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How Does the Industrial Digitization Affect Carbon Emission Efficiency? Empirical Measurement Evidence from China's Industry

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Abstract: Based on the panel data of China's industrial carbon emissions from 2015 to 2022, the S-SBM model is scientifically used to measure the industrial carbon emission efficiency, and a spatial model is constructed to empirically analyze the spatial effect of industrial digitalization on carbon emission efficiency. From the regional perspective, it is interesting to find that industrial digitization has shown an overall downward trend of the central, western and northeastern regions showing a roughly N-shaped trend of change. From an industry perspective, we also find that industrial digitization has a relatively high overall impact on the carbon emissions performance of the mining industry with significant changes in the performance of electricity and heat and gas and water production and supply industries. Therefore, the experimental results effectively provide the substantive empirical evidence for policy makers on how to best promote the development of industrial digitization and strengthen the effective application of digital technology affecting carbon emission control in China.

Keywords: carbon emission efficiency; industrial digitization; S-SBM model; spatial effect

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1. Introduction

For many years, countries around the world have been striving to reduce emissions and cooperate to reverse the growth of carbon dioxide emissions. In addition, the severity of global climate issues is increasing with the rapid development of industries, mainly due to excessive carbon dioxide emissions [1]. Moreover, after the long-term and rapid development, the economy has gradually encountered a series of problems such as the resource depletion and prominent social contradictions. Human beings are facing challenges such as environmental pollution, climate change and energy consumption. Therefore, it is absolutely necessary for us to provide important decision-making methods and management suggestions for global energy conservation and emission reduction through environmental pollution issues [2]. Concurrently, it is necessary to prioritize reducing industrial carbon emissions efficiency by establishing a hybrid efficiency theoretical framework considering the importance of industrial digitization [3]. With the rapid growth of China's economy, issues such as energy depletion and environmental pollution are becoming increasingly serious. In particular, the greenhouse effect is becoming increasingly apparent which has brought serious negative impacts on China's sustainable development. Therefore, some scholars have proposed that regional emission efficiency and influencing factors have become an important hot topic of academic attention [4]. Simultaneously, the carbon emissions and pollution problems of enterprises are the main sources of environmental problems, and the effectiveness of the reduction is directly related to China's overall carbon peak goal.

Improving carbon emission efficiency with increasing attention to climate change is of great significance for solving industrial environmental challenges. It also provides a new perspective for China and other developing countries to improve carbon emission and low-carbon transformation [5]. Based on analysis, it has been found that the synergistic effect between the development of manufacturing and productive services can significantly suppress the negative impact of industrial carbon emissions [6]. Simultaneously, scholars have analyzed the regional heterogeneity of carbon emission efficiency and the regulatory effect of air pollution regulation [7]. The development of vigorous digital technology has provided enormous potential for global carbon reduction. Research results show that regional digital development can to some extent reduce the total amount of carbon emissions [8]. Meanwhile, some scholars have proposed that carbon reduction is a key aspect for promoting sustainable development and an important path to achieving the dual carbon goals. Through experiments, it has been shown that the goal of reducing carbon emission intensity can be achieved through digital technological innovation and internal control [9]. The continuous development of the digital economy provides new impetus and energy for achieving the global goals of carbon peak and carbon neutrality [10]. Therefore, comparing and analyzing different carbon emission efficiency measures is of great significance for improving efficiency.

Environmental pollution and ecological degradation have brought negative impacts to people's survival. Achieving the dual carbon goals is of vital significance to the high-quality development of industrial enterprises and sustainable growth [11]. Concurrently, the contradiction between rapid economic development and controlling greenhouse gas emissions is also increasing day by day. Therefore, reducing industrial carbon emissions, improving carbon emission efficiency and developing a low-carbon economy are imperative. However, the digital economy is a new type of economy driven by digital technology as the core driving force and information infrastructure as an important carrier. Meanwhile, through research, it has been found that digital technologies for controlling industrial pollution have significant implications for carbon emission [12]. According to empirical data on carbon dioxide emissions from various provinces in China, in order to reduce carbon emissions in various industries under the digital background, it is necessary to consider the deep integration of digital technology, continuously improve the level of industry digitization and intelligence, accelerate the reconstruction of industrial green governance models, and promote green economic development [13]. The results indicate that the information and communication technology can help improve carbon emission efficiency and scale efficiency and technological progress [14] while analyzing the impact mechanism of the digital economy on carbon emissions through its direct, indirect and nonlinear relationships. The experimental results indicate that the development of China's digital economy can exacerbate carbon emission control [15]. Overall, the goal of reducing industrial carbon emissions through promoting regional cooperation can be achieved through the development of digital technology [16]. Therefore, our research on whether industrial digitization can significantly suppress its carbon emission efficiency is an important topic worth exploring.

Information sharing has strengthened the spillover of technological innovation, driving the total factor productivity in various regions to increase accordingly. Through relevant experimental analysis, it has been shown that the speed of economic growth and the upgrading of industrial structure play a mediating role in controlling the relationship between digital technology and carbon emissions [17]. In order to achieve the development goal of carbon reduction, it is necessary to reasonably improve the degree of industrial digitalization through various means to achieve the dual carbon targets. Particularly, the correlation between the reduction of industrial carbon emissions and sustainable development can be estimated through the measurement of carbon emission efficiency. Therefore, improving the level of industrial digitization to improve carbon emission efficiency according to local conditions can provide theoretical basis and practical experience for effectively realizing China's carbon neutrality goal [18]. The study may help policymakers understand the impact of industrial digitization on carbon emission efficiency related to China's accelerated digital infrastructure construction [19]. Simultaneously, focusing on industrial digitization can achieve the goal of sustainable development [20]. As a result, enterprises should be encouraged to use the new generation of information technology to improve their digital level and promote industrial carbon reduction. Through relevant data, it can be found that the digital economy directly and indirectly affects carbon emissions reduction. At the same time, the carbon reduction effect of the digital economy exhibits regional heterogeneity which is more prominent in the eastern region than in other regions [21]. Furthermore, exploring new driving forces with new industrial digital production factors as the main body and promoting the unity of economic and ecological benefits is the only way to achieve green development [22]. Therefore, we will develop the level of industrial digital technology and actively lay out and improve the construction of an industrial digital ecosystem. At the same time, we also found that the restriction of the carbon neutrality goal can improve the carbon emission efficiency. However, the internet economy provides an excellent opportunity to achieve the development of a low-carbon economy [23]. Consequently, it is unclear whether the development of industrial digitization can effectively improve the efficiency of carbon emissions and promote the sustainable development.

The industrial sector is not only the main source of China's economic growth but also is the main factor in carbon emissions. Energy-intensive enterprises have led to significant carbon dioxide emissions in China's metal industry especially [24]. Green innovation is an indispensable and important component of China's low-carbon development [25]. Reasonable carbon reduction regulatory tools have a certain positive impact on the total carbon emissions control of enterprises, and several suggestions are put forward for low-carbon development. In order to improve industrial carbon emission efficiency, we must accurately measure the industrial carbon emission efficiency and analyze the main driving factors and mechanisms for the growth of industrial carbon emission efficiency. Especially for Chinese industry, there is not enough attention paid to carbon reduction. At the same time, its related research is also limited. Through extensive literature research, we can conclude that many scholars are still unclear about the theoretical mechanism of corporate digitalization on carbon emissions. Most scholars are based on the theory of environmental economics and discuss how enterprise digitalization affects the total carbon emissions from three aspects: enterprise innovation, internal control and environmental information. Through the above analysis, we can conclude that the main path of industrial digitization affecting carbon emission efficiency is represented in Figure 1 as follows.

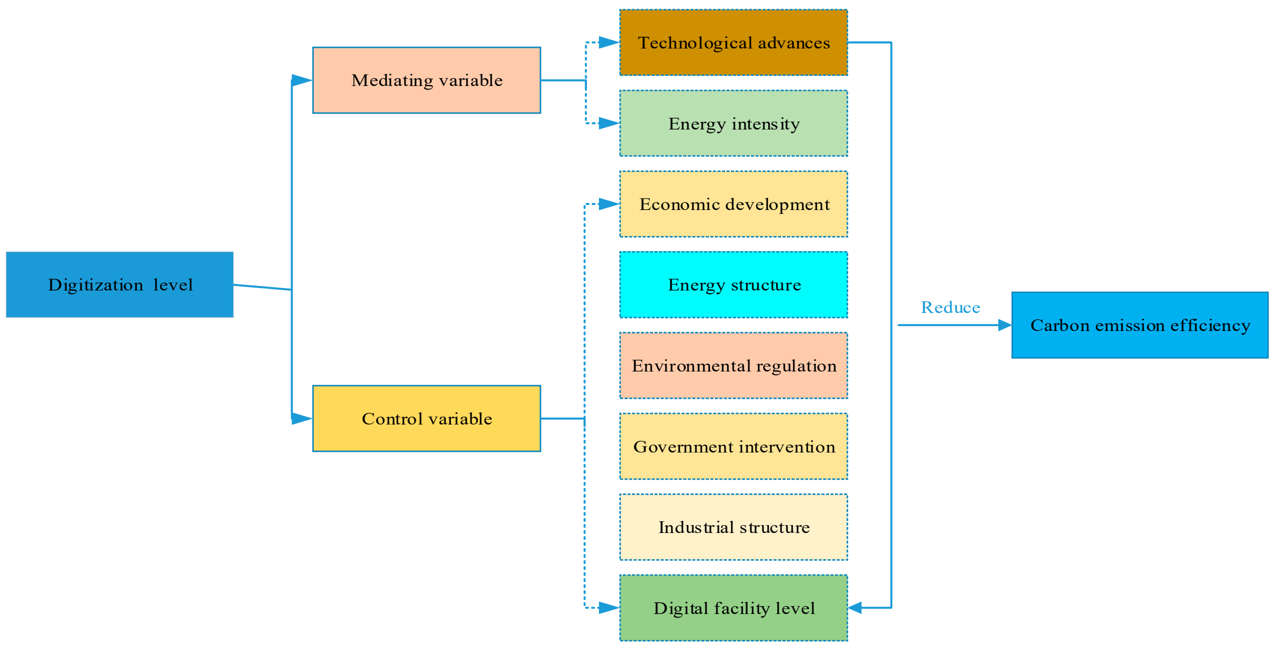

Figure 1. The main path of industrial digitization affecting carbon emission efficiency.

In summary, the following scholars have found through experimental analysis that there are three effective methods to reduce industrial carbon emission efficiency [26,27]. Firstly, carbon emission efficiency from the full factor perspective is gradually replacing carbon emission performance from a single factor perspective and has been accepted by domestic and foreign scholars. Secondly, there are two preferences in empirical research: linear and nonlinear relationships. Thirdly, the spatial econometric methods are gradually being widely used. Based on the above reasons, we will focus on in-depth comparative analysis of measurement methods for carbon emission efficiency in industrial industries and their regions and make the best and most effective choices. At the same time, the influencing factors of carbon emission efficiency are classified into linear and nonlinear technical categories, and spatial econometric methods are applied to them. This will be beneficial for further deepening research ideas on regional carbon emission efficiency. As a result, what is the impact of industrial digitization on China's industrial carbon emission efficiency at this stage? What is the mechanism of its impact? Is there a spatial spillover effect in the evolution of industrial digitization and industrial carbon emission efficiency? This is a question worth considering for China's industry to achieve carbon peak, facing significant challenges on the road toward carbon neutrality. Through in-depth analysis, the structure of this article is as follows: the second part and the third part are methods; the fourth part is experimental results and analysis, and the last part is conclusions and policy recommendations.

2. Measurement Methods for Industrial Carbon Emission Efficiency

2.1. SBM Model

The models considering the impact of unexpected outputs for study carbon emissions efficiency can be divided into two categories: stochastic frontier analysis and data envelopment analysis. Main methods include the Russell measure model and slacks-based model (SBM), range adjusted model and the directional distance function among the different methods discussed. However, the data envelopment analysis only explores the progress of input or output indicators in the same proportion. For some invalid decision-making units, there will be not only equal proportion but also partial relaxation and improvement which will lead to measurement gaps. Concurrently, it can be used for customization to more intelligently explore the projection distance between DMU and frontier states. Among them, the SBM model is an important field in management science and mathematical economics, and it has been widely employed in efficiency evaluation. However, all regard the decision units as homogeneous—that is to say, that all the decision units have the same production frontier. In addition, the SBM model is a non-parametric method which can evaluate the efficiency of the multi-input and multi-output structure more in line with the production process. At the same time, the uncertain production function can be transformed into linear programming to measure its frontier. Therefore, the SBM model based on this and previous discussions and the model which comprehensively considers unexpected outputs are specified as follows.

$$min\ \eta = \frac{1 - \frac{1}{m}\sum\limits_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1 + \frac{1}{s_1+s_2}\left(\sum\limits_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum\limits_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)} \quad (1)$$

where $S = (S^-, S^g)$ corresponds to the slacks variable in inputs and desirable outputs, and the η is the optimization function value—that is, the efficiency of the SBM model. In addition, the SBM model with the inputs and desired outputs remaining unchanged overestimates the carbon emissions reduction potential of the DMU. Hence, in contrast with the Russell measure model and slacks-based model taking account of the desired output, it can calculate reasonable carbon emissions efficiency.

The SBM model with the minimum distance is a good method for measuring efficiency based on relaxation variables. Meanwhile, the ineffective decision units can achieve the effectiveness of decision units by proportionally changing the distance between input or output indicators and the frontier using radial models for efficiency measurement. For the SBM model, it has the advantage that the input or output indicators of its decision-making unit do not need to increase or decrease in the same proportion. As a result, the SBM model considering the relaxation of input and output is demonstrated with the average maximum distance and the minimum distance being superior to the direction distance function of the SBM model, which is shown as follows.

$$min\ \eta = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1+\frac{1}{s_1+\cdots+s_n}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g}+\cdots+\sum_{r=1}^{s_n}\frac{s_r^b}{y_{r0}^b}\right)}$$
$$s.t\begin{cases} X_0 = \lambda X + s^- \\ Y_0{}^g = \lambda Y^g - s^g \\ Y_0{}^b = \lambda Y^b - s^b \\ s^- \geq 0; s^g \geq 0; s^b \geq 0; \lambda \geq 0 \end{cases} \quad (2)$$

where $S = (S^-, \cdots, S^g)$ corresponds to the slacks variable in inputs and desirable outputs, and η is the optimization function—that is, the eco-efficiency value of the DMU, which it can be more than 1 for the model. Moreover, each unit of model has three factors containing inputs, desirable outputs and undesirable outputs. Consequently, the SBM model can avoid the bias and impact caused by the differences in radial and angular selection and better reflects the essence of efficiency evaluation than the other models. At the same time, the SBM model considers non-expected output which is already an output, and the SBM model can consider it as an output effectively in the measurement of industrial carbon emission efficiency.

2.2. Super-Efficiency-SBM Model

The SBM model breaks the traditional efficiency limit of not exceeding 1 and conducts further efficiency comparisons. Due to the effectiveness of model selection, it is the best method to measure carbon emission efficiency. Therefore, we found that compared with stochastic frontier analysis methods, the SBM model has better rationality and scientificity when dealing with unexpected outputs. Subsequently, the super-efficient slacks-based measure (S-SBM) model appropriately improves the fact that traditional SBM model cannot include all the efficiency values of decision-making units, further achieving horizontal comparison and analysis of decision-making units. Based on the above analysis, the S-SBM model that may successfully evaluate the performance of industrial carbon emission efficiency can be expressed as follows.

$$min\ \eta_1 = \frac{\frac{1}{m+s_2}\left(\sum_{i=1}^{m}\left(\frac{\overline{X_i}}{X_{io}}\right)+\sum_{k=1}^{s_2}\left(\frac{\overline{Y_k{}^b}}{Y_{ko}}\right)\right)}{\frac{1}{s_1}\left(\sum_{r=1}^{s_1}\frac{\overline{Y_r^g}}{Y_{r0}^g}\right)}$$
$$s.t\begin{cases} \overline{X} \geq \sum_{j=1,j\neq j_0}^{n} u_j X_{ij} \\ \overline{Y}^b \geq \sum_{j=1,j\neq j_0}^{n} u_j Y_{ij}{}^b \\ \overline{X} \geq X_0, \overline{Y}^g \leq Y_0{}^g \\ \overline{Y}^b \geq Y_0{}^b, \overline{Y}^g \geq 0 \end{cases} \quad (3)$$

We have improved the SBM model based on relaxed variables and introduced unexpected outputs to make the model closer to production reality, resulting in more reasonable results. Simultaneously, the S-SBM model can take into account the undesirable outputs and effectively avoid the slackness problem. Therefore, the S-SBM model offers a much more accurate evaluation. Otherwise, the S-SBM model can convert to the following representation.

$$min\ \eta_2 = \frac{1}{m+s_2}\left(\sum_{i=1}^{m}\left(\frac{\overline{X_i}}{X_{io}}\right)+\sum_{k=1}^{s_2}\left(\frac{\overline{Y_k{}^b}}{Y_{ko}}\right)\right)$$
$$s.t\begin{cases}\frac{1}{s_1}\left(\sum_{r=1}^{s_1}\frac{\overline{Y}_r^g}{Y_{r0}^g}\right)=1, \overline{X}\geq \sum_{j=1,j\neq j_0}^{n} T_j X_{ij} \\ \overline{Y}^g \leq \sum_{j=1,j\neq j_0}^{n} T_j Y_{rj}{}^g, \overline{Y}^b \geq \sum_{j=1,j\neq j_0}^{n} T_j Y_{kj}{}^b, \\ \overline{X}\geq tX_0, \overline{Y}^g \leq tY_0{}^g \\ \overline{Y}^b \geq tY_0{}^b, \overline{Y}^g \geq 0, t\geq 0\end{cases} \tag{4}$$

where the $S = (S^-, \cdots, S^g)$ corresponds to the slacks variable in inputs and desirable outputs, and the η is the optimization function and the value of the DMU, which it can be more than 1 for the S-SBM model. Although the measured overall efficiency can partially reflect the characteristics of industrial carbon emission efficiency, there is a certain deviation from reality when using overall efficiency to replace industrial carbon emission efficiency. Furthermore, the decision-making unit that can achieve measurement efficiency value of 1 display its specific values exceeding 1 and ranks them, making it more ingenious in dealing with industrial emission reduction efficiency measurements that include unexpected outputs.

3. The Spatial Effect of Industrial Digitization on Carbon Emission

3.1. Spatial Effect Model

As is well known, China has a vast territory, and there are significant differences between the development of industrial economy and carbon emissions in various regions. In addition, the issue of spatial correlation cannot be ignored. The focus question is whether industrial digitization can help reduce carbon emissions. How does industrial digitization contribute to carbon reduction and what are the mechanisms behind its impact? From the perspective of industrial environmental performance, it will build a panel data model to study the impact of industrial digitalization on carbon emission efficiency at the provincial level. Simultaneously, we will carefully and deeply examine whether the relationship between carbon emission efficiency and industrial digitization level is linear or nonlinear, analyze the regional heterogeneity of the impact of industrial digitalization on carbon emission efficiency and test the spatial effect of industrial digitalization on marginal carbon emission efficiency and the mesmeric effect. Furthermore, the logical relationship and impact mechanism between the level of industrial digitization and the total amount of carbon emissions reduction are clarified. Nevertheless, the development of industrial digitization mainly emphasizes the application and theory of information and communication and digital technology. Through digital control, the green development of industry can be achieved. In the meantime, the improvement of digitalization level can clearly reflect the level of development and advanced level of industrial digital infrastructure. Strengthening the level of industrial digital innovation is an important prerequisite for implementing digital transformation. Consequently, the setting of spatial econometric models has a significant impact on problem analysis, so how to choose a spatial econometric model is a very important topic.

The most important task is to determine the existence of spatial autocorrelation and verify which spatial econometric model is more in line with the model settings in order to accurately measure the regression coefficients of the dependent variable. Consequently, we analyze the impact factors of the industrial digitization on industrial carbon emission efficiency and then establish a common panel benchmark regression model which is shown as follows.

$$\eta_{\mathrm{i,t}} = \alpha_0 + \alpha_1 DL_{i,t} + \sum \phi Control_{i,t} + \varepsilon_{i,t} \tag{5}$$

In the above equation, $\eta_{\mathrm{i,t}}$ is the industrial carbon emission efficiency; $DL_{i,t}$ is the industrial digitization level; $Control_{i,t}$ is the series of control variables; and $\varepsilon_{i,t}$ is the random error term. In order to avoid estimation bias caused by missing variables and reduce interference from external factors, the above variables are selected as control variables. In addition, robust standard errors are clustered to the industry-year level in all regressions. In addition, these analyses indicate that the net effect of carbon reduction in industrial digitization may be ambiguous. In order to explore the spatial spillover effect of industrial digitization on industrial carbon emission efficiency, a spatial econometric model is constructed as follows.

$$\eta_{\mathrm{i,t}} = \alpha_0 + \rho W \eta_{\mathrm{i,t}} + \alpha_1 WDL_{i,t} + \sum \phi Control_{i,t} + \alpha_2 \sum \phi Control_{i,t} + \varepsilon_{i,t} \quad (6)$$

In the above equation, $\eta_{\mathrm{i,t}}$ is the industrial carbon emission efficiency, and W is the spatial weight matrix. Through experiments, it has been proven that the closer the distance between regions is, the greater the impact is. In fact, when the weight is obtained based on the reciprocal of the distance function or a similar concept of distance attenuation, in the meantime, these weights themselves have economic implications. If they are standardized, it will result in a loss in their economic interpretation. As a result, it is very important to choose an effective spatial econometric model and spatial weight matrix. Subsequently, we can use the spatial econometric economic model based on panel data to explore the impact factors and driving mechanism of industrial digitalization on carbon emission efficiency because effective analysis of spatial econometric model parameters is the foundation of empirical analysis.

3.2. Kernel Density Model

The application research of point sample analysis modeling based on non-parametric density estimation has received increasing attention from researchers. Furthermore, the non-parametric density estimation methods do not require prior assumptions about the parameter form of the point sample distribution. Therefore, the kernel density estimation provides a new solution for the quantitative analysis and spatial modeling of unknown distribution point samples. Concurrently, the spatial characteristics exhibited by the entire spatial system are heterogeneous, and the kernel density estimation is used to infer the distribution of the overall data based on limited samples. Therefore, the result of the kernel density estimation is the probability density function estimation of the samples. According to the probability density function of the estimation, we can get the aggregation region property of the data distribution. Furthermore, the spatial heterogeneity reflects the instability of spatial behavior or spatial relationship of observation objects. In the meantime, its meaning is that due to the influence of various geographical and spatial factors on the observation object, a unit in a certain area has characteristics that are different from other units. Industrial digitization not only drives the reduction of industrial carbon emissions in the local area but also promotes the reduction of industrial carbon emissions in surrounding areas through spatial spillover effects. Therefore, the spatial spillover effect of digital economy is related to various spatial characteristics such as the geographical location and market integration level of cities. As geographic distance increases, there is a certain degree of attenuation in the spillover effect of industrial digitization space.

To accurately grasp the spatiotemporal evolution characteristics of China's industrial carbon emission efficiency, we first use spatial trend surface analysis tools to grasp the spatial variation trend of China's industrial carbon emission efficiency. Concurrently, the kernel density estimation method is used to analyze the distribution dynamics of China's industrial carbon emission efficiency, and the regional differences and sources are analyzed in combination with the Theil index and its decomposition method. As a nonparametric estimation method, kernel density estimation fits the sample data by smoothing the peak function. Based on the above analysis, we will use continuous density curves to characterize the distribution pattern of random variables and explore the dynamic evolution trend of

China's industrial carbon emission efficiency. Consequently, the density function of China's industrial carbon emission efficiency can be expressed as follows.

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{7}$$

where N is the number of sample observations, X_i is an independent identically distributed observation value, and h is the bandwidth of kernel function. The smaller the bandwidth of the kernel function is, the higher the estimation accuracy is. It has been demonstrated that Kernel density function which can be expressed as follows.

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \tag{8}$$

In order to reveal the regional differences and sources of carbon emission efficiency in the industry, the Thiel index was used to decompose the overall differences into intra group and inter group differences. Specifically, it can be represented through the above derivation and in-depth analysis as follows.

$$\begin{cases} T = \frac{1}{m}\sum\limits_{i=1}^{m}\left(\frac{Q_i}{\overline{Q}} \times \ln\frac{Q_i}{\overline{Q}}\right) \\ T_p = \frac{1}{m_p}\sum\limits_{i=1}^{m_p}\left(\frac{Q_{pi}}{\overline{Q}_p} \times \ln\frac{Q_{pi}}{\overline{Q}_p}\right) \end{cases} \tag{9}$$

where the T represents the overall Theil index and its value range from 0 to 1. The larger the value is, the greater the overall difference in China's industrial carbon emission efficiency is. In the variable description, the $T_p(p = 1, 2, 3)$ represents the index of the major regions of the eastern, central and western China, respectively. At the same time, $\overline{Q}$ and $\overline{Q}_p$ represent the average industrial carbon emission efficiency.

4. The Empirical Analysis

4.1. Experiment on Carbon Emission Efficiency of Different Regions

The data on industrial carbon emission efficiency and other control variables mainly come from China Statistical Yearbook, the China Energy Statistical Yearbook, China Industrial Statistical Yearbook, China Economic Census Yearbook, the National Bureau of Statistics, the CSMAR database and the Wind database. Meanwhile, some of the data are collected from the National Bureau of Statistics (autonomous regions, municipalities) and the meicmodel database (http://meicmodel.org.cn/, accessed on 1 January 2023). During the experiment, we applied the industrial carbon emissions data from 2015 to 2022 in the above database, as well as the standard models and methods used for measurement, to effectively measure carbon emission efficiency. Through the experimental analysis, the results of industrial carbon emission efficiency by S-SBM in different regions are shown in Table 1 as follows.

We can conclude from the above experiments that the level of industrial digitization is constantly improving and there are certain spatial differences in the overall level of industrial digitization, digital foundation, digital industry, digital application and digital innovation among different regions. Through experiments, it was found that the level of industrial digitization shows the spatial evolution pattern of strong in the south and weak in the north. Subsequently, the development level of digital infrastructure shows a spatial evolution pattern of developing from strong advantages in the eastern coastal region to strong advantages in the southeastern coastal region and gradually spreading to the central region over time. Furthermore, the experiment indicates that the effect of industrial digitization on carbon emission reduction exhibits regional heterogeneity and is more prominent in the eastern region than the others. Subsequently, we also found that regions with high levels of industrial digitalization development have demonstrated their carbon emission reduction capabilities while regions with weaker industrial digitalization development have no significant impact on carbon emission efficiency. In the meantime, the main reason for this is closely related to internal and external factors such as regional digital innovation ability and industrial structure. Therefore, in order to achieve the global dual carbon goal as soon as possible, it is entirely necessary for us to strengthen the construction of industrial digital infrastructure and improve the digitalization level.

Table 1. The results of carbon emission efficiency in different regions.

Region	2015	2016	2017	2018	2019	2020	2021	2022
Beijing	0.0951	0.21022588	0.0833	0.0465	1.01495409	0.38403260	0.52405890	0.00699
Tianjin	0.40262009	0.52220172	0.23466432	0.13842563	0.39146331	0.34994787	0.74058154	0.03344311
Hebei	0.44097544	0.50257038	0.24699326	0.28441349	0.86371524	0.47951947	0.60638583	0.08747082
Shanxi	1.39774037	1.41506572	1.93304617	1.03378951	0.59858467	1.09756534	0.96537915	0.34369882
Inner Mongolia	0.66097485	0.66562159	0.3615936	0.50256763	0.61692537	0.43832700	0.62428874	0.53934286
Liaoning	0.54466783	0.57007003	0.36650814	0.36901040	0.82503021	0.44803096	0.54045795	0.25136415
Jilin	0.37785044	0.49934743	0.26981597	0.24011127	0.28448436	0.32764030	0.53348566	0.30998750
Heilongjiang	0.43721095	0.31295935	0.26534519	0.17960445	1.00012539	0.45099191	0.51823833	0.54010656
Shanghai	0.21301023	1.23857740	0.22599494	0.18202083	1.35588329	0.44791202	0.68274115	0.0111
Jiangsu	0.25816414	0.37933624	0.31995327	0.25945633	0.89542032	0.53830316	0.59129832	0.0718
Zhejiang	0.20137266	0.28027315	0.18050180	0.14702183	0.59675100	0.39739325	0.56722846	0.0277
Anhui	0.24681159	0.36543508	0.38063625	0.31765568	0.71749749	0.51140322	0.63375616	0.12613516
Fujian	0.15709013	0.24595921	0.22983118	0.14235612	1.02143446	0.42666386	0.53872629	0.11279090
Jiangxi	1.00875251	0.69362566	0.55778802	0.38231192	0.91856072	0.43186355	0.59725332	0.14285846
Shandong	0.21480871	0.31014168	0.15569702	0.15152234	0.52124922	0.39640507	0.53836273	0.0732
Henan	0.44583387	0.44299017	0.28837989	0.22843941	0.50847086	0.41828937	0.55191051	0.0682
Hubei	0.29015405	0.32584552	0.28508461	0.25347612	0.40767866	0.36505492	0.55959406	0.17853090
Hunan	0.47031563	0.70823664	0.57243095	0.48543659	0.98489552	0.36746004	0.57876632	0.24246858
Guangdong	0.17484913	0.33660750	0.23078281	0.19594351	1.04330418	0.44663936	0.56338462	0.0465
Guangxi	0.47990126	0.45856125	0.33633787	0.18352132	0.49846703	0.42949493	0.52986240	0.27205171
Hainan	0.19621985	0.28592440	0.15485097	0.41934432	1.01046878	0.58066214	0.65500026	0.15107834
Chongqing	1.22757694	1.12687671	1.94776404	0.53725515	0.45497823	0.45031457	0.55381669	0.20332801
Sichuan	0.51829279	0.62614203	0.40941168	0.47881979	0.54686183	0.36755944	0.54181337	0.16288445
Guizhou	0.76973866	0.86748442	0.66453721	0.60033417	0.63695197	1.48127976	1.18928080	1.84306901
Yunnan	0.51839003	0.60606471	0.55196596	0.38874882	0.54348921	0.45237085	0.56789254	0.44572113
Tibet	0.36941000	0.43464162	0.11367649	0.42472982	0.0319	0.26744038	0.52834509	0.24035128
Shaanxi	0.44585862	0.49168231	0.40947819	0.43138918	0.55748468	0.43453393	0.56536133	0.23732589
Gansu	0.48561801	0.67878711	0.53509123	1.92137467	1.21304259	0.47155324	0.56165757	0.31389522
Qinghai	0.65197209	1.04029973	0.50495736	1.24996726	2.54326635	1.93260171	2.70648174	3.67030197
Ningxia	0.70841782	0.72551357	0.37960671	0.55740603	1.02092111	0.84259951	1.01205903	0.47378342
Xinjiang	1.41281205	1.11511596	0.55031254	0.67027231	0.47092202	0.62003656	0.57726804	0.46676173

4.2. Experiment on Carbon Emission Efficiency of Different Industries

The penetration and derivative of industrial digital technology can be utilized to transform traditional industries, promote the green development of industries and reduce energy consumption and carbon emissions. In addition, they can be utilized to explore industry differences by dividing them into high, medium and low efficiency levels and then examine the impact of environmental policy and technological innovation on the overall carbon emission efficiency of the industrial industry. Through a series of experiments, the results of industrial carbon emission efficiency by S-SBM are shown in Table 2 as follows.

Through experimental analysis, it is found that the results indicate that in recent years, the overall level of carbon emission efficiency in China's industry has been relatively low showing an unstable state. Simultaneously, the industrial carbon emission efficiency in various regions of China shows varying degrees of upward trend and regional differences. Based on the experimental data, we can draw the following conclusions. Firstly, the development of the industrial digitization can effectively promote the reduction of carbon emissions efficiency. Secondly, the development of the industrial digitization has a significant role in promoting the rationalization of the industrial structure. Thirdly, the industrial digitization can not only directly suppress carbon emission efficiency, but it can also indirectly have a significant inhibitory effect on carbon emission efficiency by promoting the rationalization and optimization of the industrial structure. Finally, considering the spatial spillover effect of industrial digitization on carbon emission efficiency, measuring changes of carbon emission efficiency through relevant methods may have spatial dependent effects.

Table 2. The results of carbon emission efficiency in different industry.

Industry	2015	2016	2017	2018	2019	2020	2021	2022
Agriculture, Forestry, Animal Husbandry and Fishery	0.31363787	0.27049882	0.37131055	2.57863815	1.83075385	1.13530212	1.17724685	0.33429606
Mining and Washing of Coal	0.25914716	1.09016002	1.33845469	0.36537106	0.24978090	0.22574908	0.24003849	0.19082119
Petroleum and Natural Gas	0.66280249	1.25304649	1.16458949	1.58324549	1.79209585	2.84104035	2.99931393	3.20930606
Mining and Processing of Ferrous Metal Ores	1.01304199	0.54933849	0.46186642	0.39209168	0.26677432	0.27532784	0.24006307	0.0410
Non-ferrous Metal Ores	0.23170956	0.66276124	0.74360419	0.16213756	0.14750445	0.10778008	0.08772911	0.0672
Non-metal Ores	0.41020163	0.29991690	0.24322007	1.68051252	1.14936075	0.47049967	0.36869590	0.10010636
Professional and Support Activities for Mining	0.49699051	0.36009547	0.56628490	0.47946327	1.08908928	1.19908183	0.47366740	0.19541757
Mining of Other Ores	0.21868992	0.48372725	0.53804804	0.0124	0.0643	0.00821	0.00462	0.03745332
Processing of Food from Agricultural Products	0.36720531	0.35764145	0.50954998	0.52042317	0.19818372	0.18114136	0.20690403	0.12352186
Manufacture of Foods	0.31780970	0.38269759	0.52368413	0.48956174	0.18687287	0.21273620	0.21475288	0.15745583
Manufacture of Liquor, Beverages and Refined Tea	0.28481700	0.35976354	0.51144498	0.48749769	0.20497393	0.21411694	0.26698262	0.20718563
Manufacture of Tobacco	0.34167926	0.23633940	0.34415730	0.0713	0.0392	0.0355	0.0545	0.0316
Manufacture of Textile	0.21007448	0.19278439	0.29786741	0.21253574	0.0940	0.0747	0.0770	0.0504
Textile, Wearing Apparel	0.14939979	0.24211198	0.28179001	0.29540358	0.11507153	0.10695993	0.08314279	1.60174701
Leather, Fur and Feather and Related Products and Footwear	0.20419619	0.60731074	1.00670390	0.12421550	0.0606	0.0413	0.0578	0.0129
Timber, Manufacture of Wood, Bamboo, Rattan, Palm	0.52905806	1.05585869	0.57404404	0.37747241	0.17808246	0.14694173	0.11537849	0.10204101
Manufacture of Furniture	1.90363823	0.47796029	0.52582958	0.12521447	0.0221	0.0263	0.0149	0.01141613
Paper and Paper Products	0.33718063	0.32073782	0.40387620	0.25783736	0.19894071	0.19690667	0.19258988	0.14796265
Printing and Reproduction of Recording Media	0.33835471	0.32727006	0.59527538	0.0999	0.0189	0.0160	0.00752	0.00728
Culture, Education, Arts and Crafts, Sport and Entertainment	0.34044126	0.56015807	0.54165483	0.20920196	0.0688	0.0234	0.0167	0.00553
Processing of Petroleum, Coal	0.63345679	0.51664702	0.34557068	1.36488620	1.05337821	0.62541196	0.61543164	0.34401272
Raw Chemical Materials and Chemical Products	0.35117602	0.33222316	0.44329243	0.26967978	0.19223289	0.15043767	0.16440723	0.10657712
Manufacture of Medicines	0.19051740	0.53634264	0.45504346	0.13229037	0.0687	0.0588	0.05040464	0.0422
Chemical Fibers	0.49836261	0.42537095	0.53021796	0.31754596	0.17827450	0.1316500	0.14545946	0.0700
Rubber and Plastics Products	0.33683957	0.70963344	0.91052844	0.0662	0.0540	0.0412	0.0413	0.0334
Non-metallic Mineral Products	0.62274271	1.60024885	1.47679459	0.59339157	0.48460691	0.45031646	0.48490330	0.32431551
Smelting and Pressing of Ferrous Metals	1.38918631	0.53695690	0.60758440	0.64901500	0.57645341	0.53305615	0.51326665	0.54956712
Non-ferrous Metals	0.52583045	0.32035404	0.41011334	0.74181122	0.59739844	0.48629726	0.40444038	0.57676893
Manufacture of Metal Products	0.29084526	0.33081093	0.62811152	0.0905	0.0588	0.0703	0.0475	0.01363233
General Purpose Machinery	0.33414119	0.39600950	0.70437450	0.29574164	0.04028195	0.11429229	0.0874	0.0254
Special Purpose Machinery	0.42784584	0.50188014	0.73286407	0.14909991	0.0651	0.0518	0.0446	0.0119
Manufacture of Automobiles	0.43216187	0.30549752	0.66184967	0.0536	0.0324	0.0275	0.04122744	0.0155
Railway, Ship, Aerospace and Other Transport Equipment	0.27288971	0.30760347	0.30851541	0.0589	0.0254	0.0244	0.0781	0.0231
Electrical Machinery	0.26807559	0.45408467	0.58793936	0.11313690	0.0898	0.0841	0.12181900	0.0441
Computers, Communication	0.37152506	0.36207075	0.47443444	0.0251	0.00651	0.0101	0.0149	0.00330
Manufacture of Measuring Instruments and Machinery	0.30742344	0.47742647	1.25398660	0.00563	0.0222	0.00605	0.00473	0.000253
Other Manufacture	0.42616851	0.39798319	0.41792243	0.0812	0.00559	0.00707	0.00476	0.0314
Utilization of Waste Resources	0.31356990	0.71623365	1.50392417	0.18161063	0.0890	0.0735	0.0839	0.04752245
Metal Products, Machinery and Equipment	0.57674252	0.77927709	0.78106877	0.0532	0.10545762	0.0262	0.0269	0.0120
Electric Power and Heat Power	1.01959984	1.18232842	0.55670416	1.04227223	0.51224165	0.52216062	0.52636775	0.47810577
Production and Supply of Gas	1.8092777	1.79461241	0.66260668	0.16215132	0.33890180	0.29187683	0.14854611	0.27597389

4.3. Experiment on Spatial Effects of Carbon Emission Efficiency

To control the impact of other factors that may cause bias in the estimation results of the model, we introduce control variables into the spatial econometrics model. In addition, the carbon emission efficiency of inter-provincial industrial industries exhibits strong positive correlation and spatial agglomeration characteristics in spatial distribution. As a result, the descriptive statistics of each variable obtained through the above analysis are shown in Table 3 as follows.

Table 3. The descriptive statistics of variables.

Types	Variables	Specific Variables	Sample Size	Average Value	Standard Deviation	Minimum Value	Maximum Value
Explained variable	CE	Carbon emission efficiency	500	0.6125	0.2698	0.2258	1.2036
Explanatory variable	DL	Digitization level	500	−0.8956	1.8639	−5.5240	2.3058
Mediating variable	TA	Technological advances	500	0.3021	0.2937	0.00015	1.1026
	EI	Energy intensity	500	2.5362	1.6230	0.8542	8.9652
Control variable	ED	Economic development	500	4.4326	2.7853	0.9062	11.2358
	ES	Energy structure	500	0.8521	0.5218	0.09564	2.5245
	ER	Environmental regulation	500	2.7564	0.9865	0.02105	4.6859
	GI	Government intervention	500	0.7214	0.7120	0.0426	3.6102
	IS	Industrial structure	500	4.5211	4.5689	1.0245	18.2560
	DFI	Digital facility level	500	2.9052	1.6324	0.2015	7.6857

We conducted empirical tests on the basic model using Stata17.0 software based on spatial econometric models. In the meantime, the coefficient of industrial digitization was initially positive at the significance level of 5%, indicating that industrial digitization could become a driving force for improving industrial carbon emission efficiency. At the same time, we included time factors and control variables in the second and third columns using the same method as in the first column. As a result, the results of benchmark regression analysis are presented in Table 4 as follows.

Table 4. The test results of benchmark regression analysis.

Variables	(1)	(2)	(3)
	CE	**CE**	**CE**
DL	0.0356 *** (0.00652)	0.0305 ** (0.00125)	0.0201 ** (0.0106)
ED			0.0652 ** (0.0258)
ES			0.0456 *** (0.0192)
ER			−0.0218 *** (0.0104)
IS			0.0203 (0.0340)
GI			−0.0645 (0.0569)
DFI			0.0209 (0.0302)
_cons	0.725 *** (0.00461)	0.762 *** (0.0502)	0.6100 *** (0.106)
Time fixed effect	No	Yes	Yes
N	500	500	500
R^2	0.215	0.309	0.512

Notes: ** $p < 0.05$, *** $p < 0.01$, The parentheses indicate standard error.

In order to explore the mechanism by which industrialization affects the level of digitization and the efficiency of industrial carbon emissions, we will include intermediary variables for in-depth analysis, and the impact mechanism results are shown in Table 5 as follows.

Table 5. The impact mechanism results of the variables.

Variables	TA	CE	EI	CE
DL	0.9025 *** (0.2051)	0.0521 *** (0.01)	−0.3014 *** (0.0206)	0.04125 *** (0.01)
TA		0.0851 ** (0.0502)		
EI				−0.0302 *** (0.0050)
Control variable	Control	Control	Control	Control
Time fixed effect	Yes	Yes	Yes	Yes
p-value	0.0358 *** (0.0028)	0.0358 *** (0.0028)	−0.0202 *** (0.0025)	−0.0202 *** (0.0025)
N	500	500	500	500
R2	0.865	0.721	0.853	0.756

Notes: ** $p < 0.05$, *** $p < 0.01$, The parentheses indicate standard error.

From the above experiments, it can be clearly seen that the inhibition of industrial digitalization on energy intensity is significantly positive at the level of 1%, indicating that there is the significant intermediary effect between industrial digitalization and energy intensity. At the same time, it was found that industrial digitization can drive technological progress to promote the improvement of industrial carbon emission efficiency. Simultaneously, the experiments can show that industrial digitalization can also improve carbon emission efficiency by inhibiting energy intensity. Combined with the research results, we can see that the mediating effect of restraining energy intensity and improving carbon emission efficiency is obviously better than that of technological progress. In general, the above findings can provide how to best promote the development of the carbon emission control by industrial digitization.

Through the analysis, we can not only capture the spatial heterogeneity of carbon emission intensity but also ensure the significant effect of industrial digitalization on carbon emission coefficient. In order to investigate the mechanism of carbon emission reduction rigorously, the kernel density method is also adopted in this paper to further test the spatial heterogeneity effect. In this section, we discuss the changes in the density function to reflect the dynamic changes, where the icdf represents the industrial centers density function. Through a series of experimental analysis, the results of industrial centers density function are shown in Figures 2–5 as follows.

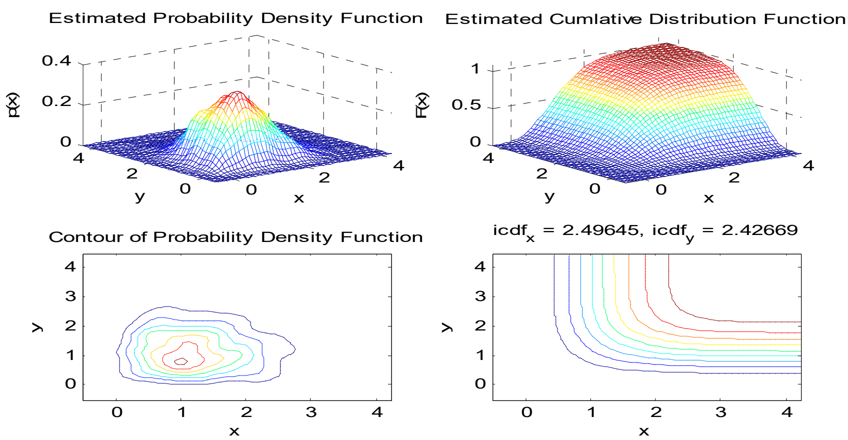

Figure 2. The simulation results of icdf in western China.

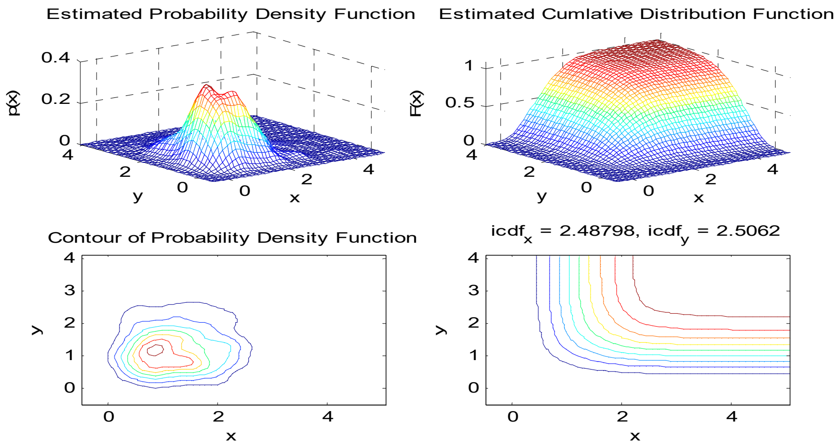

Figure 3. The simulation results of icdf in Central China.

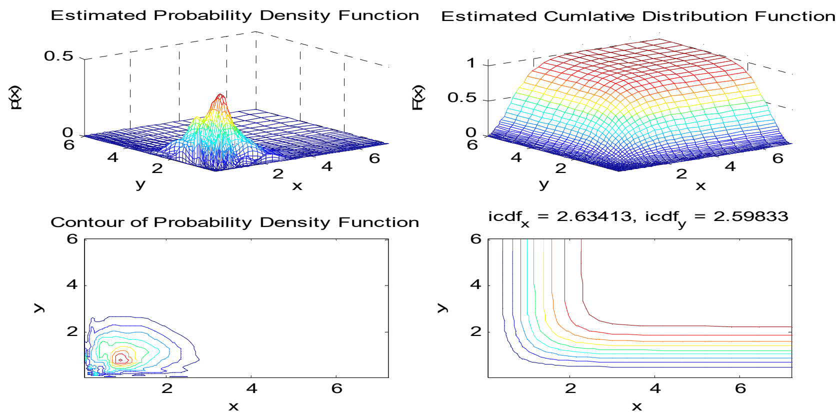

Figure 4. The simulation results of icdf in Northeast China.

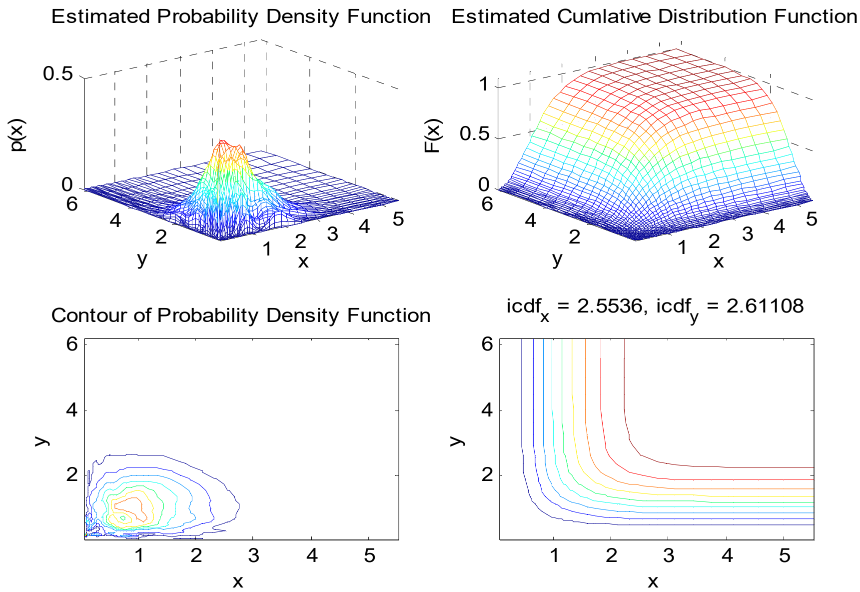

Figure 5. The simulation results of icdf in Eastern China.

Through the above experiments, it was found that the development of industrial digitization significantly drives the improvement of carbon emission efficiency in the eastern region, while the impact on the central and western regions is relatively small. The series of experimental results indicate that the issue of inconsistent industrial carbon emission efficiency in the eastern region remains a very prominent issue. However, compared to the central and western regions, the growth rate of its Theil index is relatively slow, and it is relatively stable in improving industrial carbon emission efficiency. Although the Theil index in the central and western regions is relatively low, its growth rate is astonishing. Especially, we found that the lower the level of economic development is, the faster the regional difference in industrial carbon emission efficiency grows. The further analysis reveals that there is regional heterogeneity in the impact of industrial digitization on industrial carbon emission efficiency, and it is the more significant in the eastern region. The main reason is due to the relatively high level of environmental testing in the eastern region. However, the digitalization level of industries in the central and western regions is very limited. Therefore, the conclusions reveal the importance of optimizing the level and quality of industrial digitization and adopting the digital development policies based on regional differentiation to achieve carbon reduction.

5. Conclusions and Policy Suggestions

With the increasingly prominent constraints of energy, resources and environment, how China's industry should respond to the relationship between industrial digitization and the carbon emissions has become an increasingly important issue. Based on the analysis of the spatiotemporal evolution trend and characteristics of industrial carbon emission efficiency, it can be observed that the overall carbon emission efficiency of Chinese industry shows a slow upward trend over time. The phenomenon can be explained as follows: industrial digitization will significantly improve the level of industrial carbon emission efficiency in this region, but the coefficient of indirect effects is significantly negative. At the same time, it also indicates that improving the level of industrial digitization in surrounding areas will have a restraining effect on the improvement of industrial carbon emission efficiency. Nevertheless, the impact of industrial digitization on carbon emission intensity varies regionally. Compared to the eastern region, central cities and large-scale cities, the level of industrial digitization has a more significant carbon reduction effect in the central and western regions and peripheral cities. From an industry perspective, we also found that with different industrial structures, there is a significant change in carbon emission performance, and the overall impact of industrial digitization on the carbon emission performance of the mining industry is relatively high. Therefore, we should strengthen and pay attention to the carbon emission levels and sustainable development of similar enterprises. From a regional perspective, it is interesting to observe that the overall performance of industrial carbon emissions in the eastern region is showing an upward trend, while the central, western and northeastern regions are roughly showing an N-shaped trend of change. From an industry perspective, the overall carbon emission performance of the mining industry is relatively high with significant changes in the performance of the electricity and heat and gas and water production and supply industries. In conclusion, it can be said that its spatial econometric analysis process and the results have good reference value for improving industrial carbon emission efficiency.

Based on the preceding research methodology and findings, we should increase efforts to enhance the level of industrial digitization, increase policy support, actively promote industrial digitization transformation in various field and development efforts in industrial digitization and help improve the efficiency of industrial green development. First of all, we will accelerate the application of industrial clean production technology, achieve technological transformation of boundary production and implement upgrading and transformation of industrial enterprise exhaust gas purification. Second, we will give play to the driving role of technological progress and the restraining role of energy intensity to help improve industrial carbon emission efficiency. Then, the efforts should be made to promote the coordinated development of industrial digitization among regions, strengthening cooperation on improving industrial carbon emission efficiency. In order to achieve carbon peaking and carbon neutrality of China's industry, we must fully consider the spatial heterogeneity and spillover of the regional industries. Furthermore, the government should vigorously strengthen the construction of information infrastructure, thereby improving the digital level of the overall industry in the region and reducing the total carbon emissions. In addition, the different digital development strategies should be adopted for different regions and different types of enterprises. Therefore, we should reasonably improve the industrial energy consumption structure, optimize the industrial structure and accelerate technological progress. The above methods can effectively reduce regional industrial carbon emissions. Subsequently, all the enterprises need to increase investment in technology and development of core hardware and basic software, build big data analysis platform for information processing, digitize information enterprise business and realize intelligent and automatic processes.

This research has some limitations, and there is scope for further research in these areas. Firstly, the heterogeneity of industrial digital technology was not taken into account in the differentiation research process of carbon emission efficiency. Secondly, how to improve the reliability and stability of the model is a question worthy of further discussion. Therefore, we will use the new dynamic model and dynamic panel data to analyze the impact mechanism and transmission mechanism of industrial digitalization on industrial carbon emission efficiency. At the same time, we pointed out that the study of relationship between low-carbon policy tools and regional industrial carbon emissions will be an important topic in the future. Meanwhile, we will study how heterogeneous environmental policies affect the level and development of industrial ecological efficiency in China.

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