.0155	0.0117	0.0154	0.0015	0.0015	0.0025
AR(2)	0.1501	0.5255	0.4045	0.5714	0.4555	0.1512
Sargan	0.2021	0.4255	0.1750	0.4015	0.2557	0.2251

Notes. Standard errors are shown in brackets; ***, ** and *, respectively, represent significance at 1%, 5%, and 10% levels.

regarding the gross domestic product (GDP) is measured by the per capita GDP of each region.

In this study, panel data of 30 provinces in China from 2003 to 2018 were obtained from China Urban Statistical Yearbook, China Demographic Statistical Yearbook, China Industrial Statistical Yearbook, China Science and Technology Statistical Yearbook, etc. Based on the scientific principle of research samples, this paper uses household consumption index, industrial producer price index, GDP deflator, etc. to reduce all monetary quantities to comparable prices in the base period of 2000. At the same time, in order to avoid the impact of dimensional and order of magnitude differences of variables on test results, the original values of panel data in this paper are standardized. The summary statistics of main variables are shown in Table 1.

5. Empirical Results and Discussions

5.1. Baseline Regression Results. Table 2 reports the basic model regression results of the impact of digital economy on carbon emission efficiency of China's industrial sectors. According to model (1) in Table 2, without the inclusion of control variables, the estimated coefficient of the digital economy variable (Digital) is 0.114, which is significant at the 1% level, indicating that every 1% increase in the development level of Digital economy, the Carbon emission efficiency will increase by 11.4%. Meanwhile, models (2)–(6) further incorporate control variables based on Model (1). We can find that the estimated coefficient values and significance of digital economy variables have not fundamentally changed, and the digital economy is still positively promoting the carbon emission efficiency of China's industrial sector. This also verifies the first hypothesis where "digital economy can effectively stimulate the carbon emission efficiency of the industrial sector." In terms of control variables, GDP, Inv, Gov, and FDI are positively correlated with carbon emission efficiency, indicating that rising incomes, accelerating capital accumulation, government support, and foreign-invested factories are important drivers of carbon emission efficiency, which can enhance the infrastructure construction of the digital economy. In addition, there is a significant negative correlation between Ex and carbon emission efficiency. It is because that the existing international trading system is mainly biased in favor of the economically advanced countries, and the negative attitude of developed countries to foreign trade is not conducive to improving the carbon emission efficiency of China's industrial sector.

5.2. Regional Heterogeneity Analysis. Table 3 reports the regional heterogeneity test results of the digital economy on the carbon emission efficiency of the industrial sector. The results from Model (1) to Model (4) show that digital economy has a significant promoting effect on carbon emission efficiency in eastern and central China, where the influence coefficient of eastern region is the highest, which is 0.2528, and is much higher than 0.0767 of central province. Model (5) and Model (6) show that digital economy has a significant negative impact on carbon emission efficiency in western China, while export trade and income levels have a positive impact on it, which is opposite to that in eastern China. The results confirm that digital economy has significant regional differences in carbon emission efficiency.

Table 3: Regional heterogeneity analysis results.

	Eastern region		Central region		Central region	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Cons_	1.2476^{***} (0.042)	1.2642^{***} (0.046)	1.7224^{***} (0.001)	1.7788^{***} (0.002)	1.0524^{***} (0.052)	1.0257^{***} (0.065)
LnDigital_{it}	0.2528^{**} (0.161)	0.2512^{**} (0.174)	0.0767^{**} (0.102)	0.0572^{*} (0.105)	-0.0048^{***} (0.180)	-0.0022^{*} (0.181)
Lnfdi_{it}		0.0642^{***} (0.066)		0.0812^{**} (0.115)		−0.0762 (0.017)
LnInv_{it}		0.0177^{***} (0.007)		0.0058^{***} (0.077)		0.0056^{***} (0.006)
LnEx_{it}		-0.1250^{***} (0.027)		-0.0761^{**} (0.051)		0.0682^{*} (0.052)
LnGov_{it}		0.0002 (0.002)		−0.0464 (0.001)		−0.0524 (0.002)
Lngdp_{it}		-0.7146^{***} (0.164)		-0.0814^{**} (0.247)		0.0685 (0.264)
AR(1)	0.0445	0.0411	0.0218	0.0041	0.0082	0.0091
AR(2)	0.1409	0.2001	0.2126	0.6802	0.1986	0.5984
Sargan	0.6626	0.4466	0.2541	0.4259	0.1109	0.2066

Notes. Standard errors are shown in brackets; ***, ** and * respectively represent significant at 1%, 5% and 10% levels.

Table 4: Threshold estimators from sampling test results.

Threshold variable	The threshold number	Estimated value	F	10%	5%	1%
Digital	Single	10.753^{***}	27.51	23.578	26.716	34.692
	Double	11.541^{**}	25.50	20.061	25.365	35.601
	Triple	9.707	9.13	19.502	24.163	37.714

The authors believe that the main reasons for the above results are as follows: China's regional industrial development gap is relatively large, and the industrial layout has also undergone fundamental changes in recent years, showing a trend of gradient transfer of industries from the east to the central and western. The Internet + initiative was launched earlier in the eastern region, and the development level of the digital economy is relatively high. Energy-consuming industries have been moving to the central and western regions. During the implementation and promotion of the strategy of the rise of central China, the central region has gradually increased the construction of network infrastructure and improved the allocation level of regional network resources. Overall, the eastern and central regions have achieved an effective connection for the development of the digital economy, which makes the digital economy in the eastern and central regions promote carbon emission efficiency. Due to the relatively lagging development of the Internet and the low level of digital economy in western China, its economic development mainly depends on government policies and investment. At the same time, the promotion process of digital economy is accompanied by the undertaking of energy consumption industry, which makes the development of digital economy in western China show the result of restraining carbon emission efficiency.

Above all, carbon emissions are closely related to economic development, and economic development requires energy consumption. China proposes two-stage carbon reduction targets (dual carbon strategic goal), to peak carbon dioxide emissions by 2030 and become carbon neutral by 2060. This goal will not be achieved without the help of digital development.

5.3. Threshold Effects of Digital Economy. According to the above theoretical analysis, there may be a nonlinear relationship between digital economy and carbon emission efficiency. In order to further verify the correlation between the two, this paper adopts the threshold panel technology proposed by Hansen to set digital economy as the threshold variable, sampling 500 times and estimating the critical value for F statistic and threshold variable. Table 4 reports the test results of digital economy as the threshold variable, where the digital economy variable presents its characteristics of significant under single threshold and double threshold while being not significant under triple threshold. The estimated value of single threshold is 10.753, and the estimated value of double threshold is 11.541. The dynamic threshold effect under different digital economy levels can be analyzed according to the different intervals divided by the double threshold.

As can be seen from the threshold regression results reported in Table 5, when LnDigital <10.753, the estimated coefficient is −0.021, which is significantly negative. In the sample grouping data of this paper, Anhui, Heilongjiang, Jiangxi, Gansu, and other western provinces with relatively

Table 5: Threshold model regression.

Variable	Estimated value	Standard error	P
LnDigital (LnDigital < 10.753)	-0.021^{*}	0.0045	0.000
LnDigital (10.753 ≤ LnDigital ≤ 11.541)	0.098^{***}	0.0895	0.082
LnDigital (LnDigital > 11.541)	0.152^{*}	0.0043	0.226
Lnfdi_{it}	0.042^{***}	0.0042	0.000
LnInv_{it}	0.026	0.0586	0.225
LnEx_{it}	-0.071^{**}	0.0056	0.043
LnGov_{it}	0.088^{***}	0.0402	0.007

Notes. ***, ** and *, respectively, represent significance at 1%, 5%, and 10% levels.

Table 6: Robustness checks.

	Model (1)	Model (2)	Mode l(3)	Model (4)	Model (5)	Model (6)
Cons_	2.142^{***} (0.134)	2.140^{***} (0.133)	2.143^{***} (1.134)	2.144^{**} (1.131)	2.147^{*} (1.132)	2.241^{***} (1.136)
$\mathrm{LnDigital}_{it}$	1.114^{***} (0.002)	1.142^{***} (0.004)	1.142^{***} (0.004)	1.117^{***} (0.003)	1.110^{***} (0.001)	1.102^{***} (0.001)
Lnfdi_{it}		0.030^{**} (0.001)	0.040 (0.003)	0.043^{***} (0.001)	0.042^{*} (0.000)	0.038^{***} (0.002)
LnInv_{it}			-0.072^{**} (0.022)	-0.074^{*} (0.019)	−0.075 (0.020)	-0.077^{*} (0.024)
LnEx_{it}				0.022 (1.001)	-0.065^{**} (1.012)	-0.063^{**} (1.005)
Lngdp_{it}					0.651^{***} (0.001)	0.659^{***} (0.002)
LnGov_{it}						0.191^{**} (0.012)
AR(1)	0.0412	0.0447	0.0413	0.0241	0.0341	0.0141
AR(2)	0.4204	0.1413	0.4042	0.1743	0.4131	0.4146
Sargan	0.3043	0.4211	0.3710	0.2041	0.4127	0.3514

Notes. Standard errors are shown in brackets; ***, ** and *, respectively, represent significance at 1%, 5%, and 10% levels.

backward economic development level are in this range, indicating that, with the improvement of digital economy, the carbon emission efficiency of these regions decreases. In recent years, the development level of digital economy in western China lags far behind the central and eastern regions, and there is a huge "digital gap" between western China and developed regions. Although the region vigorously promotes the integrated development of 'Internet +' and traditional manufacturing, it mainly combines industrial enterprises with heavy pollution. Therefore, with the continuous development of digital economy, carbon emission efficiency is low.

When 10.753 ≤ LnDigital ≤ 11.541, the estimated coefficient is 0.098, indicating that, with the improvement of digital economy, carbon emission efficiency increases significantly. Fujian, Guizhou, Sichuan, and other provinces in central China are in this range. Although the low-carbon industry in central China started later than that in eastern China, its low-carbon industry develops at a faster speed, with higher average annual growth rate of relevant indicators of low-carbon industry development and greater potential for industrial low-carbon development. Taking Guizhou as an example, according to the 2019 China Big Data Industry Development Report released by China Industrial Information Security Development Research Center, the big data industry development Index of Guizhou is 76, ranking third in the country after Beijing and Guangdong.

When LnDigital > 11.541, the estimated coefficient is 0.152, which is significantly positive. The possible reason is that the six samples in this region, that is, Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, and Guangdong, are all relatively developed eastern provinces and cities. These provinces have already played a leading role in the development of digital economy. In the development process of digital economy, it has successfully seized the initiative in e-commerce model, digital supply chain, etc. and pioneered the integration of the digital economy with the physical industry. The industries initially applied the integration with high pollution and high energy consumption have been gradually transferred to the central and western regions. At present, the development of digital economy is mainly integrated with high-end manufacturing such as artificial intelligence. The higher the development level of digital economy, the higher the carbon emission efficiency, and this is significantly correlated.

5.4. Robustness Checks. In order to ensure the robustness of the research results, the green total factor productivity of the industrial sector, which emphasizes the "win-win situation between the environment and the economy," is selected as a proxy indicator to measure the explained variables, and the model is reestimated. As shown in Table 6, the results of reestimating the model show that the digital economy has a positive and significant impact on the green total factor productivity of China's industrial sector, supporting the research conclusion that developing digital economy is conducive to energy conservation and emission reduction in China's industrial sector. Thus, the empirical results of substitution variables have verified the robustness of the previous research conclusion.

6. Conclusion

With the improvement of the development level of digital economy, its development level has affected the carbon emission efficiency of China's industrial sector.

Based on existing research, the digital economy is seen as increasingly important for improving the efficiency of carbon emissions. However, there are few studies on the impact of the digital economy on the carbon emission efficiency of China's industrial sector. Based on the data of 30 Chinese provinces from 2003 to 2018, this paper examines the impact of digital economy on carbon emission efficiency from both linear and nonlinear perspectives and conducts a threshold test on the heterogeneous impact of digital economy in different regions on carbon emission efficiency of China's industrial sector.

The development of digital economy inevitably produces unnecessary output, which means that although it is expected that its development can make GDP continue to grow, it is accompanied by a certain carbon emission. Therefore, the TNDDF model can be used to measure the carbon emission efficiency more effectively. From the perspective of regional carbon emission efficiency, China's carbon emission efficiency is currently at a low level, and there are significant regional differences. The development level of digital economy in eastern China is higher than that in central and western China, and its carbon emission efficiency is also significantly higher. It can be said that digital economy plays a significant role in promoting carbon emission efficiency. In order to find the optimal interval for its development, this paper conducts threshold effect analysis and concludes that although double threshold has passed the significance test, only in the appropriate interval, the development of digital economy will contribute to the growth of carbon emission efficiency. At present, the most significant interval is the eastern coastal region.

According to the research conclusions of this paper, the following policy implications can be obtained. First, steadily improve the development level of the digital economy, give full play to its incentive effect on carbon emission efficiency, and strive to narrow the information gap and "digital divide" between regions. Secondly, the Chinese government should fully consider the regional and industrial heterogeneity of real industry development and formulate targeted policies for digital economy development. The eastern region should maintain a reasonable and scientific speed of digital economic development, while the central and western regions should promote the application of new digital technologies such as big data and cloud computing in real industry and strive to narrow the "digital divide" between regions and industries. Third, the deep integration of digital economy and real industry is an effective way to improve China's carbon emission efficiency. On the one hand, China should promote collaborative innovation platforms with the digital economy as the carrier and promote the public sharing and rational flow of innovative elements such as knowledge, information, technology, and talent among high and small schools. On the other hand, through the comprehensive promotion and application of new technologies and new models, industrial enterprises are promoted to network and digital evolution, thus improving the carbon emission efficiency.

Data Availability

As the paper used unofficial government data such as carbon emissions in its analysis, it is requested not to disclose the original data and processing process.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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