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Evaluation and Factor Analysis of Industrial Carbon Emission Efficiency Based on "Green-Technology Efficiency"—The Case of Yangtze River Basin, China

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Abstract: In the context of low-carbon development, effectively improving carbon emission efficiency is an inevitable requirement for achieving sustainable economic and social development. Based on panel data of 11 provinces and municipalities in the Yangtze River Basin (YRB), ranging from 2000 to 2019, this paper uses green-technology efficiency to measure industrial carbon emission efficiency via stochastic frontier analysis (SFA) incorporated with carbon productivity. This provides a comprehensive analytical framework for assessing the carbon emission efficiency, quantitatively measuring the reduction potential, and clarifying the incentive channels. The results are as follows: (1) The industrial carbon emission efficiency (ICEE) of YRB presents an increasing trend. Although differences in emission efficiency among provinces and municipalities are narrowing, their emission efficiency is still prominently imbalanced. (2) The potential for reducing industrial carbon emissions in this region shows an upward-to-downward trend. The decline in such potential of each province and municipality in recent years indicates that further reduction is becoming more difficult. (3) Effective means to improve ICEE are to improve the level of industrialization, promote technological innovation in industrial low-carbonization, and raise industrial productivity. Meanwhile, the significant spatial spillover effect of ICEE further emphasizes the necessity of strengthening the coordination of carbon reduction policies in YRB. The research in this paper adds a new perspective to the evaluation of ICEE and also provides reference and technical support for the government to enhance ICEE and formulate green and sustainable development policies.

Keywords: green-technology efficiency; industrial carbon emission efficiency; industrial carbon reduction potential; factor analysis; Yangtze River Basin

1. Introduction

1.1. Research Motivation

Against the backdrop of global warming, the low-carbon development mode is becoming an important solution to, and a prerequisite for, solving the world's ecological problems and climate change [1–3]. To this end, countries around the world have adopted a global compact to reduce carbon emissions by upgrading "carbon peak" and "carbon neutrality" to national strategies and proposing a vision of a carbon-free future [4,5]. As the second-largest economy in the world, China has also become the largest carbon emitter [6]. In a joint effort to address global climate and ecological issues, China is taking active measures to control carbon emissions. At present, China has already reached the milestone of reducing its carbon emission intensity by 40% to 50% [7]. Furthermore, it commits itself to a carbon peak by 2030 and carbon neutrality before 2060 [8].

China's economic achievements over the past decades are attributed to the enormous dividends from its industrialization process. As its industrialization continues to deepen, however, extensive and high-energy-consuming industrial development has put tremendous pressure on the ecological environment and poses a great challenge to the "double carbon" goals [9]. According to the Climate Analysis Indicators Tool (CAIT) database of the World Resources Institute (available at https://www.climatewatchdata.org/data-explorer/ (accessed on 12 July 2021)), China's carbon emission in 2019 reached 9.79 billion metric tons, of which the industrial sector accounted for 84.53%, much higher than the 7.47% and 0.93% for the transportation and agriculture sectors, respectively. To achieve its "carbon neutrality" mission, therefore, China should attach importance to effectively improving the efficiency of industrial carbon emissions, promoting the green transformation of the industrial sector, and improving the ecological environment. Thus, it is practically significant to scientifically measure the carbon emission efficiency and reduction potential of the industrial sector and profoundly analyze the influencing factors. All this will help promote low carbonization in industries and achieve the "double carbon" goals, thereby realizing sustainable economic and social development.

Theoretically, it is essential to grasp the connotations of carbon emission efficiency before reasonably evaluating such efficiency in the industrial sector. Early literature primarily equates carbon efficiency with carbon productivity (the GDP output per unit of carbon emissions) [10], the carbon index (indicating the price and liquidity of carbon trading market) [11], or carbon intensity (carbon emissions per unit of GDP) [12]. These concepts emphasize the trade-off between the desired and undesired output and reflect the endogenous link between carbon emissions and economic development, though they ignore the impacts from input sources. Efficiency, however, indicates how efficiently resources are used or to which extent the optimal output is achieved under such conditions as given inputs and technology [13]. Hence, focusing only on the output has great limitations. Further, carbon emission efficiency results from a combination of factors, such as resource inputs, management experience, production technology, and types of output, all of which need to be assessed holistically. Such complex efficiency implies that it should be evaluated through a total-factor measurement method [14–16]. Only on this basis will it be of practical significance to discuss carbon reduction and explore pathways to reduce emissions more efficiently.

While the existing literature investigates carbon emission efficiency extensively, there are still some areas for improvement. Firstly, stochastic frontier analysis (SFA) has the advantage of stripping the interference from stochastic disturbances and can improve the estimation accuracy of technical efficiency [17]. Although scholars apply various methods to measure carbon emission efficiency in a total-factor way, few researchers combine SFA with the evaluation of carbon emission efficiency and carbon reduction potential. In this regard, we try to introduce the concept of carbon productivity [10] on the basis of SFA by setting average carbon output as the dependent variable of the model and use the corresponding technical efficiency to assess the efficiency of industrial carbon emissions. Logically, via given input resources and production technology, technical efficiency based on SFA measures the ratio of actual output to the optimal output. Using carbon productivity as an output variable implies that technical efficiency is measured by controlling carbon emissions. We refer to such technical efficiency as green-technology efficiency (occasionally "GTE" for short). Carbon emission efficiency in the context of low-carbon development also requires maximizing desired output while minimizing undesired output (carbon emissions), conditional on a given resource input. Therefore, carbon emission efficiency is consistent with what green-technology efficiency means. In other words, the technical efficiency represented by the ratio of the actual average carbon output to its optimal value also reflects the carbon emission efficiency at the current level of green production technology. Secondly, there is little discussion of the carbon reduction potential, and regional reduction potential is mainly compared on a qualitative or simulative basis, still lacking quantitative approaches [18]. Complementary to technical efficiency, technical efficiency loss indicates the difference between the average carbon output of a production unit and the corresponding optimal level. When this loss exists, it means that there is room to reduce carbon emissions for the unit. Therefore, technical efficiency loss provides us with a suitable tool for quantifying carbon reduction potential, thus further contributing to carbon reduction policies. Thirdly, the literature rarely explores the influencing factor of carbon emission efficiency while considering the spatial dimension. The regional conditions (such as economic development, technology level, resources, etc.) are quite uneven in China. It should be noted that ignoring the spatial element may lead to biased results, since this element implies the potential spatial spillover effect of carbon emission efficiency, reduction potential, and relevant influencing factors. Hence factor analysis entails spatial econometrics analysis. Fourthly, most studies delve into carbon emission efficiency from one or two aspects of efficiency evaluation, spatial and temporal characteristics, reduction potential measurement, or factor analysis, though a unified analytical framework is yet to be established. The complementarity of technical efficiency and its loss also provides us with an opportunity to assess carbon emission efficiency and reduction potential simultaneously, and makes the analysis of their influencing factors internally consistent.

Motivated by the above background and analysis, we aim to add a new perspective to the evaluation of industrial carbon emission efficiency. We also expect to provide a systematic framework for assessing carbon emission efficiency, quantitatively measuring the reduction potential, and identifying the influencing channels. To this end, we use the green-technology efficiency approach to assess industrial carbon emission efficiency and calculate the potential of the industrial sectors of 11 provinces and municipalities in YRB to reduce industrial carbon emissions. At the same time, we apply several spatial econometric models to identify specific influencing channels of emission efficiency. Overall, by empirically testing this framework, this paper offers a reference for the research on other yardsticks or sector objects, lays a scientific basis for formulating carbon reduction policies, and ultimately serves the goal of carbon neutrality.

1.2. Literature Review

Carbon emission efficiency has always been a major research focus, with topics ranging from measurement methods, reduction potential, spatio-temporal characteristics, and investigation of the influencing factors.

To measure carbon emission efficiency, researchers have adopted different methods, among which the most commonly employed are data envelopment analysis (DEA) and its extensions since they integrate environmental factors and require no parameter estimation [16,19,20]. Using DEA, Meng et al. [21] calculate the carbon emission efficiency of 30 provincial-level divisions of China and find that the efficiency gradually declines from the east to the west. Through the same method, Wang et al. [22] estimate the carbon emission efficiency of China's service sector, uncovering that its emission efficiency is consistent with the level of regional economic development. Moreover, studies have introduced the Malmquist carbon emission index (MCPI)—DEA [23,24], the slack variable-based super-efficiency (SBMSE)—DEA [25,26], and the non-radial directional distance function (NDDF)—DEA [16,27] to measure the carbon emission efficiency of the world's high-carbon emitters or specific industries and then to explore their dynamic evolution patterns. Considering that DEA is subject to the interference of stochastic disturbances from environments, several researchers have also attempted to address this issue through SFA. Sun et al. [17], for example, evaluate the greenhouse gas emission efficiency in 26 industrial sub-sectors of China, and Zhang and Chen [28] estimate the carbon emission efficiency of the Yangtze River Economic Belt. One problem of their analyses is that they both directly take undesirable emissions as the input variable. Yet placing emissions on the input side is unreasonable when energy consumption is already in place. This is because carbon emission efficiency characterizes the proportional relationship among carbon emissions, economic growth, and energy consumption [29].

Research into carbon emission efficiency aims partly to promote carbon reduction. As research progresses, the carbon emission reduction (potential) has also captured increasing attention. Yang et al. [18] construct a carbon reduction potential index for urban construction land in 30 provincial-level divisions of China, indicating that 17 of them, with an index above one, face mandatory reduction pressure. By decomposing total carbon emissions, Song and Zhang [30] calculate the theoretical values of carbon reduction for 19 countries and regions and find that only five reach the theoretical values. Wang et al. [6] identify China's "lagging carbon-reduction regions" based on whether a province or municipality has achieved its milestone reduction targets, and then proposed, for such a province or municipality, optimized paths to carbon reduction through "efficiency and cost" analysis. Overall, these studies usually analyze this issue qualitatively. Furthermore, some literature has also attempted to quantify the carbon reduction potential under various reduction scenarios by using counterfactual inference methods. Based on Monte Carlo simulation, for example, Lin and Xie [31] estimate the potential of China's transport sector, revealing that this potential would be 304.59 (422.99) million tons under a moderate (advanced) emission-reduction scenario, respectively. Similarly, Guo et al. [32] simulate the potential to mitigate China's carbon intensity in business-as-usual and planned scenarios, concluding a 34.22% and a 37.64 % potential for the two scenarios, respectively. These analyses, however, only allow us to perceive the possible room for carbon reduction, and their results may largely deviate from the existing situation.

Under different conditions of economic development and resource endowment, carbon emission efficiency and its reduction potential vary among regions. Scholars are also interested in the spatial characteristics and the changing trends presented by efficiency and potential. For instance, Yang et al. [33] compared the regional differences in carbon emission efficiency among 30 Chinese provincial-level divisions between 1998 and 2015. They suggest that the eastern coastal areas of China emit carbons more efficiently than the central and western inland regions, a result consistent with that of Ma [34] and Zhang and Yu [35]. In the meantime, they also confirm that these efficiency differences are decreasing, showing a convergence in efficiency. Furthermore, Du et al. [20] look into the spatial distribution dynamics of provincial carbon emission efficiency in China's construction sector and similarly observe a decreasing trend from east to west. Explorations of the spatio-temporal evolutions of emission efficiency and reduction potential offer us additional insights into the actualities of carbon mitigation. Overall, existing studies focus more on the spatio-temporal characteristics of efficiency but less on reduction potential.

In the long run, understanding the intrinsic mechanisms and identifying the drivers of carbon emission efficiency will lay an important foundation for formulating carbon reduction policies. One strand of literature uses the Logarithmic Mean Division Index (LMDI) to factorize carbon emissions, highlighting the importance of energy emission intensity, energy structure, energy intensity, and output scale at the aggregate level [36,37]. Many others explore how factors influence carbon emission efficiency from the angles of economy, society, technology, or management system [23,28,38]. Based on a quantile regression of panel data for 56 countries, Xie et al. [39] prove that technological progress is crucial to promoting carbon emission efficiency. Li and Cheng [38] point out that poor management is the root cause of carbon inefficiency in China's manufacturing sector. Dong et al. [40] discover a long-term equilibrium relationship among industrial structure upgrading, economic growth, and carbon emissions. Yang et al. [33] unfold that industrial carbon emission efficiency is positively impacted by foreign direct investment, the level of economic development, technological progress, and government intervention, and negatively by the energy consumption structure. On the other hand, an extensive literature has demonstrated that significant spatial spillover effects exist in carbon emission efficiency in China's industrial sectors. This result illustrates that the spatial dimension is also important to research the influencing factors of emission efficiency [20,33,41]. As for the influencing factors, however, there is little discussion about their spillover effects.

2. Research Area and Methods

2.1. Research Area

The Yangtze River Basin (YRB or the Basin) spans two municipalities and nine provinces (a municipality or province is a provincial-level administrative region, occasionally referred to as "(provincial-level) division" or "region") from the west to the east of China, accounting for about 21% of the total land area of the country. The River connects these divisions, making their economies, societies, and ecologies spatially correlated and yet heterogeneous. Figure 1 shows the YRB's geographical location and basic socio-economic data. In 2019, the population of YRB was 602 million, nearly 43% of China's total; its GDP amounted to 45.78 trillion RMB, 46.2% of China's total. As one of China's most significant economic and demographic regions, YRB is not only a critical gateway to the coordinated development of China's regional economy but also an important ecological space for developing China's resources and environment sustainably.

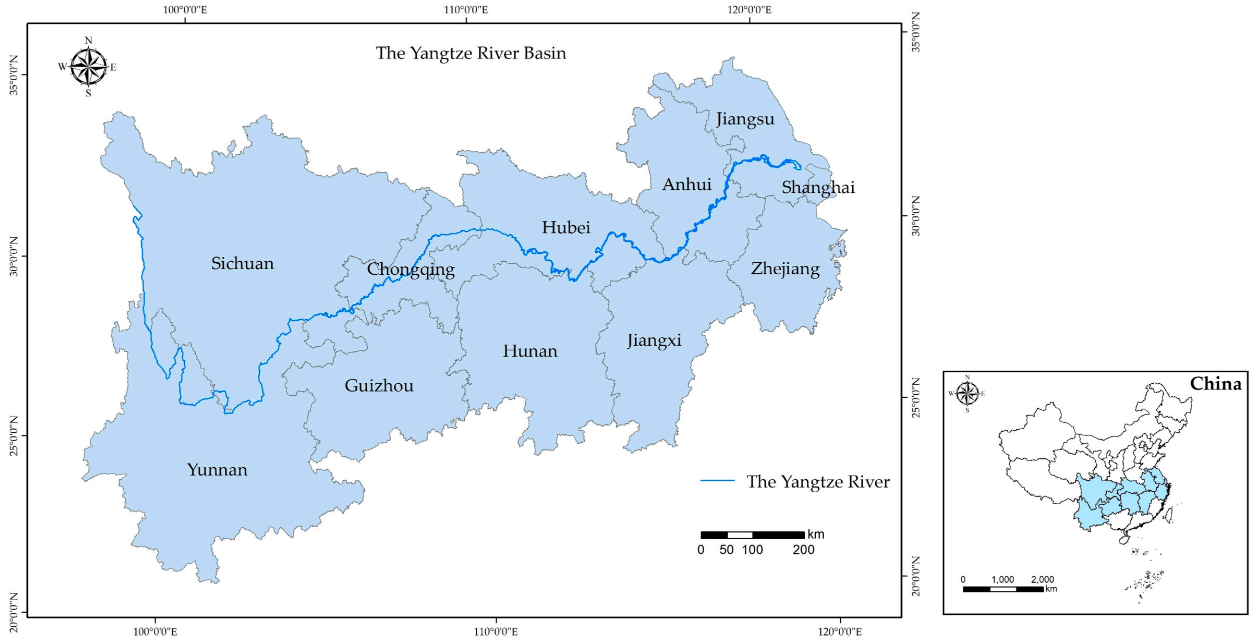

Figure 1. Geographical location and socio-economic development of the research area.

In terms of industrial structure, Figure 2 plots this for each division in YRB in 2019. It can be seen that the proportion of secondary industry in YRB is relatively high, especially for Jiangxi and Jiangsu, indicating that this industry provides essential support for economic development in the Basin. Besides, Shanghai has a leading proportion of tertiary industry (72.7%) and a reasonable industrial structure, owing to its transition to high-tech and service industries. More specifically, we calculate for these divisions the ratio of industrial GDP to total GDP. In 2019, the ratios ranged from 23.25% to 37.97%. This result corroborates that YRB is primarily in the transitional period between industrialization and post-industrialization [28]. In addition, the aggregated industrial GDP of YRB reached RMB 14.80 trillion, accounting for 47.44% of China's total industrial GDP. Therefore, while YRB witnesses ballooning economic aggregates, it inevitably faces ecological and environmental pressure from the industrial sector. In this context, studying ICEE and finding specific ways to reduce emissions is crucial for upgrading YRB's industrial sector and accelerating the coordinated development of the regional industrial economy and ecological environment.

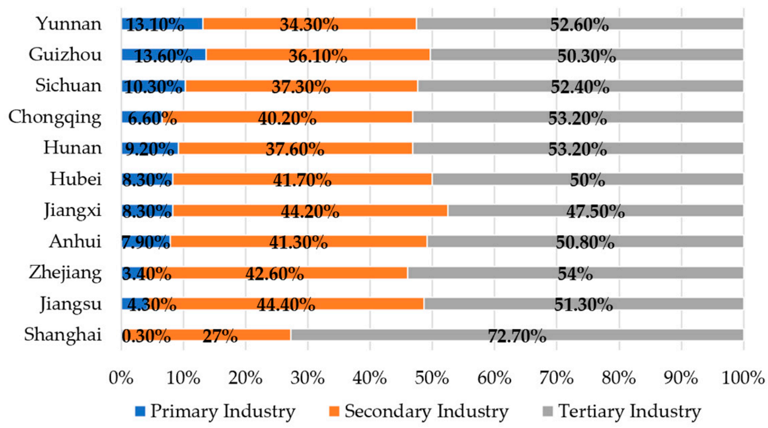

Figure 2. Industrial structure of provinces and municipalities in YRB in 2019.

2.2. Methods

2.2.1. Models for Industrial Carbon Emission Efficiency and Reduction Potential

Green-Technology Efficiency

Compared with the cross-sectional model, the panel data model contains a time dimension. This provides individual dynamic information and avoids missing variables caused by the time-invariant heterogeneity of individuals. On this basis, we use the panel SFA model to measure technical efficiency following Battese & Coelli [42].

$$y_{it} = f(X_{it};\beta)\cdot \exp(v_{it} - u_{it}),\ u_{it} = u_i\cdot\eta_{it},\ \eta_{it} = \exp(-\eta t),\ i = 1,\ldots,I,\ t \in \Psi(i) \quad (1)$$

where y_{it} denotes the output of production unit i at time t, X the vector of input resources for unit i at time t, β the vector of parameters to be estimated, and $\Psi(i)$ the duration of production unit i in the observation period T. u_{it} is a non-negative technical inefficiency term, which is independently and identically distributed and follows a non-negative truncated (at zero) normal distribution. When $u_{it} = 0$, it means that unit i is on the frontier of production and that in the production process, there is no loss of technical efficiency. η_{it} is a function of time t, indicating the time trend of technological inefficiency. v_{it}, independent of u_{it}, represents the stochastic shock in production activities.

In the model, we set the production function f using the trans-log function. This function considers how the interplay among inputs affects the output and overcomes the limitation of the Cobb-Douglas function where the elastic sum of inputs equals one. Formally, the trans-log function is the second-order Taylor expansion of the production function at the zero-input point, as follows,

$$\begin{aligned} \ln y_{it} &= \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_{nit} + \tfrac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{M} \beta_{nm} \ln x_{nit} \ln x_{mit} \\ &\quad + \sum_{n=1}^{N} \beta_{nt} t \ln x_{nit} + \beta_t t + \beta_{tt} t^2 + v_{it} - u_{it} \end{aligned} \quad (2)$$

where N indicates the number of input elements; $t = year - year_0$, in which $year_0$ is the benchmark year; $\varepsilon_{it} = v_{it} - u_{it}$ is the mixed error. Since v_{it} and u_{it} cannot be estimated directly, Battese & Coelli [42] also transformed the parameters u and v into the following,

$$\sigma_\varepsilon^2 = \sigma_v^2 + \sigma_u^2,\ \gamma = \sigma_u^2/\sigma_\varepsilon^2 \quad (3)$$

where γ specifies how the error resulting from the environmental setting contributes to the overall error. If γ is large and significant, we should bring in technical inefficiency. Moreover, γ is also used to examine the feasibility of SFA model. When γ approaches 1, the model is reasonable [17,28]. To measure ICEE based on green-technology efficiency, we take the average-carbon industrial GDP ($y_{i,t} = IGDP_{i,t}/C_{i,t}$) as the output variable, and use the annual average number of employees in industry $IL_{i,t}$, industrial capital stock $IK_{i,t}$, and industrial energy consumption $IE_{i,t}$ as the input variables. Considering that under the condition of given constant inputs, technological change may alter ICEE, we use time trend t to measure technological progress. Then we obtain the trans-log regression model, as follows,

$$\begin{aligned} \ln IGDP_{i,t}/C_{i,t} &= \beta_0 + \beta_1 \ln IL_{i,t} + \beta_2 \ln IK_{i,t} + \beta_3 \ln IE_{i,t} + \beta_t t + \tfrac{1}{2}\beta_{11}(\ln IL_{it})^2 + \tfrac{1}{2}\beta_{22}(\ln IK_{it})^2 \\ &+ \tfrac{1}{2}\beta_{33}(\ln IE_{it})^2 + \tfrac{1}{2}\beta_{tt}t^2 + \tfrac{1}{2}\beta_{12}\ln IL_{it}\ln IK_{it} + \tfrac{1}{2}\beta_{13}\ln IL_{it}\ln IE_{it} \\ &+ \tfrac{1}{2}\beta_{23}\ln IK_{it}\ln IE_{it} + \beta_{1t}t\ln IL_{it} + \beta_{2t}t\ln IK_{it} + \beta_{3t}t\ln IE_{it} + v_{it} - u_{it} \end{aligned} \quad (4)$$

Accordingly, we calculate the GTE of the production unit i at time t and use it to measure the ICEE,

$$GTE_{it} = \frac{f(X_{it};\beta)\cdot \exp(v_{it} - u_{it})}{f(X_{it};\beta)\cdot \exp(v_{it})} = \exp(-u_{it}) \quad (5)$$

Green-Technology Efficiency Loss

GTE measures how the actual average-carbon industrial output of a production unit is close to its optimal level under certain input resource and production technology conditions. Evidently, the loss of GTE estimates the difference between the actual average-carbon industrial output and the optimal value. Complementarily, the green-technology efficiency loss (GTEL) indicates that due to the limited green production technology, the production unit fails to utilize the available resources in a sufficiently low-carbon way. This results in high carbon emissions. Therefore, the industrial carbon reduction potential (ICRP) can be defined as the reduction in carbon emissions or the increase in industrial output that stems from a potential increase in GTE. More specifically, the potential for improving GTE refers to the room to change GTE from the actual value to the optimal value (i.e., the scale of GTEL). On this basis, we measure the carbon reduction potential of the industrial sector in each division in YRB.

According to formula (5), we calculate the GTEL of industrial carbon emissions as,

$$GTEL_{it} = 1 - \exp(-u_{it}) \quad (6)$$

Then, the ICRP is estimated as follows,

$$ICRP_{it} = C_{it} \times GTEL_{it} = C_{it} \times \{1 - \exp(-u_{it})\} \quad (7)$$

2.2.2. Spatial Effect of Industrial Carbon Emission Efficiency

We employ the global Moran' I index [43,44] to test whether the ICEE of the divisions in YRB is spatially autocorrelated and thus exhibits spatial agglomeration. Moran' I index is calculated as,

$$Moran'I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}(x_i - \overline{x})^2},\ i \neq j \quad (8)$$

where x_i and x_j are the industrial carbon efficiency, n the number of provinces and municipalities in YRB, and w_{ij} the spatial weight matrix defined as the spatial adjacency matrix. When i and j are adjacent, w_{ij} = 1; otherwise, it equals zero. $\overline{x}$ is the average value of ICEE of each division. Moran's I above zero indicates a positive spatial correlation. The larger the value, the higher the agglomeration of ICEE in YRB. Conversely, Moran's I below zero indicates a negative spatial correlation. The smaller the value, the greater the difference in ICEE. Moran's I at zero, however, means that the ICEE of each division is randomly distributed.

2.2.3. Factor Analysis of Industrial Carbon Emission Efficiency Based on the Spatial Effect Influencing Factor

Existing literature has explored factors that may impact carbon emission efficiency, from economic, societal, institutional, and technological perspectives. On this basis, we select for ICEE several possible influencing factors, as follows:

(1) Level of industrialization, defined as the proportion of the industrial GDP to that overall. Improved industrialization implies optimized industrial structure, advanced production technology, and increased labor productivity [45,46]. Only low-carbon industrial development can be conducive to raising energy use efficiency and reducing industrial carbon emissions. Literature suggests that the impact of the industrialization level on energy consumption and carbon emissions is related to the stage of industrialization, and that there is an inverted U-shaped relationship between industrial carbon emissions and industrialization level, similar to the Environmental Kuznets Curve [47]. Therefore, the specific impact of industrialization level on ICEE needs to be further examined.

(2) Industrial foreign direct investment (IFDI) ratio, defined as the ratio of IFDI to the total industrial investment. Some argue that foreign direct investment (FDI) promotes the spillover effect of foreign environment-friendly technologies to the local industrial sector [48,49], thereby increasing the ICEE. In contrast, the "pollution haven" hypothesis suggests that foreign firms may transfer through direct investment the heavy-pollution and high-emission production projects to regions with lower environmental constraints, inducing lower industrial carbon efficiency in these regions [50,51]. Therefore, the effect of the ratio of FDI on ICEE has yet to be checked.

(3) Technological innovation, defined as the proportion of internal industrial R&D expenditures to the overall R&D ones. Industrial low-carbon technological innovation helps promote technology in industrial production, facilitate the transformation and upgrading of energy-intensive industries, and improve industrial pollution control. It thus helps to increase the ICEE [52,53]. We use the industrial R&D expenditure ratio as the proxy for industrial low-carbon technological innovation, expecting that it is positively correlated to ICEE.

(4) Energy consumption intensity, defined as the ratio of industrial energy consumption to industrial GDP. The numerator is directly related to industrial carbon emissions. The higher the industrial energy consumption per unit of industrial GDP in a region, the more extensive the regional industrial economic development mode, the more serious the energy loss in industrial production, and the lower its ICEE [54]. Thus, we expect that energy consumption intensity is negatively associated with ICEE.

(5) Energy consumption structure, defined as the ratio of coal-based energy consumption in total industrial energy consumption. Within China's relatively simple energy consumption structure, coal-based energy consumption contributes mainly to industrial carbon emissions [55]. Restructuring industrial energy consumption towards low-carbon energy sources, such as photovoltaics, wind power, and hydropower, can help mitigate carbon emissions. Therefore, a high ratio of coal-based energy consumption is projected to reduce the ICEE.

(6) Level of productivity, defined as the level of labor productivity in the industrial sector. This factor is closely related to the management experience and production technology. Efficient organization or management system and advanced production technology help effectively allocate industrial resources, improve industrial energy utilization, and facilitate ICEE. Therefore, industrial productivity should be positively correlated with ICEE [45,56].

Spatial Effect Models

To avoid model errors arising from the neglect of the spatial element, we analyze the influencing factors on ICEE via the spatial panel model. The general form of this model is as follows [57],

$$y_{i,t} = \rho \sum_{j=1}^{n} w_{i,j} y_{j,t} + \sum_{k=1}^{K} \beta_k x_{i,t}^{k} + \sum_{q=1}^{Q} \delta_q \sum_{j=1}^{n} w_{i,j} x_{j,t}^{q} + \mu_i + \gamma_t + \varepsilon_{i,t},\ \varepsilon_{i,t} = \lambda \sum_{j=1}^{n} w_{i,j} \varepsilon_{j,t} + v_{i,t} \quad (9)$$

where $w_{i,j}$ is the (i, j) elements of the spatial weight matrix W; ρ measures the spatial lag effect; β_k is the regression coefficients of K number of independent variables; δ_q is the regression coefficients of Q (varying) number of spatially-lagged independent variables that measure the independent variables' effects of neighboring regions on the dependent variable of the local region, and $w_{i,j}x_{j,t}^q$ is the mean of the spatially-lagged independent variables in adjacent regions; μ_i denotes the individual fixed effect; γ_t denotes the time fixed effect; λ measures the spatially lagged effect of the disturbance term; and $v_{i,t}$ follows a standard normal distribution.

When $\lambda = 0$, model (9) becomes the spatial Durbin model (SDM). SDM considers the spatial-lag correlation of the independent and dependent variables. The model is,

$$y_{i,t} = \rho \sum_{j=1}^{n} w_{i,j} y_{j,t} + \sum_{k=1}^{K} \beta_k x_{i,t}^k + \sum_{q=1}^{Q} \delta_q \sum_{j=1}^{n} w_{i,j} x_{j,t}^q + \mu_i + \gamma_t + v_{i,t} \tag{10}$$

When $\lambda = 0$ and $\delta_q = 0$, model (9) becomes the spatial lag model (SLM). SLM only considers the spatial-lag correlation of the dependent variables. The model is,

$$y_{i,t} = \rho \sum_{j=1}^{n} w_{i,j} y_{j,t} + \sum_{k=1}^{K} \beta_k x_{i,t}^k + \mu_i + \gamma_t + v_{i,t} \tag{11}$$

When $\rho = 0$ and $\delta_q = 0$, model (9) becomes the spatial error model (SEM). SEM considers the spatial-lag correlation of the error term. The model is,

$$y_{i,t} = \sum_{k=1}^{K} \beta_k x_{i,t}^k + \mu_i + \gamma_t + \varepsilon_{i,t},\ \varepsilon_{i,t} = \lambda \sum_{j=1}^{n} w_{i,j} \varepsilon_{j,t} + v_{i,t} \tag{12}$$

Empirically, we use the spatial adjacency matrix as the weight matrix and take the above six factors as independent variables to investigate their effects on ICEE. The selection of fixed and random effects is based on the Hausman test, and the spatial effect model selected via the Likelihood ratio test (LR). Considering the endogeneity of independent variables in the spatial econometric model, we estimate the model parameters using the maximum likelihood estimation (MLE) method.

3. Data Source and Summary Statistics

The research data on socio-economic development and industrial energy consumption are mainly obtained from the National Bureau of Statistics of China (available at https://data.stats.gov.cn/ (accessed on 12 July 2021)), the China Statistical Yearbook, and the China Industrial Statistical Yearbook (available at https://data.cnki.net/yearbook/Navi (accessed on 12 July 2021)), as well as the statistical yearbooks and statistical bulletins on the national economic and social development of each division in YRB (available at the official website of each provincial statistics bureau). The sample period spans from 2000 to 2019 (same period for each variable introduced).

The annual average number of industrial employees, industrial capital stock, and industrial energy consumption are taken as input variables of labor, capital, and energy, respectively. The average-carbon industrial GDP is used as the output variable. The industrial capital stock is calculated by subtracting the year-end industrial fixed capital from the current year's accumulated depreciation. Industrial energy consumption is converted to standard coal based on the conversion coefficients published in the 2006 IPCC Guidelines for National Greenhouse Gas Emissions Inventories [58]. Given that carbon emissions are primarily in the form of carbon dioxide, we calculate the total industrial carbon emissions as total carbon dioxide emissions from the apparent consumption of various energies [59]. The conversion coefficients for each type of energy are shown in Table 1. According to the provincial fixed asset investment price index and GDP price index, we deflate the industrial capital stock and average-carbon industrial GDP to the comparable prices in 2000. The summary statistics for each variable are shown in Table 2. Additionally, taking the industrial GDP per unit of CO_2 as an example, we present in Figure 3 detailed changes in the variables introduced for these divisions from 2000 to 2019.

On the whole, the industrial GDP per unit of CO_2 of each division generally exhibits an upward trend within the sample period.

Table 1. Coefficients of converting different types of energy into standard coal and carbon emission.

Energy Type	Standard Coal (kg)	Carbon Emission (t/tce)	Energy Type	Standard Coal (kg)	Carbon Emission (t/tce)
Coal (kg)	0.7143	1.9003	Fuel oil (kg)	1.4286	3.1705
Coke (kg)	0.9714	2.8604	Diesel oil (kg)	1.4571	3.0959
Clenedcoal (kg)	0.9000	2.4044	Natural gas (m^3)	1.3300	2.1650
Gasoline (kg)	1.4714	2.9251	Electricity (kwh)	0.1229	2.4930
Crude oil (kg)	1.4286	3.0202			

Note: tce denotes the ton for standard coal equivalent. Carbon emissions are calculated based on the standard coal equivalent converted from each type of energy.

Table 2. Summary Statistics (Sample period: 2000~2019).

Variables	Description	Mean	S.D.	Min	p25	Median	p75	Max
				Input-Output				
Industrial GDP per unit of CO_2	in 10 thousand RMB/ton of standard coal	0.25	0.13	0.07	0.14	0.23	0.34	0.65
Industrial capital stock	in 100 million RMB	10,354.74	6227.85	3665.18	6251.82	8070.65	12,179.82	32,256.06
Industrial energy consumption	in 10 thousand tons of standard coal	8487.84	5479.35	1500.22	4956.90	6027.66	11,211.64	23,587.77
Number of industrial employees	in 10 thousand units	292.82	253.09	63.5	128.96	220.31	320.04	1153.88
				Influencing factor				
Industrialization level	%	0.29	0.06	0.17	0.23	0.28	0.35	0.40
IFDI ratio	%	0.15	0.13	0.01	0.06	0.10	0.19	0.51
Technological innovation	%	0.61	0.17	0.19	0.45	0.63	0.76	0.86
Energy consumption intensity	ton of standard coal/10 thousand RMB	1.93	1.07	0.56	1.07	1.56	2.67	5.15
Energy consumption structure	%	0.69	0.30	0.06	0.51	0.68	0.84	0.89
Level of productivity	Industrial GDP per capita	21.90	11.52	5.59	13.22	19.28	28.42	63.85

Note: S.D. denotes the standard deviation. p25 and p75 indicate the 25th and 75th percentiles, respectively.

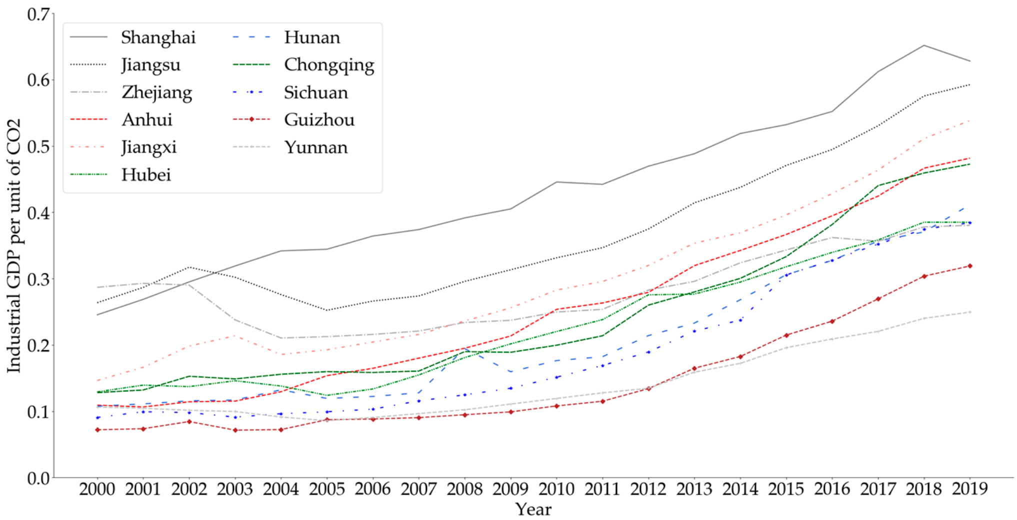

Figure 3. Industrial GDP per unit of CO2 for provinces and municipalities in YRB from 2000 to 2019.

4. Empirical Analysis

4.1. Evaluation of Industrial Carbon Emission Efficiency

There are two hypotheses for the GTE Equation (4), i.e., the existence of technical change and interaction terms, though they remain to be empirically validated. We take Equation (4) as the baseline model, denoted as model 1. On this basis, we progressively change the hypotheses. First, we remove the technical change and retain the interaction terms (including the square terms of input variables), thus having $\beta_t = \beta_{1t} = \beta_{2t} = \beta_{3t} = \beta_{tt} = 0$, denoted by model 2. Then, we further remove the interaction terms, i.e., all the coefficients, except for β_0, β_1, β_2, and β_3, are zero. We denote this model as model 3. Next, we keep the technical change and its interaction items, getting $\beta_{11} = \beta_{22} = \beta_{33} = \beta_{12} = \beta_{13} = \beta_{23} = 0$, denoted as model 4. Finally, we retain the technical change but exclude all interaction terms, leaving only β_0, β_1, β_2, β_3, and β_t being non-zero, denoted by model 5.

Table 3 shows the regression results of these GTE models, from which we determine the optimal model for measuring ICEE and the potential for carbon reduction. All the γ statistics of five models are close to one, indicating that the SFA model incorporated with average carbon output is feasible in measuring ICEE. More specifically, in Model 1, the coefficient of *LnIK* is −6.496, significant at the 1% level, which means that for every 1% increase in industrial capital stock, ICEE in YRB will decrease by 6.496%. The inflow of capital, however, often brings more advanced technology, helping to promote emission efficiency. The regression results tend to contradict reality. The coefficient on *LnIE* is also statistically insignificant (with a *t*-value of 0.924), a result inconsistent with the fact that undesired output is closely subject to energy input. Model 2 has the same problem as model 1, i.e., a negative coefficient for the industrial capital stock. At the same time, green-technology inefficiency μ of the model is relatively large, implying possible overestimation of μ. In Model 3, μ is further magnified to 1.600 with a *t*-value of 8.84. The result indicates that ignoring the impact of technological progress can lead to the overestimation of technical inefficiency. Both models 4 and 5 incorporate the impact of technical change, although model 5 dispenses with the interaction terms between technical change and input variables. The results of these two models show that μ and γ (0.210 and 0.810) for model 5 are smaller than the values in model 4 (0.252 and 0.869), suggesting that model 5 better rectifies the overestimation of technical inefficiency. In the aggregate, the setting of model 5 is the most reasonable of all the five models. In addition, the statistic γ reaches 0.8108, representing that the technical inefficiency accounts for 81.08% of the total disturbance. In other words, disturbance mainly derives from technical inefficiency.

Table 3. Regression results of the green-technology efficiency model.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	16.968 *** (2.65)	27.154 (4.16) ***	3.181 *** (5.57)	−3.235 ** (−2.44)	0.443 (1.31)
LnIK	−6.496 *** (−3.64)	−7.545 *** (−4.07)	0.591 *** (7.81)	1.016 *** (5.50)	0.428 *** (6.95)
LnIL	2.392 *** (2.72)	4.153 *** (5.10)	0.395 *** (12.30)	0.174 *** (2.73)	0.435 *** (14.55)
LnIE	0.924 (1.00)	−0.429 (−0.51)	−1.106 *** (−24.22)	−0.963 *** (−15.30)	−0.959 *** (−24.52)
t	0.185 *** (3.40)			0.228 *** (4.60)	0.067 *** (16.99)
$LnIL^2$	−0.146 *** (−2.86)	−0.101 ** (−2.12)			
$LnIK^2$	0.652 *** (3.77)	0.706 *** (3.89)			
$LnIE^2$	−0.154 (−1.23)	−0.045 (−1.02)			
t^2	−0.000 (−0.10)			0.001 (1.42)	
LnIL×LnIK	−0.519 *** (−3.27)	−0.613 *** (−3.59)			
LnIL×LnIE	0.476 *** (4.71)	0.329 *** (3.60)			
LnIK×LnIE	−0.193 (−1.26)	−0.173 (−1.24)			
LnIL×t	0.003 (0.72)			0.016 *** (4.37)	
LnIK×t	−0.022 ** (−2.47)			−0.029 *** (−3.54)	
LnIE×t	0.008 (1.37)			−0.001 (−0.18)	
μ	0.248 *** (4.59)	1.508 *** (8.85)	1.600 *** (8.84)	0.252 *** (4.81)	0.210 ** (2.45)
η	0.057 *** (13.49)	0.042 *** (12.27)	0.040 *** (12.95)	0.062 *** (13.77)	0.057 *** (13.06)
σ_ε^2	0.029 ** (2.17)	0.031 ** (2.50)	0.033 *** (2.67)	0.030 ** (2.42)	0.025 ** (2.02)
γ	0.831 *** (10.53)	0.874 *** (16.88)	0.833 *** (13.00)	0.869 *** (7.92)	0.810 *** (7.69)
Log likelihood	288.2033	263.9615	227.2509	254.4775	244.1887

Notes: The values in parentheses are the corresponding *t* statistics. ** and *** represent the significance levels of 5% and 1%, respectively.

We therefore specify the ICEE model as follows,

$$\ln \frac{IndGDP_{i,t}}{C_{i,t}} = 0.443 + 0.435 \ln IL_{i,t} + 0.428 \ln IK_{i,t} - 0.959 \ln IE_{i,t} + 0.067t + v_{it} - u_{it} \tag{13}$$

where $u_{it} = u_i \times \exp(-0.057t)$, and u_i follows $iidN^{+}(0.210, 0.021)$. Furthermore, the model for ICRP is as follows,

$$ICRP_{it} = C_{it} \times \{1 - \exp(-u_i \times \exp(-0.057t))\} \tag{14}$$

From this, we can calculate the ICEE and the corresponding reduction potential of each division in YRB.

4.2. Spatial and Temporal Dynamics of Industrial Carbon Emission Efficiency

4.2.1. Temporal Dynamics

Table 4 exhibits the temporary dynamic evolution of ICEE for the divisions in YRB from 2000 to 2019. Chronologically, the ICEE as a whole showed an upward trend during the sample period, with the average emission efficiency climbing from 0.541 in 2000 to 0.800 in 2019 (i.e., an annual growth of 2.427%). More specifically, Shanghai underwent the lowest change of 0.037, whereas Guizhou saw the highest increment of 0.357 with an annual growth of 3.960%. Cross-sectionally, the difference between the highest efficiency (Shanghai) and the minimum (Guizhou) declined from 0.614 in 2000 to 0.447 in 2019, indicating that the ICEE of these divisions was constantly converging. The result can also be confirmed by the standard deviation of their emission efficiency in the cross-section, which decreased from 0.216 in 2000 to 0.106 in 2019.

Table 4. Temporal dynamic evolution of ICEE.

	2000	2003	2006	2009	2012	2015	2019	Average	A.G. (%)
Shanghai	0.943	0.951	0.959	0.965	0.971	0.975	0.980	0.964	0.206
Jiangsu	0.735	0.772	0.804	0.832	0.856	0.877	0.901	0.830	1.077
Zhejiang	0.815	0.842	0.865	0.885	0.902	0.917	0.933	0.883	0.715
Anhui	0.460	0.520	0.576	0.628	0.676	0.719	0.769	0.628	2.745
Jiangxi	0.441	0.502	0.559	0.613	0.662	0.706	0.758	0.613	2.897
Hubei	0.656	0.701	0.741	0.777	0.809	0.836	0.867	0.775	1.480
Hunan	0.551	0.606	0.655	0.700	0.741	0.777	0.818	0.699	2.097
Chongqing	0.346	0.409	0.470	0.530	0.585	0.637	0.698	0.533	3.777
Sichuan	0.337	0.400	0.462	0.522	0.578	0.630	0.693	0.525	3.864
Guizhou	0.329	0.391	0.454	0.514	0.571	0.623	0.686	0.517	3.960
Yunnan	0.336	0.399	0.461	0.521	0.577	0.630	0.692	0.526	3.874
Mean	0.541	0.590	0.637	0.681	0.721	0.757	0.800	0.681	2.427
S.D.	0.216	0.199	0.180	0.162	0.144	0.127	0.106	-	-

Note: Average and A.G. indicate the time-series average and annual growth rate of ICEE (GTE) for each division, respectively. Mean and S.D. indicate the cross-sectional average and standard deviation across the divisions each year, respectively.

To conduct a more in-depth analysis, we further use the kernel density estimation to examine the dynamics of ICEE. We choose the Epanechnikov Kernel as the kernel function and use cross-sectional data in 2000, 2005, 2010, 2015, and 2019 to plot the kernel density curves (see Figure 4). In the Figure, the kernel density curve of ICEE slowly shifts to the right, implying an increasing trend of ICEE. At the same time, according to the change in curve kurtosis, the broad-peaked curve gradually develops into a sharp-peaked one from 2000 to 2019, indicating convergent emission efficiency. These findings are consistent with the previous comparison results. Nevertheless, the imbalance in ICEE remains prominent, even though the distribution evolves from a four-peak shape in 2000 to a three-peak one in 2019.

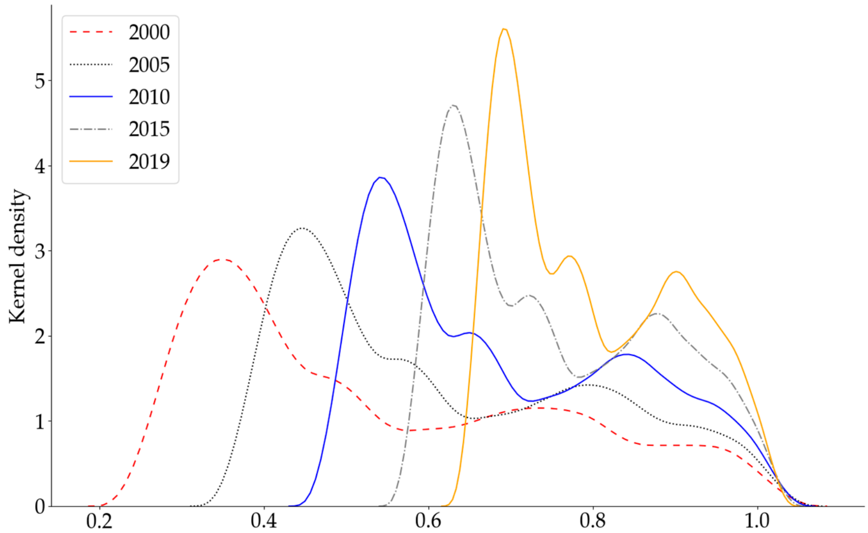

Figure 4. Kernel density estimation of ICEE spanning 2000 to 2019.

In short, the overall ICEE of YRB is improving progressively. Although the gap in emission efficiency is gradually narrowing, inconsistency and imbalance still exist. Thus, there is still room for improvement.

4.2.2. Spatial Dynamics

We also explore the spatial distribution dynamics of ICEE of YRB. Using the natural breakpoint method, we sort the 11 divisions into four sub-regions based on their efficiency values each year. Relevant results for the year 2000 and year 2019 are presented in Figure 5.

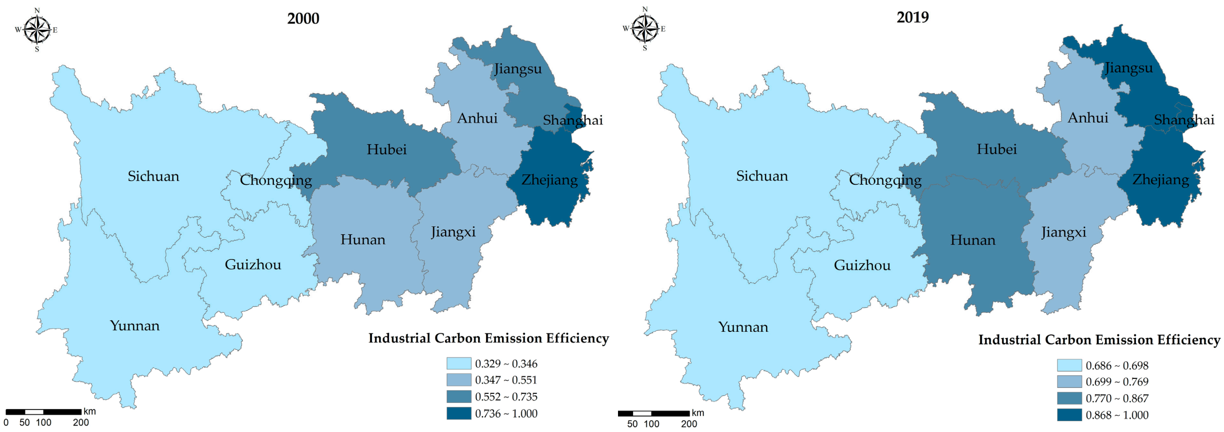

Figure 5. Spatial dynamics of the ICEE in YRB.

In 2000, Shanghai and Zhejiang were the most efficient in industrial carbon emissions. This is mainly due to the national policy of "The Rich Helping and Guiding Others to Become Rich Later," which provides the provinces in the lower reaches of YRB with a comparative advantage in receiving advanced industrial production technology and capital. In contrast, the ICEE in the upper reaches (including Sichuan, Chongqing, Yunnan, and Guizhou) was relatively low. In 2019, under the influence of several national strategies (such as the "Rise of Central China" and the construction of the "Triangle of Central China"), the spatial pattern of ICEE in YRB presented an "N-shaped" distribution. Specifically, Shanghai, Jiangsu, and Zhejiang in the lower reaches had the highest ICEE, about 0.101–0.402 higher than YRB's average. Close to the average were the second most efficient Hunan and Hubei provinces in the middle reaches. Slightly lower than the regional average were Anhui and Jiangxi provinces at the second-lowest point in the spatial efficiency distribution. The four divisions in the upper reaches showed the lowest emission efficiency, about 0.114–0.212 below the regional average. Overall, YRB's ICEE between 2000 and 2019 showed a spatial order of "lower reaches > middle reaches > upper reaches," one that matched the economic development of these sub-areas.

Furthermore, we checked the spatial autocorrelation of such ICEE via the global Moran's I index. The Moran's I values and their significance statistics for each year are shown in Figure 6. As we can see, the index climbed from 0.400 to 0.413. Correspondingly, the Z statistic varied from 2.761 to 2.779, implying that the Moran's I index was significant at the 1% level over the sample period. Therefore, the ICEE of YRB had a significantly positive spatial correlation, meaning that the emission efficiency of a province or municipality was radically affected by its neighbors. Therefore, this result also illustrates that the spatial element matters in analyzing the influencing factors of ICEE.

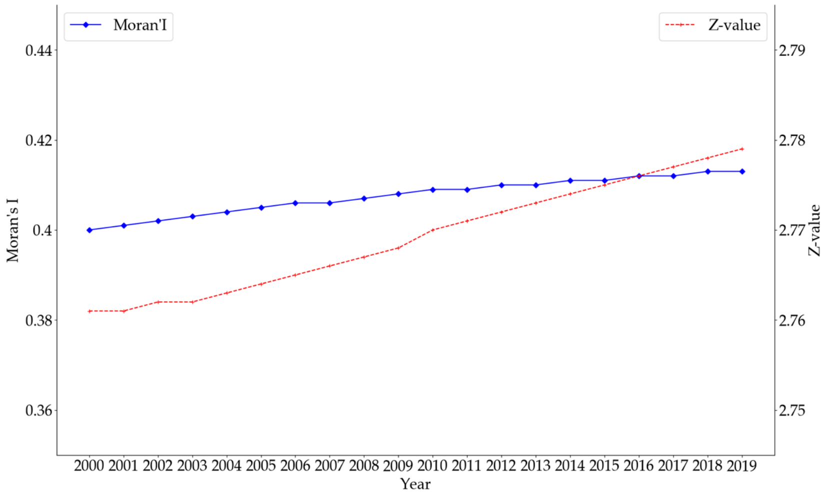

Figure 6. Global Moran's I and Z-value dynamics of the ICEE in YRB from 2000 to 2019.

4.3. Industrial Carbon Reduction Potential (ICRP)

Formulas (7) and (14) show that the total industrial carbon emissions and the loss of emission efficiency jointly determine YRB's potential for reducing industrial carbon. That potential, affected by the total amount of carbon emissions, showed an upward-to-downward (non-monotonic) trend, though during the sample period the green-technology efficiency loss in YRB steadily slid (see Figure 7). Specifically, YRB was in a stage of rapid industrialization, and various industries formed a coal-dominated energy consumption structure from 2000 to 2011. The total industrial carbon emissions of the region continuously increased over the period, causing its reduction potential to rise gradually from 460.29 million tons in 2000 to 816.77 million in 2011. YRB's total industrial carbon emissions were brought under control and thus its reduction potential declined, as China imposed restrictions on carbon emissions (e.g., the carbon emission intensity goal was included in China's national "Twelfth Five-Year Plan" in 2011) and initiated green development concepts (such as "green water and green mountains are golden and silver mountains"). By 2019, YRB's potential was reduced to 566.27 million tons.

On average, the reduction potential for a province or municipality in YRB ranged from 40 to 75 million tons. Notably, Sichuan had a much higher potential than the other divisions. The reason is that, as an economically strong and populous province in western China, Sichuan has developed a comprehensive industrial industry system, and its industrial carbon emissions have been at a high level; but a large proportion of its total emissions are inefficient due to low emission efficiency (see Table 4), thus leading to its large carbon reduction potential. Moreover, the reduction potential of each division basically peaked in 2011 or 2012 and then gradually declined. This phenomenon reflects the difficulty in further reducing industrial carbon emissions. It is also noteworthy that the decline in such potential markedly slowed down in recent years, and the reduction potential of Hubei even slightly rebounded in 2019, indicating the seriousness of carbon reduction tasks. Figure 8 exhibits the spatial pattern of the industrial carbon reduction potential of these divisions in 2019. Among them, Sichuan and Shanghai were the regions with the highest and the lowest potential, respectively.

Figure 7. Evolution of ICRP for provinces and municipalities in YRB from 2000 to 2019.

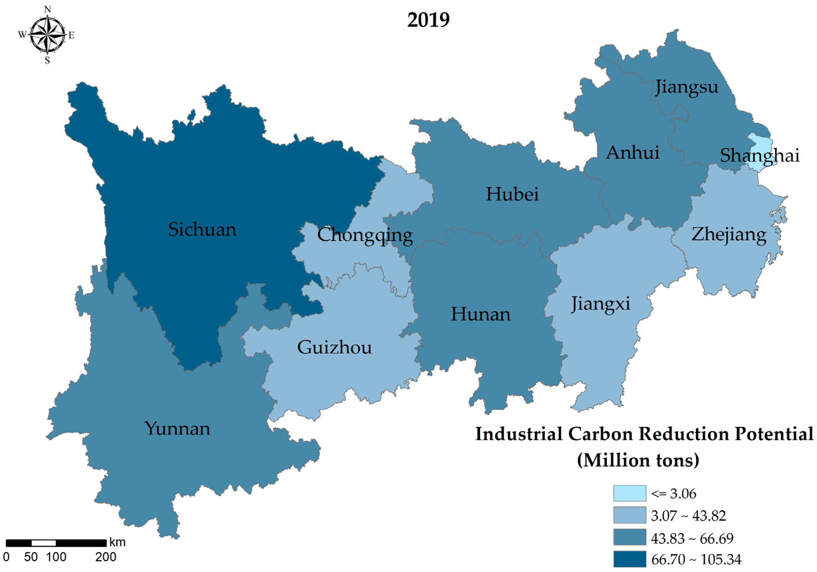

Figure 8. The scale of ICRP for provinces and municipalities in YRB in 2019.

We further use the ratio of industrial carbon reduction potential to industrial carbon emissions to measure how hard it is to promote emission reduction. The method provides a new perspective on comparing the reduction potential based on reduction difficulty. A higher ratio implies more room and less difficulty. Figure 9 plots the evolution of the above-mentioned ratio for each division. In each of them, we can see a decreasing trend, meaning greater difficulty in industrial carbon reduction. On the other hand, the difference in reduction potential ratio between the divisions also narrowed. By 2019, the difference declined to 29.37% (from 61.39% in 2000). Figure 10 shows the spatial distribution of such a ratio for YRB in 2019. While the three in the lower reaches remained below 10%, the four in the upper reaches had a ratio of about 30%, making it easier for the latter to further reduce emissions.

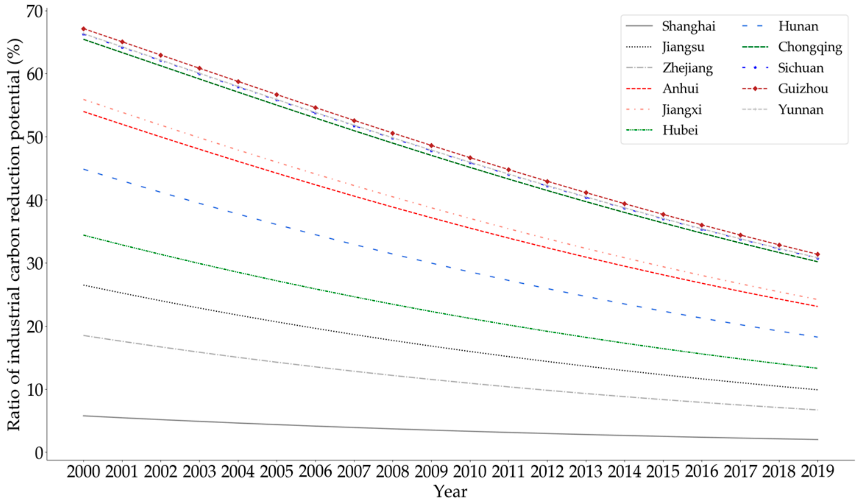

Figure 9. Evolution of the ratio of ICRP for provinces and municipalities in YRB from 2000 to 2019.

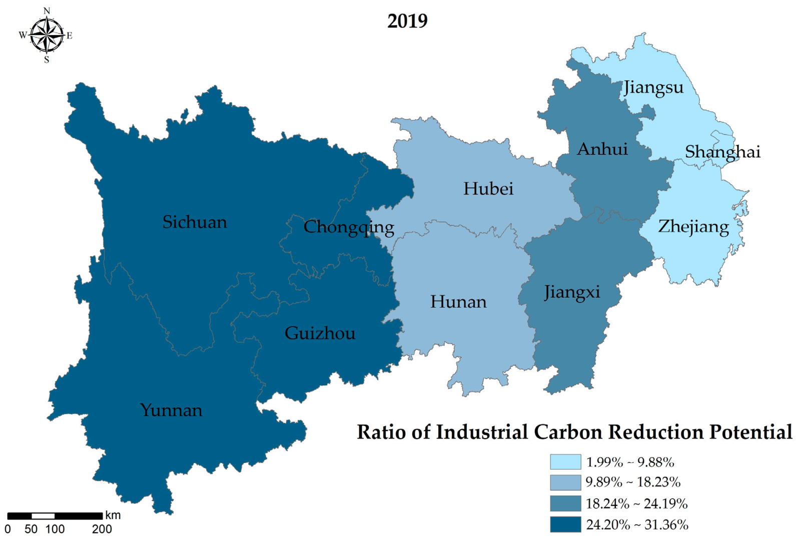

Figure 10. The ratio of ICRP for provinces and municipalities in YRB in 2019.

5. Factor Analysis

We then conduct the regression analyses, using the estimated ICEE as the dependent variable and the level of industrialization (IND), ratio of industrial foreign direct investment (FDIR), technological innovation (RDP), energy consumption intensity (EINT), energy consumption structure (ECS), and productivity (PROD) as the independent variables.

5.1. Factor Analysis on the ICEE

Firstly, we select the fixed effects model, since the statistic of the Hausman test is 61.86 with its p-value less than 0.001 (detailed results are available upon request). Secondly, the statistic of the likelihood ratio (LR) test for comparing SDM with SLM (SEM) is 117.52 (184.35) with a p-value less than 0.001. This test rejects the hypothesis that SDM may degenerate into SLM (SEM), and we thus choose the SDM as the baseline model. Table 5 reports the regression results for the panel SDM. A further LR test shows that the two-way (individual and time) fixed effects model has an LR-statistic of 59.04 (568.46) against the individual (time) one. Thus, the two-way fixed effects model is superior.

Table 5. Regression results for the panel spatial Durbin model with fixed effects (FE).

	Individual FE Model	**Time FE Model**	**Individual and Time FE Model**
IND	0.824 *** (13.76)	1.341 *** (10.02)	0.799 *** (14.09)
FDIP	−0.034 (−0.92)	0.335 *** (4.79)	−0.039 (−1.14)
RDP	0.021 ** (1.96)	0.016 (0.39)	0.054 *** (3.54)
ECS	−0.107 *** (−7.00)	−0.054 ** (−2.16)	−0.077 *** (−4.83)
EINT	−0.0117 *** (−3.44)	−0.0047 (−0.51)	−0.0254 *** (−6.50)
PROD	0.000 (0.46)	0.005 *** (6.54)	0.008 ** (2.21)
W × IND	−0.372 ** (−2.51)	0.022 (0.07)	−0.168 (−1.02)
W × FDIP	0.058 (1.10)	0.261 ** (2.22)	0.040 (0.59)
W × RDP	0.083 *** (5.16)	0.088 (1.15)	0.024 (0.76)
W × ECS	−0.057 ** (−2.26)	−0.243 *** (−3.41)	−0.025 (−0.73)
W × EINT	−0.024 *** (−4.90)	−0.050 *** (−2.79)	−0.051 *** (−6.78)
W × PROD	0.002 *** (5.30)	−0.011 *** (−4.79)	0.001 * (1.90)
R^2	0.4378	0.7791	0.5360
Log Likelihood	635.9517	381.2465	665.4741
Spatial ρ	0.157 ** (2.02)	0.088 * (1.80)	0.234 ** (2.41)

Note: The values in parentheses are the corresponding t values. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

The spatial parameter ρ is 0.234 (t-value = 2.41) for the two-way fixed effects model, indicating that the ICEE in YRB has a positive spatial spillover effect. This means that the increase in emission efficiency of a certain division can significantly promote that of its neighbors. In terms of the influencing factors, positive ones include IND, RDP, and PROD, while negative ones are EINT and ECS. Notably, FDIR remains insignificant. In detail, the positive effect of IND indicates that YRB is developing in a modernized and ecological way, a trend that improves the effective utilization of energy and boosts the ICEE. The negative coefficient of FDIR indicates that the effect of IFDI in YRB supports the "pollution paradise" hypothesis; in other words, foreign direct investment tends to flow into heavy-pollution or high-emission industries. Yet the coefficient of FDIR is statistically insignificant, with a relatively small magnitude of effect. The impacts of RDP and PROD suggest that the progress of green production technology and the efficient allocation of input resources can significantly facilitate ICEE. In addition, the coefficients of EINT and ECS are notably negative, implying that the extensive production modes impede ICEE. The result also highlights that YRB on the whole still faces highly intense energy consumption, which entails further transformation of the structure.

Based on the results of the two-way fixed effects model, we further decompose the total effect of each factor into the direct and indirect effects. The direct effect measures the factor's marginal contribution to ICEE, while the indirect effect reflects the spatial spillover effect of each factor. As demonstrated in Table 6, the marginal (direct) effects of these factors are consistent with the previous findings (see Table 5), i.e., IND, RDP, and PROD hold positive marginal contributions to ICEE, whereas ECS and EINT have the opposite effect. We thus focus on their spillover (indirect) effects.

Table 6. Direct and indirect effects based on the coefficients of the panel spatial Durbin model.

	Direct Effect	**Indirect Effect**	**Total Effect**
IND	0.824 *** (13.82)	−0.117 (−1.49)	0.707 *** (3.90)
FDIP	−0.039 (−1.11)	0.060 (0.51)	0.021 (1.32)
RDP	0.052 *** (3.64)	0.007 (0.27)	0.059 * (1.84)
ECS	−0.076 *** (−4.84)	−0.007 (−0.25)	−0.083 *** (−2.71)
EINT	−0.022 *** (−6.14)	−0.039 *** (−6.02)	−0.061 *** (−7.70)
PROD	0.002 ** (2.17)	0.001 * (1.91)	0.003 *** (4.83)

Note: The values in parentheses are the corresponding t values. *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Specifically, the industrialization level shows a negative spillover effect, probably because the adjacent regions of a certain division shift their high-emission industries into the division itself (the local area) after their industrial upgrading. The spillover effect of the energy consumption structure is also negative, confirming the agglomeration of coal-based structures in YRB. Conversely, the IFDI ratio has a positive spatial spillover effect. This result is consistent with the "pollution haven" hypothesis and suggests that the FDI inflow in adjacent divisions of an area may squeeze out their carbon-efficient projects to the area itself. In addition, the technological innovation of neighbors also exhibits a promoting effect on the local emission efficiency of a division. Unlike the overall insignificant spillover effects of these four factors, the indirect effects of energy consumption intensity and productivity level reach −0.039 (t-value = −6.02) and 0.001 (t-value = 1.91), respectively, which are statistically significant. The results imply that an increase in energy consumption intensity (productivity level) of adjoining divisions significantly suppresses (promotes) the ICEE of the local area.

5.2. Robustness Checks Based on Other Spatial Econometric Models

As robustness checks, we also apply SLM and SEM to analyze the effectiveness of the influencing factors on ICEE. The results are displayed in Table 7. For SLM and SEM, ρ and λ are 0.425 (t-value = 9.38) and 0.104 (t-value = 1.98), respectively, illustrating significant spatial spillover effect of neighbors' emission efficiency (or random error). More specifically, regardless of which model we use, the industrialization and the productivity levels positively affect ICEE, whereas the intensity and structure of energy consumption are negatively correlated to the emission efficiency. These results are similar to the relevant findings of SDM. Notably, the coefficient of technological innovation is only −0.003 (t-value = −0.29) under SLM; the same coefficient, however, reaches 0.047 (t-value = 3.17) when we use SEM. A possible implication is that SLM may not capture the impact of technological innovation well. All in all, the significant influence mechanisms for the ICEE of YRB are fairly robust.

Table 7. Regression results of the spatial lag model and the spatial error model.

	Spatial Lag Model	**Spatial Error Model**
IND	0.843 *** (13.97)	0.996 *** (13.44)
FDIP	−0.035 (−1.17)	0.018 (0.51)
RDP	−0.003 (−0.29)	0.047 *** (3.17)
ECS	−0.077 *** (−5.19)	−0.118 *** (−6.23)
EINT	−0.012 *** (−3.55)	−0.022 *** (−5.65)
PROD	0.002 *** (6.46)	0.004 *** (14.54)
R^2	0.6105	0.5082
Log Likelihood	606.7165	573.2985
Spatial parameter ρ or λ	0.425 *** (9.38)	0.104 ** (1.98)

Note: The values in parentheses are the corresponding t values. Spatial parameter ρ (λ) corresponds to SLM (SEM). ** and *** represent the significance levels of 5% and 1%, respectively.

6. Discussion

Carbon emission efficiency (reduction potential) and green-technology efficiency (loss) are linked both conceptually and logically. Based on the green-technology efficiency measurement method, this study forms a comprehensive analytical framework for carbon emission efficiency. By profoundly studying the industrial sector of a typical region in China, our research reflects the urgent need to promote ICEE and facilitate relevant reduction in China. From a practical standpoint, carbon reduction in the industrial sector is a complex and systematic project, requiring a good balance between emission reduction and industrial development. We therefore suggest that the basic prerequisites for low-carbon and high-quality development throughout all aspects of industrial production are to maintain a stable share of the manufacturing sector, to ensure the security of the industrial supply chain, and to meet reasonable demand for industrial products. Meanwhile, it should be noted that the industrial sector will, for some time to come, remain a key driver of China's economy, which implies that this sector still necessitates some total carbon emissions. As the ICEE improves, the room for further carbon reduction lessens. The sector needs to reduce emissions more profoundly, towards the "carbon peak" and "carbon neutrality" goals. It is, therefore, pivotal to clarify the spatial and temporal characteristics of ICEE and its specific influencing channels, so that policymakers can take appropriate and effective measures against excessive carbon emissions.

6.1. Policy Implications

Based on a comprehensive study of ICEE for the provinces and municipalities in YRB, we add to the understanding of the current status of ICEE in the YRB and the challenges facing emission reduction. To develop a low-carbon economy and achieve emission reduction targets, we propose several policy recommendations accordingly. Firstly, the spatial heterogeneity and imbalance in ICEE across YRB require differentiated carbon emission reduction policies. The divisions with high emission efficiency should research and develop more low-carbon technologies and facilitate the free flow and optimal allocation of personnel, technology, and capital. By contrast, those with low emission efficiency are expected to accelerate the "green" upgrading of their industries by eliminating "high-emission" and "high-energy-consuming" production capacities. Secondly, effective means of enhancing ICEE are to improve industrialization and productivity and promote green technological innovation. Thus, all divisions in YRB should raise investment to bring in low-carbon technologies, deepen low-carbon industrialization, and foster the capability of employees to improve the level of productivity. Thirdly, the excessive energy consumption intensity, the coal-dominated energy consumption structure, and the IFDI yield a negative effect on ICEE. Accordingly, these divisions also need to consume less energy and reduce reliance on coal by developing low-carbon industries and optimizing industrial structures. In the meantime, they are supposed to put in place reasonable policies to restrict the entry of high-polluting foreign production projects. Finally, there is a significant spatial spillover effect for the ICEE of YRB. Based on the above discussion, we suggest piloting low-carbon cities as an example and leading role. When a region introduces policies on reducing carbon emissions, it should consider its adjacent regions comprehensively, coordinate reduction policies, and cooperate in low-carbon technologies.

6.2. Research Limitations and Prospects

Overall, this paper achieves our research objectives. It measures the ICEE across YRB from the green-technology efficiency perspective, quantitatively assesses the ICRP based on technical efficiency loss, obtains the spatial and temporal patterns of ICEE and ICRP, and defines their main influencing factors including the spatial dimension. The paper also has some limitations. Firstly, it lacks a thorough investigation into the relevant efficiency of industrial sub-sectors, one that helps introduce and implement more specific reduction policies. Several studies have explored the driving factors that impact the carbon emission efficiency in the service, manufacturing, electricity, gas, water, or metallurgical industries, but these analyses have been conducted primarily at the national level [25,60–62]. Similarly, due to the unavailability of industry-specific data (especially on the influencing factors) of divisions in YRB, this paper lacks further investigation into the ICEE of industrial sub-sectors. Secondly, it fails to figure out all the possible influence mechanisms of the multifaceted issues of carbon emission efficiency and its reduction. To perform mechanism analyses, we select, based on prior literature, six factors that potentially impact ICEE. Although such selection involves multiple aspects, the R^2 of the spatial econometric regression corresponding to the two-way fixed effects model is merely 0.5360. This result indicates that our method dispenses with other effective influencing channels—channels that need to be further explored. Thirdly, while we reveal, via panel data, several significant drivers of ICEE in YRB as a whole, our analysis cannot reflect the heterogeneity of the influencing factors for different divisions. The collective significance of a driver does not necessarily imply its significance for each individual. Thus, another research dimension is to analyze the heterogeneous impacts of the influencing factors on ICEE and ICRP in YRB. Furthermore, such market-based instructions as carbon taxes and carbon trading are also important tools to promote carbon reduction in the industrial sector within the context of the "dual-carbon" goals [63]. Little literature, however, examines in detail the relationship between these tools and carbon emission efficiency. Further research could also be conducted in this direction.

7. Conclusions

Effectively improving the carbon emission efficiency of the industrial sector and promoting its green upgrading is essential for China's efforts to respond to the international consensus on carbon emission reduction and achieve its low-carbon development goal (carbon neutrality). By introducing average carbon output into the SFA model, this paper measures the industrial carbon emission efficiency (ICEE) or green-technology efficiency (GTE) and emission reduction potential of each provincial-level administrative division in YRB from 2000 to 2019. With the help of statistical and spatial econometric methods, we not only analyze YRB's spatial and temporal characteristics for ICEE and its reduction potential, but also clarify several significant influencing channels on emission efficiency, thus forming a complete research paradigm. On this basis, we obtain the following findings:

(1) The γ statistics of all five specific SFA models approach 1, illustrating the reasonability of the SFA method incorporated with average carbon output in measuring ICEE. Moreover, the model that takes into account technological change (model 5) is the best one for estimating the efficiency of industrial carbon emissions for YRB.

(2) On the whole, the ICEE of YRB presents an increasing trend during the sample period. Although the differences in emission efficiency between those regions gradually narrow, the imbalance of ICEE in YRB is still prominent. Spatially, the ICEE of YRB shows an order of "lower reaches > middle reaches > upper reaches," echoing the economic realities in the three sub-areas.

(3) The overall potential for industrial carbon reduction exhibits an upward-to-downward trend with a peak around 2011. Sichuan's potential is much higher than that of other divisions. Notably, in recent years such potential has slowed down, reflecting the serious difficulty facing further reduction. In this regard, the lower reaches of YRB face more challenging tasks.

(4) The ICEE in each division of YRB has a significant spatial spillover effect, and the emission efficiency is influenced by a variety of factors. Specifically, industrialization level, technological innovation, and productivity level have a positive effect on ICEE, while a negative effect comes from energy consumption intensity and a coal-based energy consumption structure. The IFDI ratio, though, is not a significant influencing factor. Additionally, productivity level also exhibits a positive spatial spillover effect, indicating that higher industrial productivity levels in neighboring regions can promote the local ICEE through the flow of experienced personnel, green production technology, or low-carbon-oriented capital.

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