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Regional Differences and Influencing Factors of Carbon Emission Efficiency in the Yangtze River Economic Belt

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Abstract: This paper attempts to measure the carbon emission efficiency of the Yangtze River Economic Belt, which has nine provinces and two cities, by analyzing the panel data of the economic belt from 2010 to 2019. Firstly, we used a three-stage DEA (data envelopment analysis) model to eliminate the influence of environmental factors and random noise and measured the carbon emission of the Yangtze River Economic Belt. Secondly, we used a spatially lagged time-fixed effects model to conduct an in-depth analysis of the factors affecting carbon emissions efficiency in the Yangtze River Economic Zone. The study shows that: (1) There is a significant positive spatial correlation related to the carbon emission efficiency of the Yangtze River Economic Zone. (2) There is a significant regional variability in carbon emission efficiency, and scale efficiency is the primary constraint on its improvement. (3) The higher the share of coal energy, the higher the level of urbanization, and the higher the population density, the less conducive to carbon efficiency. The more developed a region's economy is, the more open it is to the outside world. The stronger its technological capabilities and ecological development, the higher the carbon emission value. (4) Carbon emission efficiency is influenced by a variety of factors, and each factor has a different influence on the carbon emission efficiency of the region and neighboring regions.

Keywords: carbon emission efficiency; the Yangtze River Economic Belt; three-stage DEA; spatial lag model



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1. Introduction

As one of the world's most critical natural resources and wetland ecosystems, the Yangtze River has a unique and complete natural ecosystem. The Yangtze River Economic Zone contains nine provinces and two cities, including Jiangsu, Anhui, Hubei, Zhejiang, Sichuan, Guizhou, Chongqing, Jiangxi, Hunan, Yunnan, and Shanghai, which accounts for more than 40% of China's population and economic output, making it an important area for economic development. As a typical representative of the basin economy, a large number of key industries such as petrochemicals, steel, electromechanical, and automobiles are concentrated in the Yangtze River Economic Belt. On the one hand, these industries promote the development of the Yangtze River Economic Belt; on the other hand, they are the main culprit of environmental pollution.

In particular, massive fossil energy consumption emits excessive carbon dioxide, placing huge pressure on carbon dioxide emission reduction in the Yangtze River Economic Belt and affecting the sustainable development of the Yangtze River Economic Belt. To this end, the Chinese government puts forward that the Yangtze River Economic Belt should follow the principle of "to steep up conservation of the Yangtze River and stop its over development", and adhere to the new way of green development.

To achieve the emission reduction target of the Yangtze River Economic Belt and boost the sustainable economic development, we need to analyze regional differences and influencing factors in carbon emission efficiency of the Yangtze River Economic Belt, so

as to provide a scientific basis for the government to formulate corresponding emission reduction policies. As there are few studies on the carbon emission efficiency of the Yangtze River Economic Belt in the existing literature, this paper will use a three-stage model to study the carbon emission efficiency in the Yangtze River Economic Belt. It will have a crucial theoretical and practical significance and provide targeted policy recommendations for the green and sustainable development of the Yangtze River Economic Belt.

2. Literature Review

Definitions of carbon emission vary among scholars. Generally speaking, the process of humans emitting carbon dioxide and other substances to the outside world in their human production and operating activities is called “carbon emissions”. The ratio between the actual output and the optimal output per unit of carbon dioxide emissions determines its emission efficiency and is called “carbon emission efficiency”. In recent years, many scholars have conducted a lot of research on carbon emissions and other related issues.

Among the research objectives of carbon emission efficiency, scholars have primarily focused on the agriculture and transportation industry sector in recent years. For example, Ball et al. [1], Jane M. F. Johnson [2], John LF et al. [3], and Shang J et al. [4] all studied carbon emission efficiency and its influencing factors from the perspective of agriculture. Maria Mendiluce [5], V.Andreoni [6], and Shao HQ et al. [7] all considered carbon emission efficiency and its influencing factors from the perspective of the transportation industry. In contrast, among the region-based studies, most scholars take cities as example for an in-depth analysis, such as Norman and Mac Lean [8], and Gaigne and Riou [9], who analyzed the influence of various factors in urban development on carbon emissions. Generally speaking, there are few studies on river basins, such as the Yangtze River Economic Belt recently.

There have been much research in the academic circles on measuring carbon emission efficiency, and the most widely used methods are stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Pardo et al. [10] used the SFA model to study the emission intensity of Swedish manufacturing. Ramanathan R [11] used the DEA model to measure the carbon emission efficiency in many countries. Zhou et al. [12] used the DEA model and MCPI index to evaluate the carbon emission efficiency in high-emission countries. Pan et al. [13] used the DEA model to measure the efficiency of comprehensive atmospheric CO₂ emissions management in major polluted regions of China. In addition, there is also a strong relationship between environmental pollution and regional spatial distribution (Repkine A and Min D) [14]; some distance methods are commonly used to measure carbon emission efficiency to estimate the total efficiency of carbon emissions, and thus provide an in-depth analysis of the distribution of spatial agglomerations of efficiency (Wang et al.) [15].

To study the factors affecting carbon emission efficiency, different scholars have analyzed it from different aspects. Fan Ying et al. used the STIRPAT model to analyze the impact of population, economy, and technology on carbon emissions in countries with different levels of development from 1975 to 2000 and found that the impact varied from country to country [16]. On the basis of EKC theory, Iwata studied the impact of the proportion of nuclear power generation and trade in GDP, and the urbanization rate on France’s carbon emissions [17]. Jorgenson et al. used the data of 52 countries to establish a panel data model analysis and found that there was a positively correlated relationship between FDI and the host country’s carbon emissions [18]. Liu Chunmei et al. studied the relationship between carbon emissions and industrial structure in five countries, including the United Kingdom and the United States, showing that the growth of primary and secondary industries can increase carbon emissions, while the increase of tertiary industry can reduce carbon emissions [19].

Literature on regional differences in carbon emission efficiency is mainly reflected in the following aspects. Firstly, different econometric methods are used to analyze regional differences. Ang [20] and Kwon et al. [21] used the factor decomposition method to analyze

the effects leading to differences in carbon emissions. Ramanathan used multiple index factors, comparing the carbon emissions of several countries with envelope analysis [22]. Secondly, there are different regional definitions. In China, for instance, the literature generally divided the area into three regions: the east, the middle, and the west. Of course, some scholars (Li Jinkai et al., 2020) conducted research according to the eight comprehensive economic zones [23]. Thirdly, there are different research perspectives. P. Zhou et al. studied carbon emission efficiency from the perspective of equity [24], while Afton [25] and Liu Y et al. [26] studied from the perspective of efficiency. As the research moves along, the defects of a single-principal perspective are becoming increasingly prominent. Therefore, scholars begin to combine these two principles for research. Wei [27] and Zhou Di et al. [28] studied the regional differences in China's carbon emissions from the perspective of equity and efficiency.

Based on a review of the relevant literature, it can be found that (1) Research on carbon emissions is well established. However, there is not much research in the literature on measuring carbon emission efficiency and the factors influencing it in the Yangtze River Economic Zone. This paper will draw on previous work to examine the carbon emission efficiency of the Yangtze River Economic Zone and the factors influencing it. (2) In terms of efficiency measurement methods, most studies still use traditional DEA models, which do not consider the influence of environmental factors and random noise. Therefore, this paper will choose a three-stage DEA model to measure carbon emission efficiency and improve the accuracy of the measurement. (3) The contribution of each factor to carbon emission efficiency is affected by the spatial distribution of regions, and the analysis of regional differences based on spatial characteristics is the most noteworthy research point in the academic circles. Therefore, this paper will adopt the most appropriate spatial econometric panel model to study the factors influencing carbon emission efficiency in the Yangtze River Economic Zone by comparing multiple spatial models.

3. Description of Data and Variables

This paper uses a panel dataset on nine provinces and two cities in the Yangtze River Economic Belt for the period between 2010 and 2019. The dataset includes total energy consumption, total year-end resident population, fixed asset input, gross domestic product, CO₂ emissions for each region, GDP per capita, the share of secondary industry, the share of coal consumption, the share of total import and export, the share of R&D expenditure, the share of the urban population, ecological environment, and population density. The above data are obtained from the China Statistical Yearbook, China Energy Statistical Yearbook, China Science and Technology Statistical Yearbook, and EPS data platform (an integrated data message service platform based on rich economic data).

Referring to the research methods of scholars (Pan et al., 2017; Li Jinkai et al., 2020) and the most commonly used carbon emission efficiency evaluation index system in the academic community, this paper takes energy consumption, labor, and capital as the input variables, GDP as the expected output variable, and carbon dioxide emissions as the undesirable output variable.

3.1. Description of Input Variables

The first input indicator is energy consumption. China's current production and consumption structure has always been dominated by coal, and this heavy reliance on coal has caused severe environmental problems. The available resources vary from province to province and region to region; energy consumption affects carbon emissions efficiency. The second input indicator is the labor force, expressed using the year-end population of each province or municipality. The larger the labor force in each region, the more carbon emissions it tends to generate. The third input indicator is the scale of fixed asset investment, and this paper chooses the annual amount of fixed asset investment in each province and city to measure the carbon emission efficiency. Industry is the most likely industry among

the three industries to increase carbon emissions, and fixed asset investment plays a very important role in industrial progress.

3.2. Description of Output Variables

The first output indicator is the gross regional product (GRP). Many studies have demonstrated that sizeable economic growth leads to increased carbon emissions. The second output indicator is carbon dioxide emissions, which are calculated by using a model for measuring carbon dioxide emissions in each year for each region. Carbon emission directly impacts the carbon efficiency, and it is an essential output indicator. To measure carbon dioxide emission, the following model is used:

$$CO_2 = \sum_{i=1}^8 A_i \times B_i \times C_i \quad (1)$$

where A_i denotes total energy consumption of the i th type; B_i denotes the discounted standard coal factor; and C_i denotes the CO_2 emission factor (as shown in Table 1).

Table 1. Correlation coefficient of carbon emission estimation.

	Coal	Coke	Crude Oil	Gasoline	Kerosene	Diesel	Fuel Oil	Natural Gas
CO ₂ emission factor	1.9003	2.8604	3.0202	2.9521	3.0179	3.0959	3.1705	3.1013
Discounted Standard Coal coefficient	0.7143	0.9714	1.4286	1.4714	1.4714	1.4571	1.4286	13.3000

Source: Institute of Sustainable Development Strategy, Chinese Academy of Sciences: China Sustainable Development Strategy Report 2009: Explore a low-carbon road with Chinese characteristics [M] Science Press, 2009.

3.3. Selection of Factors Influencing Carbon Emissions

Referring to the conclusions of Li Jianbao et al. (2020) [23], this paper selects the level of economic development, industrial structure, energy results, level of opening up, level of science and technology innovation, level of urbanization, ecological environment, and population density as the main factors affecting the energy efficiency of carbon emissions. It reflects the growth level of economic scale, the growth of the secondary industry as a percentage of the growth, the growth of energy product consumption, the scale of opening up, the level of science and technology innovation, the scale of urbanization, the ecological environment, and population density to explore the impact on carbon emission efficiency.

The final selection of variables and their descriptions are shown in Table 2.

Table 2. Variable selection and description.

Category	Index	Definition of Indicator
Input variables	Energy consumption	The total amount of energy resources consumed by a region
	Labor force	The regional population at year-end
	Investment in fixed assets	Total fixed-asset investment by region
Output variable	GDP	Gross regional product
	Carbon emission	Calculated by a model of carbon dioxide emissions
Influence factor	Economic development level	Per capita GDP
	Industrial structure	The proportion of the added value of secondary industry
	Energy structure	Coal consumption/Energy consumption
	Level of opening-up	Import and export/GROSS regional Product
	Technological innovation level	R&D expenditure/GROSS regional Product
	Urbanization level	The proportion of the urban population
	Ecological environment	Green space per capita
	Population density	Resident population/Area at year-end

4. Model

4.1. Carbon Emission Efficiency Measurement Model Construction: A Three-Stage DEA Model

With regard to carbon emission efficiency, this paper selects a three-stage DEA model to obtain the optimal decision-making unit under the expectation of minimum input for maximum output and compares the relative efficiency between the decision-making units to measure it, with the selection of the appropriate input variables and output variables. The DEA (data envelopment analysis) model was proposed by A. Charnes and W. Cooper (1978). Fried et al. (2002) investigated how to introduce environmental factors and random noise into the DEA model and proposed the famous three-stage DEA model.

The input-oriented BCC model was used in the first phase to measure the carbon efficiency of 11 provinces and municipalities, because the local governments were more flexible in regulating inputs than controlling outputs. The input-oriented BCC models are:

Min θ

$$s.t. \begin{cases} \sum_{i=1}^n \lambda_i x_{ij} + S^- = \theta x_{0j} \\ \sum_{i=1}^n \lambda_i y_{ik} - S^+ = y_{0k} \\ \sum_{i=1}^n \lambda_i = 1 \\ \lambda_i \geq 0; S^- \geq 0; S^+ \geq 0 \end{cases} \quad (2)$$

where $i = 1, 2, \dots, n$ denotes the decision unit, x and y are the input variables and output variables, respectively, S^+ denotes the slack variables, S^- denotes the residual variables, and θ denotes the effective value of the decision unit. The main objective of the first stage is to obtain the slack variable values of the input variables.

The second stage uses SFA regression to remove environmental factors and random noise. In this paper, the raw data are standardized to exclude the effect of the variable magnitude, which is a slight improvement to previous studies. The SFA regression function is:

$$S_{ni,t} = f(Z_{i,t}; \beta_n) + v_{ni,t} + u_{ni,t}, \quad i = 1, 2, \dots, I, n = 1, 2, \dots, N, t = 1, 2, \dots, T. \quad (3)$$

where $S_{ni,t}$ denotes the slack variable value of the n th input variable in year t of the i th decision unit, $Z_{i,t}$ denotes the environmental variables, β_n denotes the coefficient of the environmental variables, $f(Z_{i,t}; \beta_n)$ denotes the influence of environmental variables on input slack variables, and $v_{ni,t}$ and $u_{ni,t}$ denotes the random disturbance term and the management inefficiency term, respectively. The sum of the two is the mixed error term. $v_{ni,t}$ follows a standard normal distribution $N(0, \sigma_{iv}^2)$, and $u_{ni,t}$ follows a normal distribution truncated at zero $N^+(\mu^i, \sigma_{iv}^2)$.

The third stage is mainly based on the adjusted variable data for DEA analysis. At this point, the efficiency values have removed the influence of environmental factors and random noise, which can more truly and accurately reflect the carbon emission efficiency of each region.

4.2. Modelling the Factors Influencing Carbon Efficiency: A Spatial Lag Model

Considering that the factors influencing carbon emission efficiency are spatially related, this paper constructs spatial econometric models, including spatial Durbin model (SDM), spatial lag model (SLM), and spatial error model (SEM). According to the LM test results, this paper uses the spatial lag model (SLM) for analysis. The spatial lag model, which is an autoregressive model that considers spatial variables, is as follows.

$$y = \rho W y + \ln X \beta_1 + W \ln \bar{X} \beta_2 + \varepsilon \quad (4)$$

In the formula, y denotes the measured carbon emission efficiency, X denotes the independent variable matrix, which is the eight factors affecting the carbon emission efficiency, and all the independent variable data are taken via logarithmic processing. $\bar{X}$ denotes a non-linear variable matrix of independent variables, and W denotes a matrix of spatial distance weights. This paper selects proximity matrix as the weight matrix W

because of the easily recognizable relations in each region and the optimization of proximity for model estimation. $Wln\bar{X}$ denotes the spatially lagged variable of the mean observations in adjacent regions; β_1 denotes a vector of independent variable X 's coefficients; β_1 denotes a spatial autocorrelation coefficient of an exogenous variable to measure the marginal utility of the independent variable for the dependent variable in adjacent regions within it; ρ denotes the spatial effect coefficient; and ε denotes a random error term satisfying a normal cell-independent co-distribution.

5. Empirical Analysis

5.1. Analysis of Carbon Emission Efficiency in the Yangtze River Economic Zone

(1) Analysis of second-stage SFA regression results

In the first stage, carbon efficiency was calculated through stata software, which allowed the output of initial efficiency values and their input slack variables in 11 regions. The dependent variables considered are the energy consumption slack variable, labor force slack variable, and fixed asset input slack variable. The independent variables considered includes industrial structure, level of opening up, level of science and technology innovation, level of urbanization, and ecological environment. Three SFA regression equations were established separately, the data of the independent variables were standardized, and the regression results obtained are shown in Table 3.

Table 3. SFA regression result.

Dependent Variable	Energy Consumption Slack Variables	Workforce Slack Variables	Fixed Asset Input Slack Variables
Constant term	467.679 (6210.361)	2383.457 (67,868.300)	1023.872 (5732.309)
Industrial structure	−244.922 (230.777)	−32.822 (773.264)	−584.707 *** (213.303)
Level of opening up	557.756 (560.938)	3449.640 ** (1879.534)	1133.145 *** (522.927)
Technological innovation level	−736.066 (549.891)	−7223.487 *** (1842.520)	−2176.958 *** (504.822)
Urbanization level	−1638.776 (630.665)	−7416.414 *** (2113.167)	−1536.690 *** (578.762)
Ecological environment	−65.0770 (809.369)	−4407.252 (2711.951)	−2466.451 *** (757.045)
σ^2	4,005,023 *** (540,037)	45,000,000 *** (6,063,092)	3,370,858 *** (456,607)
Wald Chi2	10.14	25.20	35.02
p value	0.0714	0.0001 ***	0.0000 ***

Note: ** means significant at the level of 1%; *** means significant at the level of 0.1%.

As shown in Table 3, the p -values of the regression equations for the slack variables of labor force and fixed asset input are less than 0.05, and the Wald chi-square statistics are relatively large, indicating that there is a significant influence of environmental and random factors on the calculation of efficiency as a whole. The p -value of the regression equation for the slack variable of energy consumption exceeds 0.05, indicating it statistically insignificant by environmental and stochastic factors. Columns 1–3 indicate the effect of environmental factors on energy consumption redundancy, labor force redundancy, and fixed asset input redundancy, respectively. The coefficient of industrial structure is significantly negative, indicating that an increase in the share of secondary industry will weaken the redundancy of the three input variables, thus enhancing carbon emission efficiency. The coefficient of the level of openness to the outside world is significantly positive, indicating that as the volume of import and export trade increases, the greater the value of redundancy of the three input variables, and the lower the carbon emission efficiency. The coefficients of the level of science and technology innovation, the level of urbanization, and the ecological

environment are harmful and have a significant effect on the labor force slack variable. The coefficients for the level of science and technology innovation, the level of urbanization and the ecological environment are harmful, and significantly negative for the slack variables of fixed asset input, indicating that as the level of science and technology innovation increases, the proportion of urban population increases and the ecological environment improves, and the redundancy of the labor force and fixed asset input decreases, which can significantly improve carbon emission efficiency; although the regressions of these three variables on the redundancy of energy consumption are not significant, there is still the same trend as above.

(2) Carbon emission efficiency analysis

The original variables of labor force inputs and the original variables of fixed asset inputs were adjusted according to the results of the SFA model for the 11 regions, and the new input values were obtained by removing the effects of environmental factors and random noise. The final efficiency values were calculated. Table 4 shows the results of carbon emission efficiency in the first and third stages, including the comprehensive technical efficiency, pure technical efficiency, and scale efficiency. Among them, the pure technical efficiency indicates the influence of enterprise management and technology on production efficiency, the scale efficiency indicates the influence of enterprise scale on production efficiency, and the comprehensive technical efficiency is equal to the product of pure technical efficiency and scale efficiency, indicating the carbon emission efficiency in each region.

Table 4. Carbon emission efficiency in the first and third stages.

Region	Stage 1 Efficiency				Stage 3 Efficiency				Ranking Changes
	Comprehensive Technical Efficiency	Pure Technical Efficiency	Scale Efficiency	Rank	Comprehensive Technical Efficiency	Pure Technical Efficiency	Scale Efficiency	Rank	
Jiangsu	0.836	1.000	0.836	6	1.000	1.000	1.000	1	+5
Shanghai	1.000	1.000	1.000	1	1.000	1.000	1.000	1	0
Anhui	1.000	1.000	1.000	1	1.000	1.000	1.000	1	0
Zhejiang	0.898	1.000	0.898	4	0.999	0.999	1.000	4	0
Sichuan	0.881	0.897	0.982	5	0.932	0.971	0.960	5	0
Hunan	0.784	0.822	0.954	9	0.905	0.974	0.930	6	+3
Jiangxi	0.787	0.815	0.961	8	0.883	0.979	0.902	7	+1
Hubei	0.726	0.752	0.966	10	0.825	0.935	0.885	8	−2
Yunnan	0.823	0.872	0.939	7	0.809	1.000	0.814	9	−2
Guizhou	0.923	0.929	0.993	3	0.748	0.974	0.771	10	−7
Chongqing	0.507	0.522	0.973	11	0.676	0.890	0.763	11	0

As shown in Table 4, the comprehensive technical efficiency of carbon emissions calculated in Stage 3 is generally higher than Stage 1. The adjusted efficiency values are significantly higher than those measured by traditional DEA, which indicates that environmental factors and random noise in each province reduce the efficiency of government investment and that traditional DEA methods can underestimate investment efficiency. After removing the environmental and noise impacts, Shanghai, Jiangsu, and Anhui reached complete efficiency. In terms of ranking changes of the overall technical efficiency ranking, Guizhou's ranking dropped the most by seven places, and Jiangsu's ranking rose the most by five places. Environmental factors and random factors influence the comprehensive technical efficiency of carbon emissions in these regions to a greater extent.

The comprehensive technical efficiency of carbon emissions in the Yangtze River Economic Belt shows apparent differences between regions. The average comprehensive technical efficiency of carbon emissions in the lower reaches of the Yangtze River is generally greater than that in the middle reaches of the Yangtze River, while the average comprehensive technical efficiency of carbon emissions in the middle reaches of the Yangtze River is generally greater than that in the upper reaches of the Yangtze River. Shanghai, Jiangsu, and Zhejiang, which are in the lower reaches of the Yangtze River, have

significantly higher comprehensive technical efficiency of carbon emissions than Yunnan, Guizhou, and Sichuan provinces, which are in the upper reaches of the Yangtze River. Shanghai and Jiangsu have a comprehensive technical efficiency value equal to 1 and are located at the production frontier side; Zhejiang has a comprehensive technical efficiency value of 0.999, which is almost close to 1. These regions are located in the developed eastern coastal region, with a fast level of scientific and technological innovation and a high level of clean technology, thus showing a higher comprehensive technical efficiency of carbon emissions. Chongqing, Guizhou, and Yunnan's comprehensive technical efficiency of carbon emissions values are almost all below 0.8, which is mainly because these regions are in western China. There are significant constraints on economic development and immature technologies related to energy conservation and emission reduction. At the same time, these provinces have great potential for improving their comprehensive technical efficiency of carbon emissions.

In terms of the differences between pure technical efficiency values and scale efficiency values across provinces and cities, the differences between pure technical efficiency and scale efficiency values are more significant in the upper reaches of the Yangtze River such as Chongqing, Guizhou, and Yunnan, indicating that the development of pure technical efficiency and scale efficiency in these three regions is uneven. The pure technical efficiency and scale efficiency of the lower reaches of the Yangtze River of Jiangsu, Anhui, Shanghai, and Zhejiang are close to 1. Overall, pure technical efficiency is almost higher than scale efficiency in all regions. At this stage, scale efficiency is the most critical constraint on carbon emission efficiency.

5.2. Analysis of Factors Influencing Carbon Emission Efficiency in the Yangtze River Economic Belt

(1) Test of spatial effects

For the measure of spatial autocorrelation, this paper uses stata software to calculate the global Moran's I index of carbon emission efficiency of provinces and cities in the Yangtze River Economic Zone from 2010 to 2019, and the results are shown in Table 5.

Table 5. Global Moran's I index.

Year	<i>I</i>	<i>E(I)</i>	<i>sd(I)</i>	<i>z</i>	<i>p</i> -Value
2010	0.175	−0.100	0.190	1.444	0.074
2011	0.442	−0.100	0.194	2.794	0.003
2012	0.468	−0.100	0.194	2.921	0.002
2013	0.364	−0.100	0.189	2.459	0.007
2014	0.322	−0.100	0.181	2.336	0.010
2015	0.327	−0.100	0.178	2.406	0.008
2016	0.333	−0.100	0.182	2.380	0.009
2017	0.280	−0.100	0.185	2.057	0.020
2018	0.190	−0.100	0.191	1.515	0.065
2019	0.178	−0.100	0.193	1.436	0.075

Except for 2010, 2018, and 2019, where each index failed to pass the 5% significance level test entirely, each index for the remaining years was significant at the 5% level, and the Moran's I average index was more significant than 0. Figure 1 is the local Moran scatter plots for 2010, 2012, 2014, 2016, 2018, and 2019. There is a clear positive spatial autocorrelation, thus requiring a spatial econometric model

(2) Selection of spatial econometric models

The spatial Durbin model (SDM) was used as the baseline model, and then LM tests were conducted on the spatial lag model (SLM) and spatial error model (SEM) results, which are shown in Table 6.

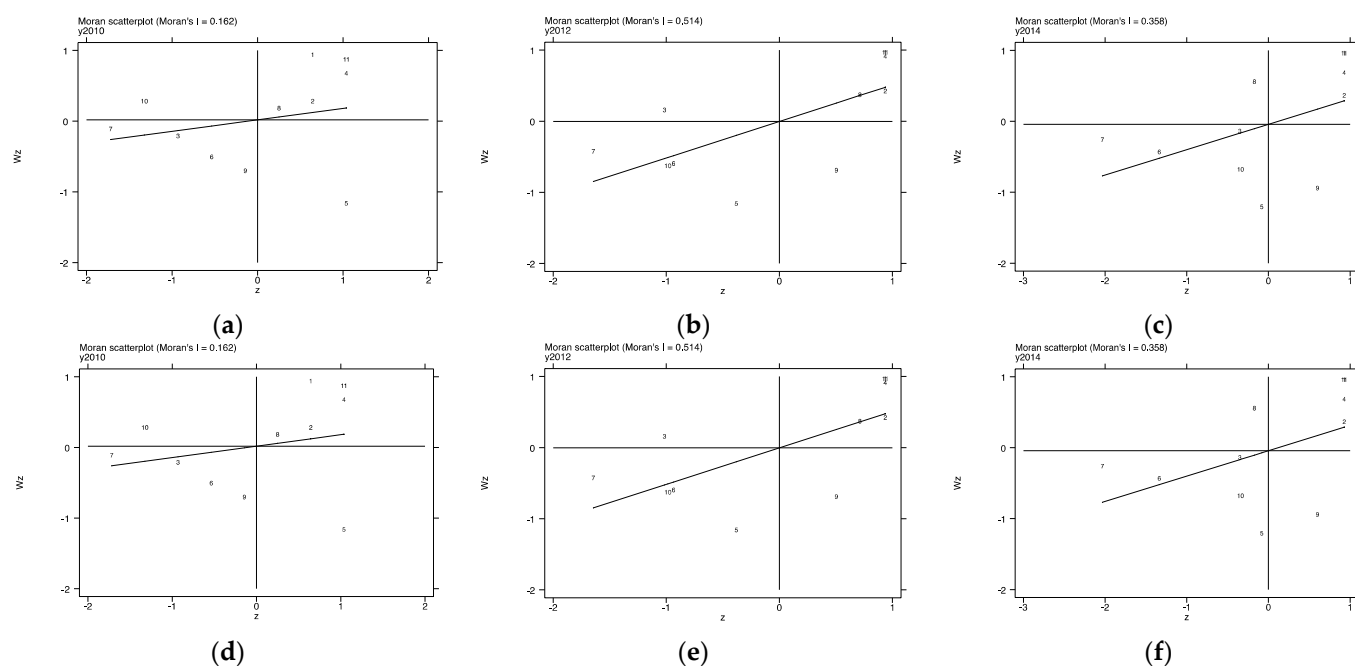


Figure 1. The local Moran scatter plots of each year. Note: Figures (a–f) show the local Moran scatter diagram of 2010, 2012, 2014, 2016, 2018, and 2019 respectively.

Table 6. LM test results.

Model	Method	Fixed Effect Model		Random Effects Model	
		Chi-Squared Statistic	<i>p</i> Value	Chi-Squared Statistic	<i>p</i> Value
Spatial lag model	LM test	100.99	0.0000	15.84	0.0438
	Robust LM test	45.97	0.0002	113.05	0.0000
Spatial error model	LM test	96.87	0.0000	15.90	0.0447
	Robust LM test	34.53	0.0002	81.70	0.0000

As shown in Table 6, all models passed the significance test. Using the spatial Durbin model as the benchmark and either the fixed effects model or the random-effects model, the values of the statistics of the spatial lag model all are greater than those of the spatial error model. Therefore, this paper tends to choose spatial lag model.

(3) Spatial lag model analysis

Table 7 presents the four spatial lag models calculated by stata software; Model 1 to 3 are fixed-effect models, and Model 4 is a random effect model. The dependent variable is the comprehensive technical efficiency of carbon emissions in the third stage, and the independent variables are logarithmic. Hausman's test's chi-square statistic is 19.33, with a *p*-value of 0.0132, suggesting that a fixed-effects model should be chosen. For the choice of temporal, individual, or two-way fixed effects models, this paper chose the model with the largest R^2 as the final spatial econometric model, with the corresponding R^2 for the three being 0.535, 0.262 and 0.244, respectively. Therefore, the temporal fixed effects spatial model was used for the subsequent analysis.

Table 7. Spatial lag model estimation results.

Model	Time Fixed Effects	Individual Fixed Effects	Two-Way Fixed-Effect	Random Effects
Level of economic development	0.1408 ** (0.0694)	−0.0272 (0.0532)	−0.0666 (0.1163)	−0.0162 (0.0635)
Industrial structure	−0.1064 (0.0892)	−0.1235 (0.0837)	−0.2541 ** (0.1125)	−0.0532 (0.0959)
Energy structure	−0.0461 ** (0.0226)	−0.0233 (0.0147)	−0.0212 (0.0156)	−0.0126 (0.0173)
Level of opening up	0.0985 *** (0.0214)	−0.0146 (0.0204)	−0.0405 * (0.0220)	0.0166 (0.0222)
Technological innovation level	0.1828 *** (0.0438)	−0.0543 (0.0549)	−0.0170 (0.0659)	0.0002 (0.0630)
Urbanization level	−0.5784 *** (0.1375)	0.0451 (0.1531)	0.2194 (0.1584)	−0.1429 (0.1794)
Ecological environment	0.0678 * (0.0395)	0.1493 * (0.0816)	0.1056 (0.0809)	0.0490 (0.0843)
density of population	−0.1390 ** (0.0587)	−2.3602 *** (0.4198)	−2.1895 *** (0.3945)	0.0633 (0.0647)
rho	−0.4612 *** (0.1226)	−0.0694 (0.1370)	−0.2943 (0.1503)	−0.1932 (0.1448)
sigma2_e	0.0052 *** (0.0007)	0.0015 *** (0.0002)	0.0013 *** (0.0001)	0.0022 *** (0.0003)
Observations	110	110	110	110
R-squared	0.535	0.262	0.244	0.233

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Most of the variables in the time-fixed effects model passed the significance test. ρ error was -0.4612 , p -value < 0.01 , significant at the 1% level, indicating that there is a spatial spillover effect of carbon emission efficiency among cities in the Yangtze River Economic Belt region. Based on their estimated coefficients, the direct and indirect effects were deduced, and the results are shown in Table 8.

Table 8. Effect decomposition of spatial lag model.

	LR_Direct	LR_Indirect	LR_Total
Economic development level	0.1517 ** (0.0751)	−0.0518 * (0.0281)	0.0999 * (0.0515)
Industrial structure	−0.1168 (0.0925)	0.0429 (0.0371)	−0.0739 (0.0577)
Energy structure	−0.0515 ** (0.0232)	0.0181 * (0.0095)	−0.0334 ** (0.0150)
Level of opening-up	0.1050 *** (0.0232)	−0.0366 *** (0.0125)	0.0684 *** (0.0151)
Technological innovation level	0.1942 *** (0.0440)	−0.0676 *** (0.0235)	0.1266 *** (0.0290)
Urbanization level	−0.6069 *** (0.1436)	0.2077 *** (0.0642)	−0.3992 *** (0.1088)
Ecological environment	0.0716 * (0.0374)	−0.0241 (0.0231)	0.0475 * (0.0261)
Density of population	−0.1522 ** (0.0630)	0.0528 ** (0.0258)	−0.0993 ** (0.0416)
Observations	110	110	110
R-squared	0.535	0.535	0.535
Number of areas	11	11	11

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2.1. Scale of Economic Development

The direct and indirect effects of the level of economic development on carbon emission efficiency are significantly positive and negative, with elastic coefficients of 0.1517 and

−0.0518, respectively, indicating that the scale of economic development has a positive effect on the carbon emission efficiency of the city and a negative effect on the carbon emission efficiency of neighboring provinces and cities. The GDP per capita of the region has a long-term and steady growth relationship with carbon emissions, and the indicator of economic development in this paper is measured by the regional GDP per capita. This means that the scale of economic development has a significant effect on the growth of carbon emission efficiency.

5.2.2. Level of Secondary Sector Share

The direct and indirect effects of industrial structure on carbon efficiency are negative and positive, respectively, but do not pass the significance test. The elasticity coefficient of the direct effect of the share of secondary industry on carbon emission efficiency is negative, indicating a tendency for carbon emission efficiency to increase as the share of secondary industry decreases. The coefficient of elasticity for neighboring provinces and cities is positive, indicating that increasing the share of the secondary sector contributes to increasing carbon emission efficiency in neighboring provinces and cities. Most of the secondary industries are new industries with high carbon emissions and energy consumption, which are important sources of carbon dioxide, and their corresponding carbon emissions are relatively inefficient.

5.2.3. Energy Consumption Levels

The direct and indirect effects of energy consumption structure on carbon emission efficiency are significantly negative and positive, respectively. The elasticity coefficient of the direct effect of energy consumption on carbon emission efficiency is −0.0515, indicating that the lower energy consumption, the higher carbon emission efficiency. The elasticity coefficient of the spatial spillover effect of energy consumption level on carbon emission efficiency in neighboring provinces and cities is 0.0181, indicating that raising the energy consumption level in the region will contribute to the improvement of carbon emission efficiency in neighboring provinces and cities. As the main source of carbon emissions, coal has a significant impact on regional carbon emission efficiency. Moreover, the regional energy consumption level will have a positive spatial spillover effect on the neighboring regions, forming a demonstration effect to push the neighboring regions to continuously optimize and upgrade their energy consumption and promote the improvement of carbon emission efficiency.

5.2.4. The Scale of Opening Up

The direct and indirect effects of opening up on carbon emission efficiency are significantly positive and negative, respectively. The direct effect coefficient of opening-up level is 0.1050, indicating that the larger the scale of openness is, the higher the carbon emission efficiency is. The elasticity coefficient of the spatial spillover effect of external openness on the carbon emission efficiency of neighboring provinces and cities is −0.0366, indicating that reducing the scale of external openness will help neighboring provinces and cities improve their carbon emission efficiency. The scale of external openness is an important factor influencing regional carbon emissions. The development of external trade will cause an increase in resource consumption, which will be detrimental to the improvement of carbon emission efficiency.

5.2.5. Level of Science, Technology, and Innovation

The direct and indirect effects of the level of STI on carbon emission efficiency are significantly positive and negative with elastic coefficients of 0.1942 and −0.0676, respectively, indicating that the level of science and technology innovation has a positive effect on carbon emission efficiency. As technology continues to innovate, there is a significant increase in energy efficiency. On the contrary, it has a negative effect on the carbon emission efficiency of neighboring provinces and cities, indicating that the technological progress in this region

may make the scale of energy exploration, exploitation, and production in neighboring regions expand, leading to a very obvious increase in energy input in neighboring regions, which to a certain extent, causes energy waste and inefficient use, which is not conducive to the improvement of carbon emission efficiency.

5.2.6. Scale of Urbanisation

The direct and indirect effects of urbanization level on carbon emission efficiency are significantly negative and positive, with elasticity coefficients of -0.6069 and 0.2077 , respectively. The scale of urbanization in the Yangtze River Economic Zone is higher, the management and technology levels are higher, but increasing the scale of urbanization is not conducive to the improvement of carbon emission efficiency, as excessive urbanization construction overdraws economic development and attracts a large number of people to move in. It is not conducive to the allocation of resource utilization. The spatial spillover effect of urbanization scale on the carbon emission efficiency of neighboring provinces and cities is positive, indicating that increasing the scale of urbanization in the city is conducive to the improvement of carbon emission efficiency in neighboring provinces and cities.

5.2.7. Ecological Environments

The direct and indirect effects of green space per capita on carbon emission efficiency are positive and negative, respectively. The direct effect is significant, with an elastic coefficient of 0.0716 , indicating that green space per capita has a positive effect on carbon emission efficiency, and ecological environmental protection is conducive to the improvement of carbon emission efficiency. All regions should further strengthen the cooperation with international ecological environment management and protection, and jointly maintain a good ecological environment, to improve carbon emission efficiency while protecting the environment. The indirect effect is not significant, indicating that the increase in green space per capita does not have a significant impact on the carbon emission efficiency of neighboring provinces and cities.

5.2.8. Population Density

The direct and indirect effects of population density on carbon emission efficiency are significantly negative and positive, respectively, and the elastic coefficient of the direct effect is -0.1522 , indicating that population density has a negative effect on carbon emission efficiency. Within a certain threshold, areas with higher values of population density tend to produce agglomeration effects, and too much population means consuming too many resources, which is not conducive to improving carbon emission efficiency. The elastic coefficient of the impact on the carbon emission efficiency of neighboring municipalities is 0.0528 , indicating that the increase in population density in the region will, to a certain extent, alleviate the population pressure in neighboring regions through population mobility, which is conducive to the improvement of carbon emission efficiency in neighboring regions.

6. Conclusions and Policy Implications

This paper uses the three-stage DEA model to measure the carbon emission efficiency of the Yangtze River Economic Belt and its regional differences. Additionally, it also uses the spatial lag time fixed effect model to analyze the factors affecting the carbon emission efficiency of the Yangtze River Economic Belt. The following conclusions are found through research:

Firstly, the results suggest that there is a significant positive spatial correlation of carbon emission efficiency in the Yangtze River Economic Belt, especially in the upper, middle, and lower reaches, which is a supplement to previous research. Since 2010, China's carbon emissions have risen yearly, with significant regional differences in carbon emission efficiency. Carbon emission efficiency in the lower reaches of the Yangtze River is obviously higher than that in the middle and upper reaches of the Yangtze River, showing

a continuous distribution of areas with higher carbon emission efficiency and lower carbon emission efficiency.

Secondly, there is an apparent regional variation in carbon emission efficiency. In terms of pure technical efficiency, the provinces and cities with completely effective efficiency values are mainly located in the lower reaches of the Yangtze River. In terms of scale efficiency, the scale efficiency value in the middle and upper reaches of the Yangtze River is low, which harms improving carbon emission efficiency. Overall, most provinces and cities in the middle and upper reaches of the Yangtze River Economic Belt have carbon emission efficiency values less than 1, indicating that there is much room for improving carbon emission efficiency in the middle and upper reaches of the Yangtze River. That scale efficiency is the main factor limiting the carbon emission efficiency improvement.

Thirdly, in the spatially lagged time-fixed effects regression model, all variables except industrial structure pass the significance test, where the higher the share of coal energy, the higher the level of urbanization, and the denser the population, the less conducive to the improvement of carbon emission efficiency; the more developed the regional economy, the higher the degree of openness to the outside world, and the stronger the technological capability and the better the ecological development, the higher the carbon emission efficiency. This conclusion is basically consistent with that of most scholars, except that the prominent role played by the industrial structure has not been found in this paper.

Fourthly, carbon emission efficiency is influenced by various factors, and each factor has a different degree of influence on the region and neighboring regions. This paper shows that the scale of economic development can improve the carbon emission efficiency of the region but has a negative impact on neighboring regions; the level of energy consumption helps to improve the carbon emission efficiency of the region and neighboring regions; the expansion of the scale of the opening up is not conducive to the improvement of carbon emission efficiency of neighboring provinces and cities; the level of scientific and technological innovation has a positive impact on the carbon emission efficiency of the region, but the opposite for neighboring regions; and the expansion of the scale of urbanization is not conducive to the carbon emission efficiency of the region. The increase in the scale of urbanization is not conducive to the improvement of carbon emission efficiency in the region and is conducive to the improvement of efficiency in neighboring regions. The ecological environment has a positive effect on the carbon emission efficiency of the region; the population density is not conducive to improving the carbon emission efficiency of the region, but the opposite for the adjacent regions through population movement.

This study will help to promote the carbon emission efficiency and green growth of the Yangtze River Economic Belt. The policy implications of this paper include the following points:

Firstly, the transformation of the regional economic development mode should be accelerated to build a resource-saving and environmentally friendly society. For the economically underdeveloped upper reaches such as Yunnan, Sichuan, Guizhou, and Chongqing, it is necessary to encourage the transformation and upgrading of traditional industries and promote green development with digital economy. In addition, it is also necessary to effectively improve the efficiency of resource utilization and pollution reduction and cultivate a group of emerging industries with high scientific and technological content, and low resource consumption and environmental pollution. For Hubei, Hunan, Jiangxi, and other middle reaches of the Yangtze River, the economic level is growing. The rapid expansion of the economy has led to increasingly serious problems such as the low scale of economic development, redundant resource inputs, and damage to the ecological environment. It is urgent to change the economic development mode. For coastal provinces and cities such as Shanghai, Jiangsu, and Zhejiang in the lower reaches of the Yangtze River, the development mode of foreign trade should be further adjusted to improve foreign trade products' quality and technological content to avoid excessive consumption of resources. Rational planning of urban layout, active introduction of low energy consumption and recyclable industries, elimination of energy-consuming, environmentally polluting, technologically backward

processes and products, and promotion of coordinated development of the ecological economy are also needed.

Secondly, encourage scientific and technological innovation to accelerate the transformation of energy consumption. Government departments should increase investment in scientific and technological innovation in the middle and upper reaches of the Yangtze River, maintaining steady development in science and technology, formulating different development strategies for industries with different levels of technology, and promoting the improvement of carbon emission efficiency of industries. Government departments should also promote the use of clean energy, change the pattern of coal as the primary energy consumption and correctly understand the critical position of the level of scientific and technological innovation in social progress to achieve a long-term endogenous emission reduction mechanism.

Thirdly, make coordinated planning and promote coordinated regional development to cope with global climate change and realize carbon emission reduction requires cooperation among regions. The Yangtze River Economic Zone has not yet formed a carbon emission pooling effect, and there is a lack of joint emission reduction practices between regions. Shanghai, Zhejiang, and other lower reaches of the Yangtze River have a high level of science and technology and strong economic effects. Efforts should be made to form a regional community and promote the flow of technology, capital, and other factors to the middle and lower reaches, especially to Yunnan, Guizhou, and Sichuan, in order to boost the overall carbon emission efficiency.

There are two main deficiencies in this paper. First of all, this paper chooses a three-stage DEA model to measure the carbon emission efficiency, mainly excluding the interference of environmental factors. However, due to data availability limitations, some potential environmental factors affecting the carbon emission efficiency have been left out of consideration. Secondly, this paper selects a proximity matrix as the spatial distance matrix, without selecting other spatial distance matrices for further comparative analysis to ensure the robustness of the results. Based on this, this paper expects to quantify some important potential environmental variables in the future and incorporate them into the model, enabling more accurate results of the three-stage DEA model. In addition, more credible conclusions can be obtained by selecting different spatial distance matrices and other robust analysis methods.

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