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Driving Factors and Spatial Temporal Heterogeneity of Low-Carbon Coupling Coordination between the Logistics Industry and Manufacturing Industry

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Abstract: The low-carbon coupling coordination of the logistics industry and manufacturing industry is an ecological innovation organization that integrates economic benefits, social benefits, and ecological benefits under strict carbon emission constraints. In order to control or reduce the carbon dioxide emission of the two industries, it is very important to understand the driving factors of emission change and formulate effective carbon policy. The Yangtze River Delta has developed manufacturing clusters and a perfect logistics system. The Yangtze River Delta region is taken as an example. Firstly, the coupling coordination model is used to calculate the low-carbon coupling coordination scheduling of the region. Then, the spatiotemporal geographically time-weighted regression model (GTWR) is used to explore the spatial heterogeneity of driving factors of low-carbon coupling coordination. The empirical results show the following: the low-carbon coupling coordination in the Yangtze River Delta is at a good coordination, and each driving factor has a positive effect on the coupling coordination. From the regional city level and time change level, the regression coefficients of each driving factors are analyzed, and it is found that the impact of driving factors on low-carbon coupling is significantly different between large cities and small and medium-sized cities, and the spatial heterogeneity of driving factors is significant. Specifically, the marginal impact of human capital, technological progress, and urbanization level on the low-carbon coupling between logistics and manufacturing in the Yangtze River Delta is increasing year by year; the marginal impact of international trade, industrial policy, and foreign investment on the Yangtze River Delta is decreasing year by year; and the marginal impact of capital investment and infrastructure on the Yangtze River Delta is relatively stable. Finally, according to the heterogeneity of driving factors in cities of different sizes, the corresponding development suggestions are put forward.

Keywords: logistics and manufacturing; low-carbon coupling coordination; driving factors

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1. Introduction

Most developed countries have promised to achieve carbon neutrality by 2050. The United Kingdom was the first to propose a "low-carbon economy". From the current foreign literature and practice, there are numerous policy efforts to achieve low-carbon development [1]. The European Union and the United Kingdom achieved a carbon peak in 1990, while the United States achieved a carbon peak around 2005. China has only committed to achieving carbon neutralization from its carbon peak in about 30 years, which is far shorter than that of developed countries [2]. Therefore, the development pressure of China's low-carbon industry is even greater.

China's logistics and manufacturing industries emit too much carbon dioxide, which has brought a heavy burden to the environment and has become the main factor restricting the sustainable development of the economy [3,4]. In September 2020, China proposed that carbon dioxide emissions should reach the peak by 2030 and strive to achieve carbon neutrality by 2060. The vision of "carbon peak" and "carbon neutral" has defined a new direction for the low-carbon development of China's logistics and manufacturing industry and put forward new requirements for accelerating the carbon emission reduction of logistics and manufacturing industry.

The coupling coordination of the logistics industry and manufacturing industry belongs to the category of industrial linkage, which means linkage and interaction. It emphasizes the internal relationship between industries and the initiative of communication and response among multiple subjects. There are many definitions and literature works about the linkage between the two industries [5,6], but in the current situation of a low-carbon economy, it is not enough to only consider the coupling coordination of economic benefits. If the high-speed development of the two industries brought by the linkage is at the cost of high input and high consumption of natural resources, it is not advisable, and it is urgent to solve the problem of low-carbon coupling coordination between the two industries.

As shown in Figure 1, this paper holds that the low-carbon coupling coordination of the logistics industry and manufacturing industry is an ecological innovation organization, which integrates economic benefits, social benefits, and ecological benefits under strict carbon emission constraints. With the support of modern energy and emission reduction technology and modern information technology, the coordinated low-carbon development of warehousing, distribution, transportation, manufacturing, and other links can be realized. Finally, the logistics industry and manufacturing industry can break through the green trade barriers in the international market. We will jointly build a green core competitiveness system of the two industries. The purpose of low-carbon coupling coordination is the continuous improvement of carbon productivity, and the essence of low-carbon coupling coordination is the low-carbon and efficient coordinated development of the two industries, so as to realize the carbon peak and carbon neutralization of the logistics industry and manufacturing industry, and to realize the healthy and sustainable development of the logistics industry and manufacturing industry.

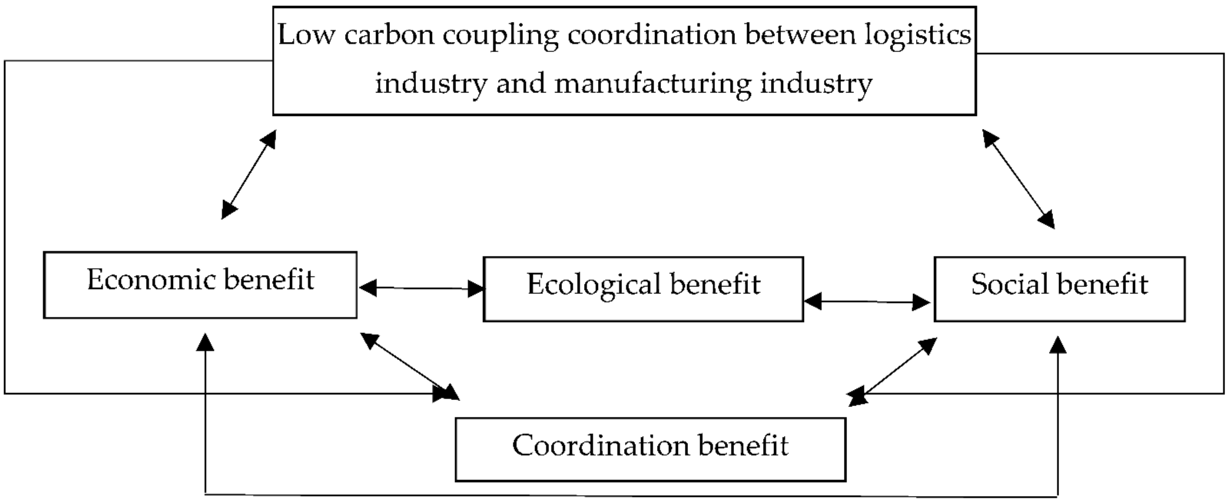


Figure 1. Low-carbon coupling coordination model between logistics industry and manufacturing industry.

As the region with the fastest economic growth and the largest economic aggregate in China, the Yangtze River Delta region has more emissions than other industrial areas in China [7]. The Yangtze River Delta is an important gathering area of China's advanced manufacturing industry. As the forefront of China's reform and opening up, the Yangtze River Delta region pays more and more attention to the interactive development of the service industry, especially the producer service industry and manufacturing industry, drives the transformation and upgrading of the manufacturing industry, improves the comprehensive competitiveness of the regional manufacturing industry, and effectively promotes the implementation of the national strategy of Yangtze River Delta integration.

The next ten to twenty years will be a period of great strategic opportunities for the development of China's logistics industry and an important period for the logistics industry to reduce costs and increase efficiency and enhance competitiveness. At the same time, China will basically realize industrialization, which is also a major opportunity period for the upgrading of China's manufacturing industry [8]. The research on the coupling coordination of the logistics industry and manufacturing industry has important practical significance for promoting the transformation and upgrading of the manufacturing industry in Yangtze River Delta, realizing the high-quality development of regional logistics, promoting the development of the regional economy, and realizing the goal of made in China 2025 (National Development and Reform Commission of the people's Republic of China, 2020).

The development of industry and the protection of the environment are always closely related to the research focus. In terms of theoretical analysis of industrial development and environmental policy, financial policy and environmental pollution [9], education and environmental policy [10], environmental policy and growth of market economy [11], and social status preference and environmental policy [12] all have relatively mature research results.

In terms of empirical research on the driving factors of low-carbon logistics industry, the following works exist: The impact of low-carbon management on corporate carbon performance [13]. The impact of logistics parks on the design of low-carbon logistics networks in urban areas [14]. The location routing problem of low-carbon logistics [15]. The impact of economic development level on low-carbon logistics [16]. Low-carbon logistics path planning of multiple distribution stations [17]. The selection of the best low-carbon logistics service providers [18].

In terms of empirical research on driving factors of low-carbon manufacturing industry, the following works exist: Low-carbon technological innovation is the key to low-carbon development of manufacturing industry [19]. Low-carbon transformation and upgrading of existing manufacturing equipment and processes is an important aspect of low-carbon development of manufacturing industry [20]. The cooperation and competition of manufacturers is the way to reduce the total carbon emissions [21]. The impact of different types of environmental regulations on low-carbon manufacturing practices [22]. Consider the impact of ordinary manufacturers and low-carbon manufacturers on carbon emissions in the supply chain [23]. The impact of environmental awareness on green innovation [24]. The impact of supply chain on carbon emissions of manufacturers in the case of asymmetric information [25]. The optimal emission reduction of low-carbon closed-loop supply chain [26].

Based on the results of the above literature, in terms of theoretical research, although the theoretical research on the relationship between industrial development and environment has been relatively mature, the amount of research on the driving factor mechanism of low-carbon industrial development is still less. In terms of empirical research, it is found that the driving factors of low-carbon logistics and low-carbon manufacturing are studied by scholars from different perspectives. However, there is still a lack of research on the impact of these driving factors on the coupling of low-carbon industries. Although some scholars have analyzed the influencing factors from the aspects of industrial interaction [27–29], industrial development stage [6], industrial synergy [30], strategic decision [31], and business environment [32], there are relatively few literatures on the spatiotemporal heterogeneity of driving factors.

In the mid-1990s, the geographically weighted regression (GWR) model was proposed and widely used as a local variable coefficient model to identify spatial non-stationarity [33]. The GWR model can overcome the spatial heterogeneity between geographical units, break through the limitations of the constant coefficient model, and draw differentiated research conclusions for different regions. Its theoretical significance and policy value of heterogeneity are more significant and it has the effect of "adjusting measures to local conditions", which is widely used in the research of different industries. However, the GWR model can only regress the cross-sectional data. Wu [34] added the time effect to the GWR model to build a geographically and temporally weighted regression (GTWR), which can capture the parameter variation of different spatial units in time and space, so it can make up for the deficiency of the GWR model. As an effective method to identify non stationarity, spatiotemporal geographically weighted regression has been well developed in theory and widely used in practice [35–37].

The above-mentioned literature has discussed the driving factors of the coupling coordination of the logistics and manufacturing industry, but the systematic analysis of the driving factors of the two industries is insufficient; the discussion of the regional differences of the driving factors of the two industries is not deep enough. In addition, the coupling coordination measure of the two industries also fails to consider the ecological and environmental factors. In order to make up for these defects, this paper constructs a coupled coordinated measurement system considering the carbon emissions of the two industries, systematically analyzes the driving factors from the internal and external aspects, and compares the spatial heterogeneity characteristics of the driving factors of coupling coordination of the two industries using the spatiotemporal geographically weighted regression model (GTWR).

The main contributions of this study are as follows: the low-carbon coupling coordination of the logistics industry and manufacturing industry is an ecological innovation organization, which integrates economic benefits, social benefits, and ecological benefits. First of all, by improving the selection of indicators for coupling and coordination, this paper has selected the unexpected output indicators of the logistics industry and manufacturing industry, overcoming the problem that the coupling and coordination measurement is not accurate enough owing to the neglect of carbon emissions in traditional indicators, so the low-carbon coupling and coordination data obtained may be more objective. Secondly, this paper uses the GTWR model to study the spatio-temporal evolution pattern and main driving factors of the low-carbon coupling development of industries in the Yangtze River Delta from different time scales and spatial scales.

This paper is divided into five parts. The second part presents the research methods. The third part provides the result analysis. The fourth part presents the discussion. The fifth part is the conclusion and suggestions.

2. Research Method

2.1. Research Hypothesis

2.1.1. The Mechanisms and Assumptions of Internal Factors

Capital Investment

The increase and agglomeration of physical capital allocation can have a positive impact on the optimization and upgrading of industrial structure, thus promoting economic growth. There is a significant substitution relationship between energy factors and capital factors. Promoting financial development, implementing supply side structural reform, and reasonably controlling industrial growth and scale expansion are conducive to energy conservation and emission reduction. The work of [38,39] shows that China's foreign direct capital investment in other countries has not led to the deterioration of carbon emissions in these countries. Therefore, this paper makes the following assumptions:

Hypothesis 1 (H1). *The more developed the capital investment, the stronger the promotion effect on the low-carbon coupling coordination of the two industries.*

Human Capital

Human capital is the capital embodied in workers. A human capital structure with high-quality talents can optimize the allocation of enterprise resources, enhance the ability of technological innovation and absorption, and is conducive to the improvement in labor productivity [40]. The improvement in human capital will reduce carbon emissions without reducing economic growth [41]. The research results of Li, X. [42] show that, in the long run, the positive changes in human capital brought about by education reduce carbon dioxide emissions. Therefore, this paper makes the following assumptions:

Hypothesis 2 (H2). *The more developed the human capital, the stronger the promotion effect on the low-carbon coupling coordination of the two industries.*

Infrastructure

Good infrastructure conditions are conducive to factor concentration and flow, improve factor productivity, promote enterprises to form economies of scale, make it easier to attract external investment, and reduce the transaction cost of enterprises. The improvement in road infrastructure configuration can enable the road network to handle traffic more effectively and reduce carbon emissions [43]. Therefore, this paper makes the following assumptions:

Hypothesis 3 (H3). *The more developed the infrastructure, the stronger the promotion effect on the low-carbon coupling coordination of the two industries.*

Technology Level

Technological progress can constantly develop new production technology, promote new equipment and new technology to transform old industries, and promote the transition from traditional industries to modern industries. In order to promote the joint development of the manufacturing industry and logistics industry, it is necessary to innovate the knowledge and technology contained in the manufacturing industry, as well as the advanced management concepts, methods, and models in the service industry, so as to promote the promotion of capital value. Technological progress is the key driving force of low-carbon development. In the "Made in China (2025)" and "Industrial Green Development Plan (2016–2020)", there are a large number of technical research areas related to the low-carbon development, and the importance of indigenous innovation has become increasingly prominent [44]. The research results of Li, R. [45] show that there is a nonlinear inverted U-shaped relationship between technological progress and CO_2 emissions. When economic development exceeds a certain threshold, the impact turns from positive to negative. Therefore, this paper makes the following assumptions:

Hypothesis 4 (H4). *The effect of the level of science and technology on the low-carbon coupling coordination of the two industries is uncertain.*

2.1.2. The Mechanisms and Assumptions of External Factors

The formation and evolution of the linkage of the two industries are carried out in a certain external social environment. This study initially establishes the evaluation index system from the external factors of urbanization level, international trade, foreign investment and industrial policy [46].

Urbanization Level

In the process of urbanization, equality of opportunity and process fairness are more widely guaranteed, which continues to deepen the development concept of mutual trust and reciprocity between the manufacturing industry and logistics industry, which can fully guarantee the sharing of benefits and long-term stable linkage between the two sides. There is a negative correlation between city size and carbon emission, indicating that urban agglomeration has a higher emission efficiency [47]. The research of Huang, Q. [48] shows that urbanization has significantly increased the carbon emissions of provinces. Therefore, this paper makes the following assumptions:

Hypothesis 5 (H5). *The effect of level of urbanization on the low-carbon coupling coordination of the two industries is uncertain.*

International Trade

International trade can pull the development of animal flow industry from the demand side, and produce a chain reaction through the "multiplier" effect; And through the import of foreign advanced equipment, new products or processes, the trade of these goods will transfer the physical and chemical technical knowledge to domestic enterprises. Through technology transfer, the scientific and technological level of domestic manufacturing logistics industry is improved, and the scientific and technological level of logistics enterprises and manufacturing enterprises is promoted [49]. The emissions contained in a country's imports and exports depend on the level and composition of trade, and more trade increases emissions [50]. Wang, L. and Khan, Y. [51,52] believe that trade openness increases production based on carbon emissions. Therefore, this paper makes the following assumptions:

Hypothesis 6 (H6). *The effect of developed of the international trade on the low carbon coupling coordination of the two industries is uncertain.*

Foreign Investment

Foreign investment affects the coupling coordination of the logistics industry and manufacturing industry through the technology spillover effect. Multinational companies have strong advantages in technology, management, and marketing. The host country enterprises can learn, imitate, and absorb each other's advanced experience through continuous learning [53]. Foreign direct investment is an important channel to obtain advanced green technology and achieve economic growth. It is one of the reasons for the increase in emissions in China at this stage. There is an inverted U-shaped nonlinear relationship between FDI and emissions [54], revealing the negative impact of FDI on carbon emissions. Therefore, this paper makes the following assumptions:

Hypothesis 7 (H7). *The effect of foreign investment on the low-carbon coupling coordination of the two industries is uncertain.*

Industrial Policy

When the market mechanism fails, the government can adjust the optimal allocation of resources among different industries through the implementation of targeted industrial policies, correct and make up for market defects, and support or inhibit the development of some industries according to social needs. Of course, industrial policy is not omnipotent and may not play its due role. Sun Fang [55] believe that policy and institutional factors have a positive impact on the coordinated development of industry. Zhang Youguo [56] analyzed the negative effects of industrial policies on the upgrading and adjustment of industrial structure. During the 12th Five-Year Plan and the 13th Five-Year Plan, the Chinese government issued a series of low-carbon development policies to curb carbon dioxide emissions. In terms of environmental policies, the Chinese government has implemented stricter environmental regulations and formed a governance system in which the government, enterprises, and the public work together [57]. Considering the significant differences in economic and social development in different regions of China, the effectiveness of policy implementation cannot be generalized. The research of Khan, Y. [52] shows that economic policy uncertainty is positively correlated with carbon emissions. The research results of Song, L. [58] show that industrial policies have a negative impact on carbon emission reduction in China's manufacturing industry. Therefore, this paper makes the following assumptions:

Hypothesis 8 (H8). *The effect of industrial policy implementation on the low-carbon coupling coordination of the two industries is uncertain.*

2.2. Method Introduction and Variable Selection

2.2.1. The Coupling Coordination Model of the Logistics Industry and Manufacturing Industry

The coupling coordination model is a relatively mature method to study the coordination relationship between industries. Owing to space constraints, this paper will not introduce it in detail here. For a detailed introduction to the method, see my other article [59].

2.2.2. The GTWR Model

Traditional OLS estimation is only an average or global estimation of regression coefficients, which cannot reflect the heterogeneity of regression coefficients in different spaces and cannot effectively explore some important and useful local features of regression relationship between dependent variables and independent variables. Based on the geographically weighted regression (GWR) model, the paper proposes a new method of global regression. The spatial heterogeneity (or spatial non-stationarity) problem is solved by the GTWR model [60]. The general expression is as follows.

$$\mathrm{Y_i} = \beta_0(\mathrm{u_i}, \mathrm{v_i}, \mathrm{t_i}) + \sum_{k=1}^{d} \beta_k(\mathrm{u_i}, \mathrm{v_i}, \mathrm{t_i}) X_{ik} + \varepsilon_\mathrm{i}, i = 1, 2, \ldots, n \quad (1)$$

In Formula (1), $\mathrm{Y_i}$ is $n \times 1$-dimensional explanatory variable; β_0 is the coefficient of the constant term; ($\mathrm{u_i}$, $\mathrm{v_i}$, $\mathrm{t_i}$) represent the latitude and longitude coordinates $\mathrm{u_i}$, $\mathrm{v_i}$, and observation time points of the I observation point, respectively; β_k ($\mathrm{u_i}$, $\mathrm{v_i}$, $\mathrm{t_i}$) is the unknown parameter of the K factor at ($\mathrm{u_i}$, $\mathrm{v_i}$, $\mathrm{t_i}$); and X_{ik} is $n \times$ K-dimensional explanatory variables. The parameters are estimated by the local weighted least square method, that is, for a given observation point, the observation value near the point is given a larger weight value and the observation value far away from the point is given a smaller weight value. By minimizing the weighted square sum of the difference between the observed value and the fitting value, the estimated value of the parameter can be obtained.

The core of the GTWR model is the setting of the spatial weight matrix, which is generally constructed as follows: w ($\mathrm{u_i}$, $\mathrm{v_i}$, $\mathrm{t_i}$) = diag ($\mathrm{w_{i1}}$, $\mathrm{w_{i2}}$, ... , $\mathrm{w_{in}}$), in which the diagonal element $\mathrm{W_{ij}}$ is the attenuation function of the spatial-temporal distance. Commonly used the weight functions include the distance threshold function, inverse distance function, Gaussian function, and truncated function. The common feature of these functions is to reflect the weight by the distance of sample points and the attenuation degree of effect with distance [33]. In this paper, the Gauss function is used as the weight function.

$$\mathrm{W_{ij}} = \exp\left\{-(\mathrm{d_{ij}}/h)^2\right\} \quad (2)$$

In Equation (2), h is the bandwidth to describe the attenuation degree of the effect with distance, which is usually calculated using the criterion of minimizing the sum of squares of errors of CV. If the predicted value $\mathrm{Y_i}$ of the model is a function (H) of the bandwidth h, the bandwidth can be expressed by Equation (3).

$$\mathrm{h} = \mathrm{minCV} = \sum\left[\mathrm{y_i} - \hat{\mathrm{y}}_{\neq \mathrm{i}}(\mathrm{h})\right]^2 \quad (3)$$

In Equation (3), $\mathrm{D_{IJ}}$ is the space–time distance between I and J. The measurement of the space–time distance involves two dimensions of time and space, and the space scale parameters λ and time scale parameters μ need to be set. In order to balance the differences between different dimensions, the given space distance $\mathrm{D^S}$ and time distance $\mathrm{D^T}$ are integrated into space–time distance $\mathrm{D^{ST}}$, then the space–time distance function is constructed:

$$\mathrm{d_{ij}^{ST}} = \sqrt{\lambda\left[(\mathrm{u_i} - \mathrm{u_j})^2 + (\mathrm{v_i} - \mathrm{v_j})^2\right] + \mu(\mathrm{t_i} - \mathrm{t_j})^2} \quad (4)$$

In Equation (4), when $\lambda = 0$, it means that there is no spatial effect and the space–time distance is a proportional function of the time distance. At this time, the model is set as the TWR (geographically weighted regression) model. When $\mu = 0$, this indicates that there is no time effect and the model is set as the GWR model. When $\lambda \neq 0$ and $\mu \neq 0$, it is the GTWR model. Thus, the space–time weight matrix can be expressed as follows: $(u_i, v_i, t_i) = \mathrm{diag}\,(w_{i1}, w_{i2}, \ldots, w_{in})$, where the specific calculation formula of W_{ij} is as follows:

$$W_{ij} = \exp\left\{-\left(d_{ij}^{ST}/h\right)^2\right\} = \exp\left\{-\left(\frac{\lambda\left[(u_i-u_j)^2+(v_i-v_j)^2\right]}{h^2}+\frac{\mu(t_i-t_j)^2}{h^2}\right)\right\} \quad (5)$$

In Equation (5), W_{ij} is the spatial weight between samples i and j; $d^{ST}{}_{ij}$ is the space–time distance between samples i and j; *h* is the space–time bandwidth; and λ and μ are scale factors used to determine the impact of space and time distance on different weights of the space–time distance. The scale factor is set to λ + μ = 1. By adjusting the scale factor λ, the relative size of space and time distance weights is determined, so as to improve the calculation efficiency without losing universality.

Based on model (5), this paper takes the coupling coordination (CC_{it}) of the logistics industry and manufacturing industry of each city unit from 2006 to 2019 as the dependent variable, and takes eight driving factors of capital investment, human capital, technological progress, infrastructure construction, international trade, industrial policy, foreign investment, and urbanization level as the independent variables. Taking the longitude and latitude coordinates of each prefecture level city as the location coordinates, the GTWR model is constructed as follows in model (6):

$$\begin{aligned} CC_{it} &= \beta_0(u_i,v_i,t_i) + \beta_1(u_i,v_i,t_i)\mathrm{Cap}_{ik} + \beta_2(u_i,v_i,t_i)\mathrm{Hum}_{ik} \\ &+\beta_3(u_i,v_i,t_i)\mathrm{Tec}_{ik} + \beta_4(u_i,v_i,t_i)\mathrm{Inf}_{ik} + \beta_5(u_i,v_i,t_i)\mathrm{Tra}_{ik} \\ &+\beta_6(u_i,v_i,t_i)\mathrm{Pol}_{ik} + \beta_7(u_i,v_i,t_i)\mathrm{FDI}_{ik} + \beta_8(u_i,v_i,t_i)\mathrm{Urb}_{ik} + \varepsilon_i, i = 1,2,\ldots,n \end{aligned} \quad (6)$$

In Formula (6), CC_{it} represents the low-carbon coupling coordination value of sample point i; Cap_{ik}, Hum_{ik}, Tec_{ik}, Inf_{ik}, Tra_{ik}, Pol_{ik}, FDI_{ik}, and Urb_{ik} are the values of eight factors: capital investment, human capital, technological progress, infrastructure construction, international trade, industrial policy, foreign investment, and urbanization level, respectively; β_1, β_2, β_3, β_4, β_5, β_6, β_7, and β_8 are the regression coefficients of each influencing factor at sample point *i*; and β_0 and ε_i refer to the space–time intercept and residual, respectively.

2.2.3. Construction of the Low-Carbon Coupling Coordination System

In order to verify the mechanism of the driving factors of the coupling coordination of the logistics industry and manufacturing industry, based on the analysis of the above internal and external driving factors, this paper further selects the index variables that can measure the driving factors and conducts an empirical analysis using the panel data of 25 cities in Yangtze River Delta from 2006 to 2019. The explained variable is the coupling coordination of the logistics industry and manufacturing industry (CC_{it}), which is used to measure the development level of the coupling coordination of the two industries.

According to the analysis of economic, social, and ecological benefits of the low-carbon coupling system and referring to the measurement methods of relevant scholars [27,61,62] on low-carbon efficiency and the measurement indicators of relevant scholars [63–65] on the coupling and coordination of the logistics industry and manufacturing industry, this paper constructs the evaluation index system of the coupling coordination between the logistics industry and manufacturing industry, as shown in Table 1 below. In this paper, MAXDEA ultra7.0 software is used to calculate the low-carbon efficiency of the logistics industry and manufacturing industry with the SBM-DEA model (the index system is as follows), and the low-carbon coupling coordination (CC_{it}) of the two industries is calculated with the coupling coordination model.

Table 1. Indicator system of the order parameter of the coupling coordination evaluation of the logistics industry and manufacturing industry.

Evaluation System	Pointer Type	Name of Index	Unit
Manufacturing system	Input indicators	The number of employees on the job in the manufacturing industry	Ten thousand people
		Total assets of industrial enterprises above designated size	100 million
	Output indicators	industrial added value	100 million
		Main business income of industrial enterprises above designated size	100 million
	Unexpected output	Carbon emissions from manufacturing	Tons
Logistics system	Input indicators	Number of employees in the logistics industry	Ten thousand people
		Fixed capital investment	100 million
		energy consumption	Ten thousand tons of standard coal
	Output indicators	highway freight volume	Tons
		GDP of logistics industry	100 million
		Cargo turnover	Million ton-km
	Unexpected output	Carbon emissions from transportation	Tons

China's road transport freight volume accounts for more than 70% of the total industry volume in the recent ten years [37]. Therefore, this paper uses the road transport freight volume as the output index of the logistics industry.

This paper takes the CO_2 emissions of the logistics industry and manufacturing industry as the unexpected output index. This paper refers to Xu JZ, Zhang Shiqing, Wen Long Zheng [66–68], and other relevant scholars' research on carbon emissions from logistics and manufacturing. Firstly, the primary energy consumption of 21 fuels mainly consumed by logistics and manufacturing industries, such as raw coal, diesel, kerosene, gasoline, fuel oil, liquefied petroleum, and natural gas, is selected and converted into standard coal as the total energy source consumption of the two industries. Then, the above seven energy consumption are converted according to the carbon emission coefficient in the guidelines for national greenhouse gas emission inventories of the climate change commission (IPCC), and the CO_2 emissions of the logistics industry and manufacturing industry are obtained. The calculation formula is as follows:

$$CO_2 = \sum_{i=1}^{n} E_i \times CF_i \times CC_i \times COF_i \times \frac{44}{12} \quad (7)$$

where i is the type of fuel, E_i is the consumption of i fuels, CF_i is the calorific value of i fuels, CC_i is the carbon content of i fuels, and COF_i is the oxidation factor of the fuel.

2.2.4. Variable Selection of Driving Factors

1. Capital. Referring to Zhang J's [69] measurement method of physical capital, this paper obtains the capital stock of each city from 2006 to 2019 and uses the deflator index to convert it into the constant price capital stock based on 2006.

2. Human capital (hum_{it}). Referring to the calculation method of Zhang Hu [70], the stock of human capital hit = exp (lnh_{it}) $*$ l_{it}, where h is the per capita human capital of the region and l is the total employment of the region.
3. Technological progress. To a certain extent, the number of technology patents in a region can represent the technological innovation ability of the region. Because there is a time lag between patent acceptance and authorization, and the amount of patent acceptance can directly reflect the technological innovation ability of enterprises under external intervention, we choose the amount of patent acceptance to measure technological progress.
4. Infrastructure. In order to make the stock of infrastructure construction in different regions comparable, this paper refers to the common practice of foreign scholars, where highway density is used to measure the level of infrastructure construction [71].
5. International trade. The international trade of a region reflects its degree of openness to the outside world. The evaluation of the degree of openness to the outside world of a region is generally measured by the proportion of the total export trade in the regional GDP [72]. That is, trade = total import and export/GDP.
6. Polit. As a part of the government's financial expenditure, favorable industrial policies enable enterprises to obtain government subsidies such as R&D, which reflects the government's support for enterprise innovation activities. In view of the availability of data, this paper measures the proportion of local fiscal expenditure in regional GDP. That is, Polit = local fiscal expenditure/GDP.
7. Foreign investment in FDI. Foreign investment is the main symbol of a country's scale of absorbing foreign direct investment and the potential of utilizing foreign investment, which reflects the region's ability to attract foreign investment. Total foreign direct investment (FDI) per capita represents the level of foreign direct investment [73]. That is, FDI_{it} = total foreign direct investment/total population.
8. Urbanization level. Urbanization is an important symbol to measure the level of national or regional economic and social development. The current measurement method mainly uses the proportion of urban population in the total population to calculate the urbanization rate [74]. That is, Urb_{it} = urban population/total population.

The data used in this paper are from the "Energy Statistics Yearbook (2007–2020)", "China Urban Statistics Yearbook (2007–2020)", and "Environmental Statistics Yearbook (2007–2020)" of each province. In order to avoid the influence of the heteroscedasticity of the residuals, the above data are transformed by natural logarithm (E as the base). The descriptive statistical results of each variable are shown in Table 2.

Table 2. Descriptive statistical results of variables.

Variable	Number	Minimum Value	Maximum Value	Mean Value	Standard Deviation
Cap_{it}	350	3.532	8.462	5.354	1.025
Hum_{it}	350	4.872	7.532	6.354	0.568
Tec_{it}	350	2.025	3.257	2.557	1.002
Inf_{it}	350	1.335	2.534	2.245	0.576
Tra_{it}	350	2.247	5.357	3.253	1.035
Pol_{it}	350	2.968	5.025	4.354	0.576
FDI_{it}	350	0.357	5.542	2.025	1.324
Urb_{it}	350	3.358	4.357	3.821	1.013

3. Results' Analysis

This paper uses EVIEWS 10.0 software to carry out a unit root test on each influencing factor to determine the stationarity of the data and uses Vif to test whether there is multicollinearity between their variable data. The results show that both the ADF test and PP test reject the original hypothesis of unstable data at the level of 1%, so all variables are stable and suitable for panel data regression. The results showed that the result tolerance of all variables is greater than 0.1 and the Vif value is less than 10. There is no obvious collinearity between the explained variable and the explanatory variable.

3.1. Correlation Test

In order to avoid the occurrence of pseudo regression, this paper uses ADF and PP unit root test to determine the stationary state of the data and the results are calculated by R software. In addition, the variance expansion factor (VIF) is used to test whether there is multicollinearity among the variables [75]. The specific results are shown in Table 3.

Table 3. Unit root test and Vif test results of each variable.

Variable	ADF Test			PP Test			VIF
	Dickey Fuller	Lag Order	*p*-Value	Dickey Fuller Z (alpha)	Truncation Lag Parameter	*p*-Value	
CC_{it}	−5.965	6	0.01	−298.04	5	0.01	
Cap_{it}	−5.239	6	0.01	−198.45	5	0.01	5.947
Hum_{it}	−6.276	6	0.01	−233.62	5	0.01	6.742
Tec_{it}	−6.923	6	0.01	−197.46	5	0.01	5.953
Inf_{it}	−5.638	6	0.01	−256.14	5	0.01	5.482
Tra_{it}	−6.053	6	0.01	−284.67	5	0.01	4.864
Pol_{it}	−5.894	6	0.01	−311.25	5	0.01	3.427
FDI_{it}	−6.053	6	0.01	−221.57	5	0.01	5.932
Urb_{it}	−5.894	6	0.01	−354.26	5	0.01	4.653

It can be seen from Table 3 that both the ADF unit root test and PP unit root test significantly reject the original hypothesis of unstable data at the 1% level, so all variables are stable and suitable for panel data regression modeling. At the same time, the variance expansion factor of each variable is less than the empirical value of 10, so there is no multicollinearity between variables.

3.2. Empirical Results

3.2.1. Empirical Analysis of Coupling Coordination

The year 2006 is the beginning of the eleventh Five-Year Plan. In order to analyze the results in stages, the study began in 2006. During the "11th Five-Year Plan", "12th Five-Year Plan", and "13th Five-Year Plan", China has formulated energy consumption and environmental supervision objectives, and the energy consumption and carbon emission plan will be reduced proportionally by phase. It can be seen from Figure 2 that the average value of industrial low-carbon coupling in the Yangtze River Delta is high, reaching more than 0.6; especially, since 2011, it has exceeded 0.5. It shows that the Yangtze River Delta region has better achieved the goals of energy consumption and environmental supervision formulated by China. This is more consistent with the research results of other scholars [76].

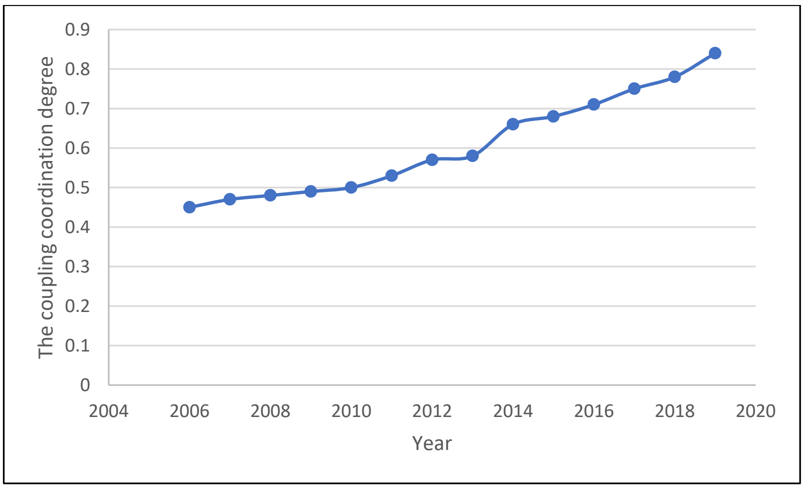


Figure 2. Calculation results of the low-carbon coupling coordination degree.

3.2.2. Empirical Analysis of Driving Factors

To some extent, ordinary panel regression reflects the action intensity of each factor, but it does not consider the factor of spatial distance, so the differences between different observations are averaged, which can only achieve a whole interdependence and cannot reflect the instability of parameters in different spaces. Therefore, this paper constructs a local weighted regression model from the perspective of time and space to estimate the parameters and uses the Gaussian kernel function method to construct the weight matrix. At the same time, combined with the cross-validation method CV and AIC to calculate the optimal bandwidth, it finally obtains the estimation results of the GWR and TWR models (see Table 4 for details). The regression results of GWR and TWR are presented in Table 4. According to the comprehensive judgment of CV, AIC, and adjusted R^2, the explanatory power of GWR is stronger than that of global linear regression and the estimated result of TWR (the smaller the AIC and CV, the stronger the explanatory power of the model). The time factor is added into the GWR model to construct the GTWR model and the parameter estimation results are obtained. See Table 5 for details.

Table 4. Estimated results of GWR and TWR of driving factors from 2006 to 2019.

Variable	GWR				TWR			
	Upper Quartile	Median	Lower Quartile	Full Range	Upper Quartile	Median	Lower Quartile	Full Range
intercept	0.2101	0.3211	0.3557	0.6243	0.1205	0.2178	0.4611	0.7562
Cap_{it}	0.0963	0.1013	0.2205	0.6471	0.1064	0.2053	0.3023	0.3859
Hum_{it}	0.1107	0.3211	0.5016	0.5835	0.0468	0.0642	0.0964	0.1763
Tec_{it}	0.2316	0.3695	0.4072	0.6053	0.0542	0.0853	0.0906	0.1672
Inf_{it}	0.1492	0.2683	0.3375	0.4562	0.0431	0.0633	0.0954	0.1635
Tra_{it}	0.0856	0.1283	0.2969	0.3903	0.1989	0.2971	0.3293	0.4335
Pol_{it}	0.1903	0.3283	0.4263	0.5739	0.0279	0.0353	0.0861	0.1729
FDI_{it}	0.0953	0.1054	0.2854	0.6848	0.0637	0.0723	0.0964	0.1256
Urb_{it}	0.0864	0.1854	0.2356	0.5524	0.0763	0. 0913	0.1905	0.2256
Adj-R^2	0.977				0.845			
Sigma	0.029				0.044			
CV	0.344				0.612			
AIV	−1632.75				−1042.35			
Bandwidth	0.102				0.273			

Table 5. Estimated results of GTWR of each factor from 2006 to 2019.

Variable	GTWR			
	Upper Quartile	Median	Lower Quartile	Full Range
intercept	0.2101	0.3211	0.3557	0.6243
Cap_{it}	0.0963	0.1013	0.2205	0.6471
Hum_{it}	0.1107	0.3211	0.5016	0.5835
Tec_{it}	0.2316	0.3695	0.4072	0.6053
Inf_{it}	0.1492	0.2683	0.3375	0.4562
Tra_{it}	0.0856	0.1283	0.2969	0.3903
Pol_{it}	0.1903	0.3283	0.4263	0.5739
FDI_{it}	0.0953	0.1054	0.2854	0.6848
Urb_{it}	0.0864	0.1854	0.2356	0.5524
Adj-R^2	0.977			
Sigma	0.029			
CV	0.344			
AIV	−1632.75			
Bandwidth	0.102			
Spatio–temporal distance rate	0.668			

In order to accurately observe the spatiotemporal heterogeneity of the impact of various factors on the low-carbon coupling of the logistics industry and manufacturing industry, Figure 3 shows the time variation trend of the regression coefficient of various driving factors in the Yangtze River Delta from 2006 to 2019.

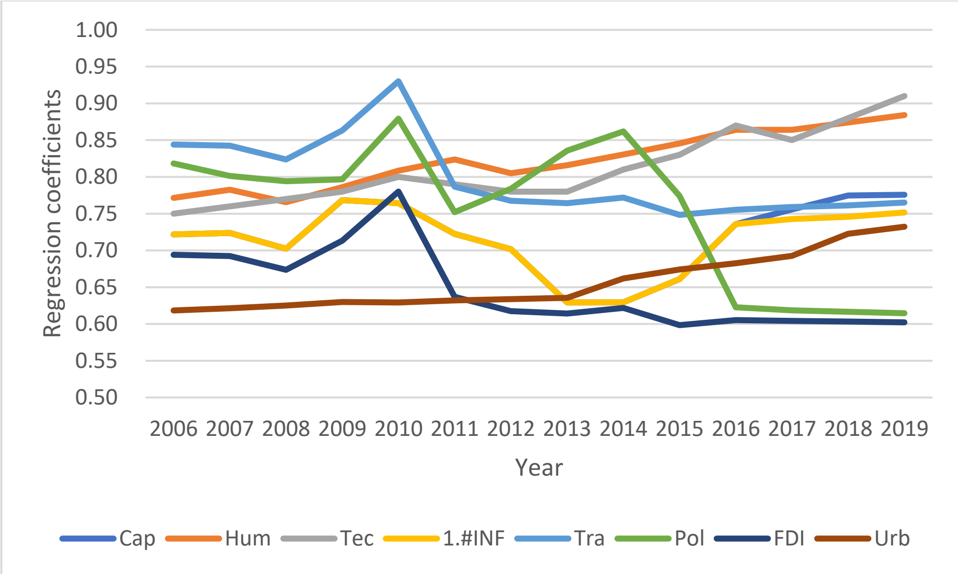


Figure 3. Time variation trend of the regression coefficients of driving factors in the Yangtze River Delta from 2006 to 2019.

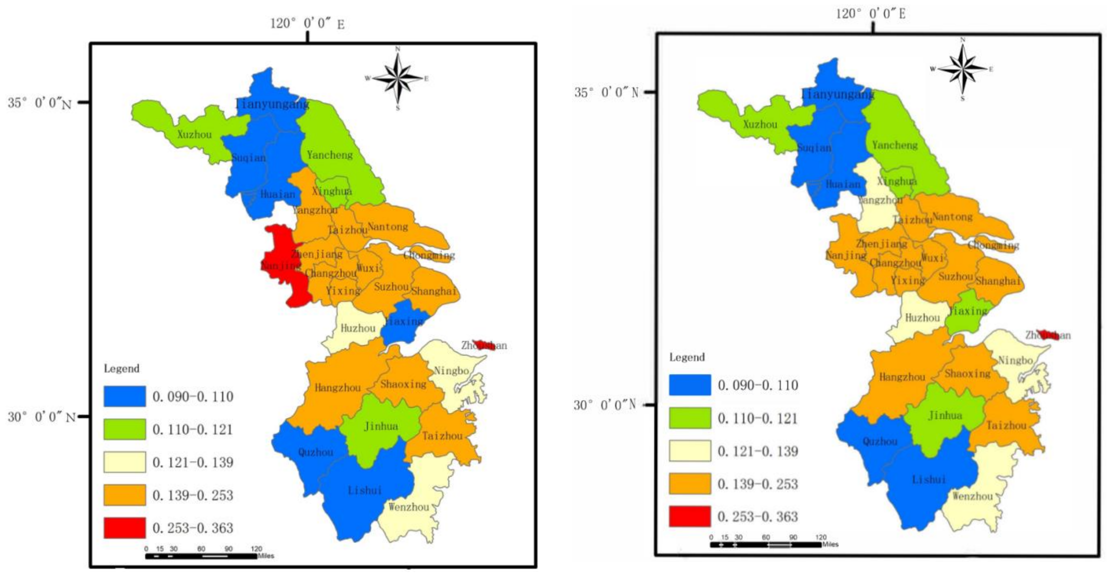
From the perspective of time change trend, the marginal impact of human capital, technological progress, and urbanization level on the low-carbon coupling between logistics and manufacturing in the Yangtze River Delta is increasing year by year; the marginal impact of international trade, industrial policy, and foreign investment on the Yangtze River Delta is decreasing year by year; and the marginal impact of capital investment and infrastructure on the Yangtze River Delta is relatively stable. Therefore, in addition to one driving factor of international trade, the assumptions put forward by other factors have been verified. The reason international trade does not have a negative impact on the low-carbon coupling in the Yangtze River Delta may be that the products imported and exported locally are mostly light industrial products, which cause less emissions than heavy manufacturing products, so it has no negative impact on the low-carbon coupling. This is consistent with the conclusions of other scholars [50].

Table 5 reports the estimated results of the GTWR model. Compared with Table 4, it can be seen that the estimation results of the three local regression models fluctuate in the corresponding interval, and there are some differences in the fluctuation intensity. This may be because different models focus on different aspects of non-stationarity. From the results of fitting, CV, and AIC, the adjusted R^2 of GTWR model is 0.977 and CV and AIC are 0.344 and -1632.75, respectively, which indicates that the goodness of fit of the GTWR model is better than that of the GWR and TWR models, so the GTWR model considering time and space factors is the best choice. The size of the city is the objective influence condition of carbon emission efficiency. In order to analyze the heterogeneous impact of the following driving factors on different city sizes, cities are divided into large cities and small and medium-sized cities with reference to Chen Jieyi [77]; the results are shown in Table 6 below.

Table 6. Division of large cities, medium-sized cities, and small cities.

Large Cities	Medium-Sized Cities	Small Cities
Shanghai	Xuzhou	Suqian
Nanjing	Changzhou	Huaian
Suzhou	Nantong	Yixing
Wuxi	Yancheng	Huzhou
Hangzhou	Jinhua	Jiaxing
Ningbo	Taizhou	Zhoushan
Wenzhou	Shaoxing	Jinhua
	Lianyungang	Quzhou
	Zhenjiang	Lishui

As can be seen from Figure 4, the capital investment coefficient is positively correlated with the coupling coordination of Yangtze River Delta. Cities with a high coefficient are mainly concentrated in Shanghai, Hangzhou, and Nanjing. This is because the logistics industry and manufacturing industry of these big cities have developed to a higher level; the marginal impact of capital is less than that of surrounding areas; and these cities are closer to big cities, so it is easier to obtain the positive promotion of big cities through industry or technology transfer. From the time change of the regression coefficient, the capital investment coefficient of Shanghai, Hangzhou, and Nanjing is declining, while the the capital investment coefficient of surrounding cities is increasing. This may be because these cities are closer to big cities and it is easier to obtain the positive promotion of big cities through industrial or technological transfer. This shows that capital investment in Yangtze River Delta should pay more attention to small and medium-sized cities around big cities, so as to obtain higher marginal benefits, and then promote the coupling coordination of the two regional industries.

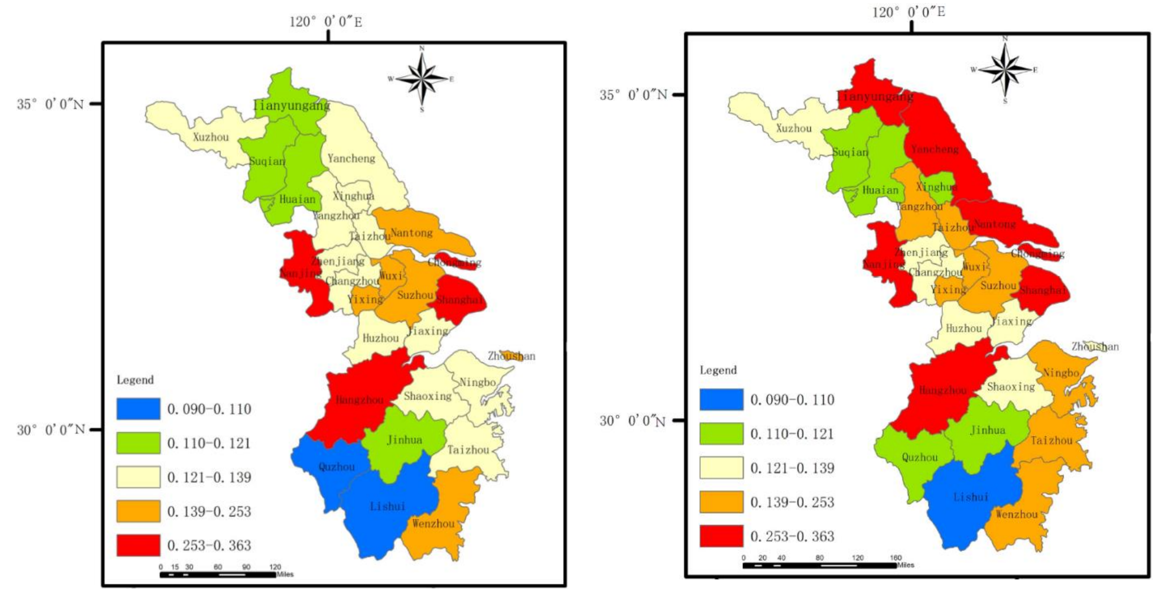


2006 2019

Figure 4. Spatial distribution of the regression coefficient of capital investment driving factors.

(1) Analysis of the driving factors of capital investment.

As can be seen from Figure 5, the human capital coefficient is positively correlated with the correlation efficiency of the two industries in the Yangtze River Delta. The human capital coefficient of big cities such as Shanghai, Hangzhou, and Nanjing in the Yangtze River Delta and coastal areas shows an upward trend. Large cities in the Yangtze River Delta are located in coastal areas, which have undertaken the transfer and investment of technology intensive industries from all over the world. The demand for high-tech talents is increasing and the marginal impact of human capital stock is also increasing. The Yangtze River Delta should pay more attention to human capital investment in big cities.

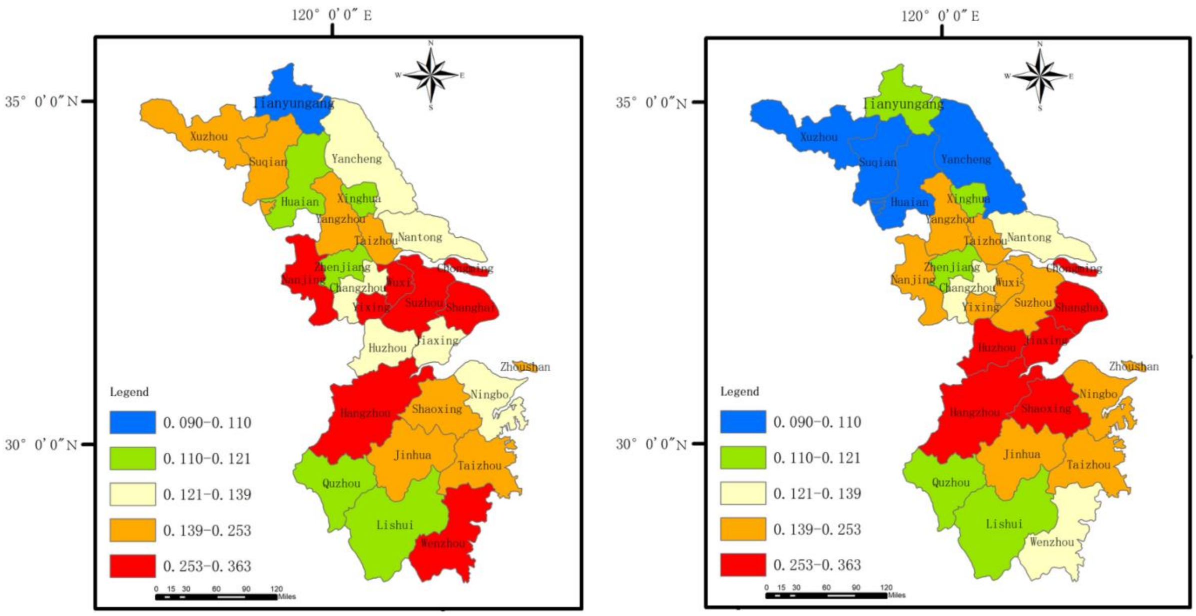


2006 2019

Figure 5. Spatial distribution of the regression coefficient of human capital driving factors.

(2) Analysis of the driving factors of human capital.

As can be seen from Figure 6, the technological progress coefficient is positively correlated with the coupling coordination of the two industries in the Yangtze River Delta, and the technological progress coefficient of Shanghai, Hangzhou, Nanjing, and other big cities and coastal areas in the Yangtze River Delta shows a relatively stable trend. This is because high and new technology has always been the need of industrial development in the region and the marginal impact of technological progress is relatively stable.

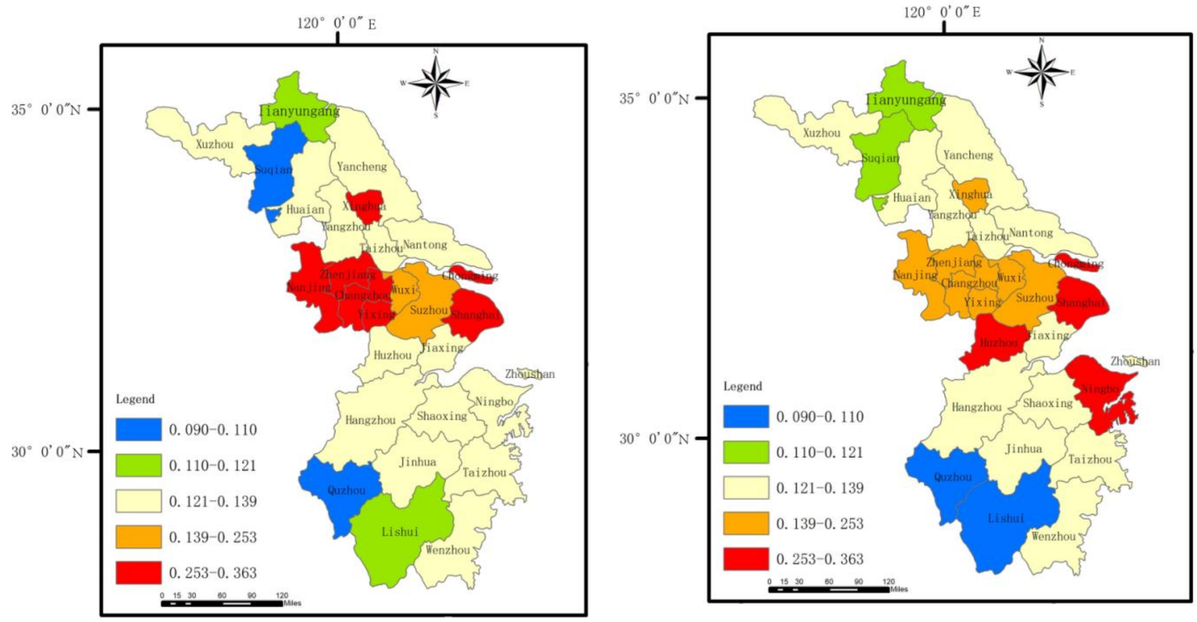


2006 2019

Figure 6. Spatial distribution of the regression coefficient of the driving factors of technological progress.

(3) Analysis of the driving factors of technological progress.

As can be seen from Figure 7, the infrastructure coefficient of the Yangtze River Delta is positively correlated with the efficiency of the two industrial linkages. The spatial distribution of the infrastructure coefficient in the Yangtze River Delta generally presents the characteristics of "high in the middle, medium in the north and south". The main reason is that the economy of the Yangtze River Delta is relatively developed; the infrastructure is generally relatively perfect; and the marginal impact of infrastructure is relatively small, except for the two underdeveloped areas in the north and south.



2006 2019

Figure 7. Spatial distribution of the regression coefficient of infrastructure drivers.

(4) Analysis of infrastructure drivers.

As can be seen from Figure 8, the international trade coefficient is basically positively correlated with the coupling coordination of the two industries in the Yangtze River Delta. The international trade coefficient of the Yangtze River Delta shows an upward trend from the eastern coastal region to the western region. This is because the ports in the eastern coastal area have brought a higher scale of import and export trade, and the marginal income is declining. Owing to the convenient transportation and developed logistics network in recent years, there is still a large space for the development of foreign trade in inland areas.

(5) Analysis of the driving factors of international trade.

As can be seen from Figure 9, the industrial policy coefficient is basically positively correlated with the coupling coordination of the two industries in the Yangtze River Delta. The industrial policy coefficient of large cities in the Yangtze River Delta generally decreases, while the coefficient of surrounding small cities generally increases. This shows that the industrial policy of Yangtze River Delta should pay more attention to the small and medium-sized cities around big cities in order to obtain higher marginal benefits.

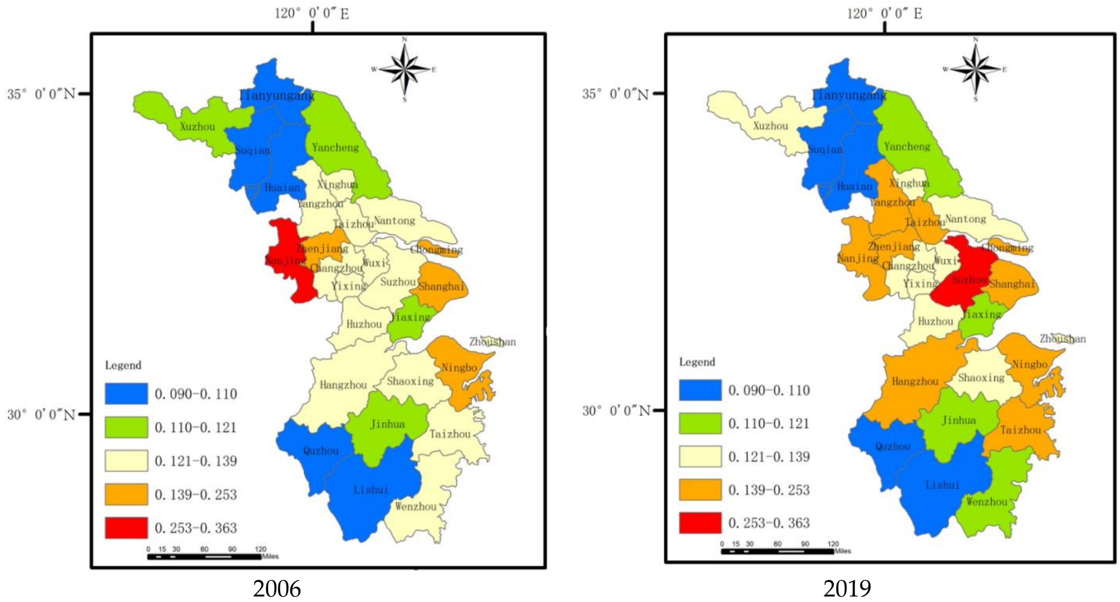


Figure 8. Spatial distribution of the regression coefficient of international trade driving factors.

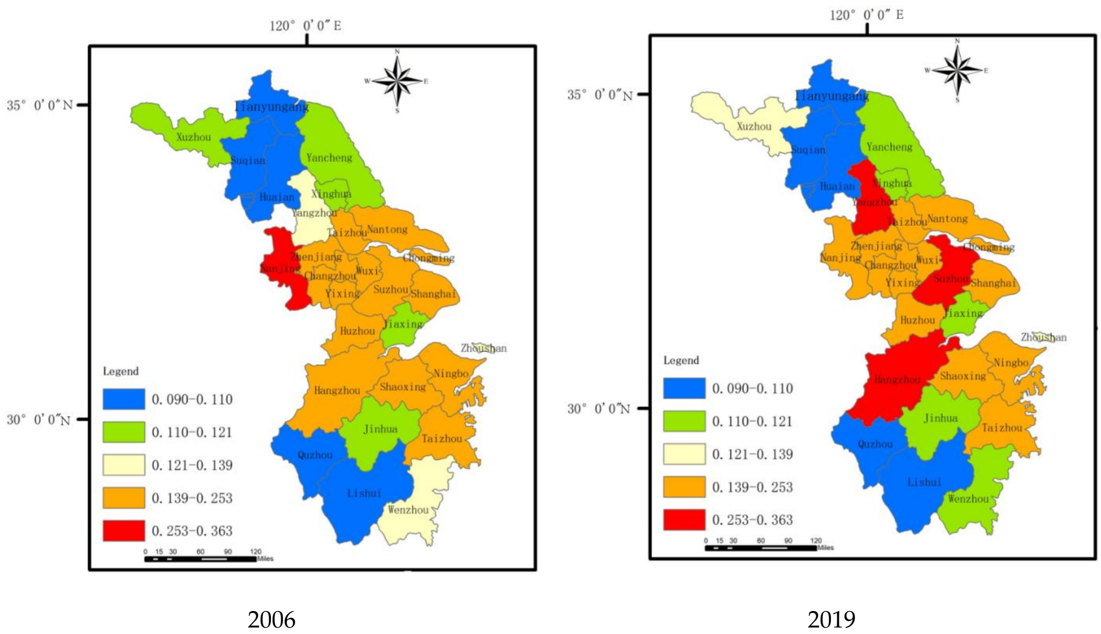


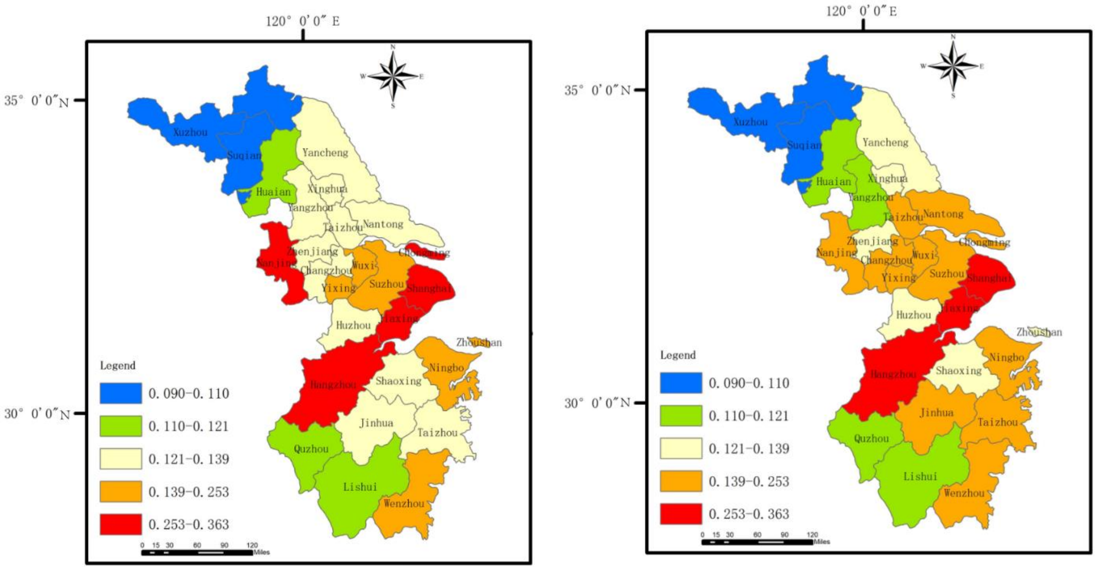
Figure 9. Spatial distribution of the regression coefficient of industrial policy driving factors.

(6) Analysis of the driving factors of industrial policy.

As can be seen from Figure 10, the foreign investment coefficient is basically positively correlated with the coupling coordination of the two industries in the Yangtze River Delta. As the eastern coastal area and the pilot area of opening to the outside world, the Yangtze River Delta is the main position to attract international high-tech industry investment transfer. Compared with big cities, FDI in small and medium-sized cities can better promote the inflow of labor, capital, and other factors, as well as enhance regional economic vitality and promote industrial development.

(7) An analysis of the driving factors of foreign investment.

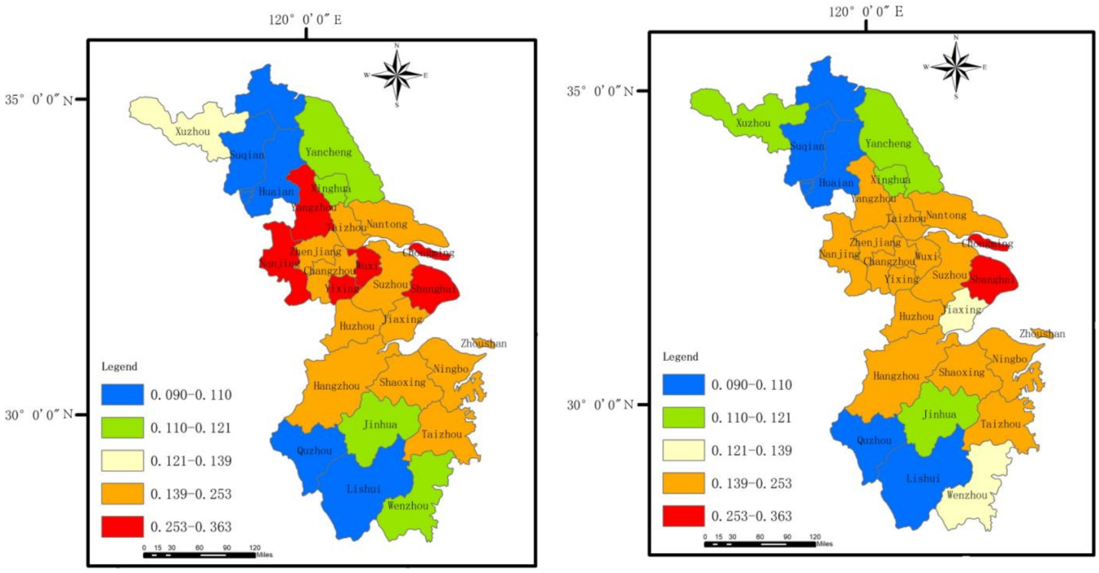
As can be seen from Figure 11, the urbanization level coefficient of the Yangtze River Delta is positively correlated with the coupling coordination of the two industries. From the time change of regression coefficient, the urbanization level coefficient of big cities in the region is declining and the coefficient of surrounding cities is increasing. This is because the improvement in urbanization can accelerate industrial agglomeration, attract high-quality human resources, and then reduce the transaction costs of logistics and manufacturing. Compared with the higher urbanization level of large cities, the promotion of urbanization in small and medium-sized cities can better promote manufacturing enterprises and logistics enterprises to form a linkage spatial structure around logistics products, which is manifested as a reasonable system for the integrated development of large and medium-sized cities based on the difference in urban function positioning and the rational division of labor among cities. Further, it provides opportunities and a platform for small and medium-sized cities around large cities in the Yangtze River Delta to participate in the regional economic division of labor.



2006 2019

Figure 10. Spatial distribution of the regression coefficient of foreign investment driving factors.

(8) Analysis of the driving factors of urbanization level.



2006 2019

Figure 11. Spatial distribution of the regression coefficient of the driving factors of urbanization level.

4. Discussion

Under the "double carbon" goal, it is of great significance to study low-carbon coupling development. China's logistics and manufacturing industries emit too much carbon dioxide, which has brought a heavy burden to the environment and has become a major factor restricting sustainable economic development. The existing research provides a theoretical basis for identifying the spatial and temporal distribution pattern and driving factors of carbon emissions, but there are still the following shortcomings: on the spatial and temporal scale, previous research only focused on the research of a single time period or single city, lacking research from the long-term scale and the mesoscale. In terms of driving factor analysis, previous studies only included various driving factors into the model to discuss the overall impact of driving factors on industrial development, ignoring the temporal and spatial differences of the impact of driving factors on the development of low-carbon industries.

In view of this, first of all, by improving the selection of indicators for coupling and coordination, this paper has selected the unexpected output indicators of the logistics industry and manufacturing industry, overcoming the problem that the coupling and coordination measurement is not accurate enough because of the neglect of carbon emissions in traditional indicators, so the low-carbon coupling and coordination data obtained may be more objective. Huang Lei's research further supports the results of this study [78].

Secondly, this paper uses the GTWR model to study the spatio-temporal evolution pattern and main driving factors of the low-carbon coupling development of industries in the Yangtze River Delta from different time scales and spatial scales. It is found that the marginal impact of human capital, technological progress, and urbanization on the low-carbon coupling of logistics and manufacturing in the Yangtze River Delta is increasing year by year; the marginal impact of international trade, industrial policies, and foreign investment on the Yangtze River Delta has decreased year by year; and the marginal impact of capital investment and infrastructure on the Yangtze River Delta is relatively stable. The coefficients of all factors are positively correlated with the low-carbon coupling coordination of the two industries. This conclusion is the same as that of existing studies [79].

Finally, this paper enriches the research on the low-carbon supply chain. It provides new ideas and methods for the realization of dual carbon goals and the low-carbon sustainable development of logistics and manufacturing industries. However, this study still has limitations: owing to the large number of manufacturing market segments, the carbon emissions of each market segment are also very different, and the manufacturing market segments in the Yangtze River Delta are very different, with limited data. Therefore, in future research, we can analyze the coupling coordination and driving factors of different sub sectors from the perspective of carbon emissions of the manufacturing industry.

5. Conclusions and Suggestions

The low-carbon coupling coordination between the logistics industry and manufacturing industry is an ecological innovation organization integrating economic benefits, social benefits, and ecological benefits, which belongs to the scope of low-carbon supply chain research. The Yangtze River Delta region is taken as an example. Firstly, the coupling coordination model is used to calculate the low-carbon coupling coordination scheduling of the region. Then, the GTWR model is used to explore the spatial heterogeneity of driving factors of low-carbon coupling coordination. The main conclusions are as follows:

(1) During the survey, the average value of low-carbon coupling and coordination between logistics and manufacturing in the Yangtze River Delta is 0.61, which is at a high development stage.
(2) This paper analyzes the eight driving factors of low-carbon coupling and coordination between the logistics industry and manufacturing industry from both internal and external aspects, qualitatively analyzes the action mechanism of the eight driving factors on coupling and coordination, puts forward the corresponding theoretical assumptions, and verifies the relevant assumptions.

(3) In terms of the time dimension, the regression coefficients of each driving factor are analyzed. Specifically, the marginal impact of human capital, technological progress, and urbanization on the low-carbon coupling of logistics and manufacturing in the Yangtze River Delta is increasing year by year; the marginal impact of international trade, industrial policies, and foreign investment on the Yangtze River Delta region has decreased year by year; and the marginal impact of capital investment and infrastructure on the Yangtze River Delta is relatively stable.
(4) In terms of spatial dimension, the regression coefficients of each driving factor have a positive impact on the coordination of low-carbon coupling. The influence of driving factors on low-carbon coupling is significantly different between large cities and small and medium-sized cities, and the spatial heterogeneity of driving factors is significant.

According to the above research conclusions, the following suggestions are put forward: strengthen the government's control on industrial carbon emissions; increase government support and improve the tax policy for low-carbon investment in enterprises; strengthen the supervision of the public and issue detailed laws and regulations on citizens' participation in environmental protection; strengthen technology introduction, introduce low-carbon technologies and equipment, and establish special R&D centers; enhance the awareness of low-carbon consumption and change the consumption model of consumers; ensure that supply chain enterprises choose low-carbon suppliers and share high-quality information; establish a green trade system and vigorously develop the trade of high-quality, high value-added green clean products; and explore the low-carbon supply chain system governance scheme of the whole industrial chain under the background of the "dual carbon" policy.

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Abbreviations

GTWR	geographically time-weighted regression model
GWR	geographically weighted regression model
Cap	capital investment
Hum	human capital
Tec	technology level
Inf	infrastructure
Tra	international trade
Pol	industrial policy
FDI	foreign investment
Urb	urbanization level
CC	low-carbon coupling coordination of the logistics industry and manufacturing industry

References

1. Wang, L.; Zhao, Y.; Wang, L. Research on Carbon Reduction Effect and Mechanism of Low Carbon Pilot Cities. *Geogr. Res.* **2022**, *41*, 1898–1912. [CrossRef]
2. Zhang, Z. China and the world under the goal of carbon peaking and carbon neutralization-green low-carbon transformation, green finance, carbon market and carbon border regulation mechanism. *People's Forum·Acad. Front.* **2021**, *14*, 69–79. [CrossRef]
3. Deng, F.; Xu, L.; Fang, Y.; Gong, Q.; Li, Z. PCA-DEA-tobit regression assessment with carbon emission constraints of China's logistics industry. *J. Clean. Prod.* **2020**, *271*, 122548. [CrossRef]
4. Yang, J.; Cheng, J.; Huang, S. CO_2 emissions performance and reduction potential in China's manufacturing industry: A multi-hierarchy meta-frontier approach. *J. Clean. Prod.* **2020**, *255*, 120226. [CrossRef]
5. Dong, Q. Linkage layout of two industries and high quality development of logistics industry. *China's Circ. Econ.* **2021**, *4*, 3–12. [CrossRef]
6. Zheng, W.-L.; Wang, J.-W.; Jiang, A.-D.; Khan, S.A.R.; Yang, X.-Q.; Zhang, X.; Zhang, Z.-Y. Study on environmental performance evaluation of different linkage development types of logistics industry and manufacturing industry considering unexpected output. *Air Waste J. Air Waste Manag. Assoc.* **2021**, *71*, 1025–1038. [CrossRef]
7. Zhu, X.H.; Zou, J.W.; Feng, C. Analysis of industrial energy-related CO_2 emissions and the reduction potential of cities in the Yangtze River Delta region. *J. Clean. Prod.* **2017**, *168*, 791–802. [CrossRef]
8. Wei, J. Current situation, problems and trends of China's logistics industry, China economic report. In *Implementation Plan for Promoting Deep Integration and Innovative Development of Logistics Industry and Manufacturing Industry*; National Development and Reform Commission of the People's Republic of China: Beijing, China, 2019; Volume 1, pp. 55–61.
9. Greiner, A. Fiscal policy in an endogenous growth model with public capital and pollution. *Jpn. Econ. Rev.* **2005**, *56*, 67–84. [CrossRef]
10. Grimaud, A.; Tournemaine, F. Why can an environmental policy tax promote growth through the channel of education? *Ecol. Econ.* **2007**, *62*, 27–36. [CrossRef]
11. Hamaguchi, Y. Environmental policy and social status preference for education in an Uzawa–Lucas model. *Bull. Econ. Res.* **2021**, *73*, 456–468. [CrossRef]
12. Pautrel, X. Environmental policy, education and growth: A reappraisal when lifetime is finite. *Macroecon. Dyn.* **2012**, *16*, 661–685. [CrossRef]
13. Lopes de Sousa Jabbour, A.B.; Chiappetta Jabbour, C.J.; Sarkis, J.; Latan, H.; Roubaud, D.; Godinho Filho, M.; Queiroz, M. Fostering low-carbon production and logistics systems: Framework and empirical evidence. *Int. J. Prod. Res.* **2021**, *59*, 7106–7125. [CrossRef]
14. Jiang, J.; Zhang, D.; Meng, Q. Impact analysis of investment coordination mechanisms in regional low-carbon logistics network design. *Transp. Res. Part D Transp. Environ.* **2021**, *92*, 102735. [CrossRef]
15. Zhou, R. Research on the Site Selection Path of Low Carbon Logistics in Textile E-Commerce. *Shanghai Text. Sci. Technol.* **2022**, *50*, 56–59. [CrossRef]
16. Che, X.; Sui, B.; Liu, X. Empirical analysis on influencing factors of China's low-carbon logistics development based on Tobit regression. *Bus. Econ. Res.* **2021**, *5*, 101–103. [CrossRef]
17. Liao, L.; Zhang, X. Low carbon logistics path planning of multiple distribution stations considering customer satisfaction. *Inf. Control.* **2020**, *49*, 420–428. [CrossRef]
18. Zhou, W. B2R low-carbon logistics decision-making method based on FEAHP method and fuzzy ideal point method. *Fuzzy Syst. Math.* **2020**, *34*, 7.
19. Liu, S.; Lu, D.; Hu, H.; Sheng, Y.; Wu, J. Research on the dynamic mechanism of low-carbon technology innovation of manufacturing enterprises under the innovation coupon. *Complex Syst. Complex. Sci.* **2022**, *2*, 96–103. [CrossRef]
20. Liu, T.; Song, Y.; Li, Y. Research on Carbon Asset Value remodeling and emission reduction benefits of machinery manufacturing enterprises from the perspective of lean production. *Ind. Technol. Econ.* **2022**, *41*, 85–96. [CrossRef]
21. Luo, Z.; Chen, X.; Wang, X. The role of co-opetition in low carbon manufacturing. *Eur. J. Oper. Res.* **2016**, *253*, 392–403. [CrossRef]
22. Cheng, F.; Sun, Y. Empirical Study on the Impact of Environmental Regulation on Low Carbon Manufacturing Practice–Taking Cement Enterprises as an Example. *East China Econ. Manag.* **2018**, *32*, 167–175. [CrossRef]
23. Wang, D.; Li, X.; Zhao, L. Research on supply chain coordination considering manufacturer competition under carbon trading mechanism. *Oper. Res. Manag.* **2018**, *27*, 62–71. [CrossRef]
24. Yang, G.; Ji, G. Impact of carbon emission regulation and customer environmental awareness on green innovation. *Syst. Eng. Theory Pract.* **2021**, *41*, 702–712. [CrossRef]
25. Li, X.; Wang, D. Research on supply chain coordination considering competition and information asymmetry under carbon trading mechanism. *Oper. Res. Manag.* **2021**, *30*, 47–52. [CrossRef]
26. Shi, C.; Guo, F.; Yan, X.; Ma, G.; Li, Q. Research on optimal emission reduction of low-carbon closed-loop supply chain based on loss averse measure. *Comput. Eng. Appl.* **2018**, *54*, 256–262. [CrossRef]
27. Gong, Y.; Yang, X.-Q.; Ran, C.-Y.; Shi, V.; Zhou, Y.-F. Evaluation of the Sustainable Coupling Coordination of the Logistics Industry and the Manufacturing Industry in the Yangtze River Economic Belt. *Sustainability* **2021**, *13*, 5167. [CrossRef]

28. Zheng, W.L.; Wang, J.-W.; Zhang, S.Q.; Khan, S.A.R.; Jiang, A.-D.; Yang, X.-Q.; Zhang, X. Evaluation of Linkage Efficiency between Manufacturing Industry and Logistics Industry Considering the Output of Unexpected Pollutants. *Air Waste J. Air Waste Manag. Assoc.* **2020**, *71*, 304–314. [CrossRef]
29. Wang, Y.; Liao, M.; Wang, Y.; Xu, L.; Malik, A. The impact of foreign direct investment on China's carbon emissions through energy intensity and emissions trading system. *Energy Econ.* **2021**, *97*, 105212. [CrossRef]
30. Gao, J. Performance evaluation of manufacturing collaborative logistics based on BP neural network and rough set. *Neural Comput. Appl.* **2021**, *33*, 739–754. [CrossRef]
31. Hanif, S.; Mu, D.; Baig, S.; Alam, K.M. A Correlative Analysis of Modern Logistics Industry to Developing Economy Using the VAR Model: A Case of Pakistan. *J. Adv. Transp.* **2020**, *2020*, 8861914. [CrossRef]
32. Zhang, J.; Luo, W.; Liu, Y. A Study on the Impact of the Business Environment on the Linkage Development of the Manufacturing and Logistic Industries. *J. Manag.* **2017**, *30*, 25–33. [CrossRef]
33. Fotheringham, A.S.; Charlton, M.; Brunsdon, C. The geography of parameter space: An investigation of spatial non-stationarity. *Geogr. Inf. Syst.* **1996**, *10*, 605–627. [CrossRef]
34. Wu, B.; Li, R.; Huang, B. A geographically and temporally weighted autoregressive model with application to housing prices, International. *J. Geogr. Inf. Sci.* **2014**, *28*, 1186–1204. [CrossRef]
35. Fotheringham, A.S.; Crespo, R.; Yao, J. Geographical and Temporal Weighted Regression (GTWR). *Geogr. Anal.* **2015**, *47*, 431–452. [CrossRef]
36. Guo, Y.; Tang, Q.; Gong, D.-Y.; Zhang, Z. Estimating ground-level PM 2.5 concentrations in Beijing using a satellite-based geographically and temporally weighted regression model. *Remote Sens. Environ.* **2017**, *198*, 140–149. [CrossRef]
37. Liu, J.; Zhao, Y.; Yang, Y. A mixed geographically and temporally weighted regression: Exploring spatial-temporal variationsfrom global and local perspectives. *Entropy* **2017**, *19*, 53. [CrossRef]
38. Ouyang, X.; Gao, B.; Du, K.; Du, G. Industrial sectors' energy rebound effect: An empirical study of Yangtze River Delta urban agglomeration. *Energy* **2018**, *145*, 408–416. [CrossRef]
39. Shinwari, R.; Wang, Y.; Maghyereh, A.; Awartani, B. Does Chinese foreign direct investment harm CO_2 emissions in the Belt and Road Economies. *Environ. Sci. Pollut. Res.* **2022**, *29*, 39528–39544. [CrossRef]
40. Zhang, N.; Fan, H.; Mu, H. The Analysis of Economic Growth Based on Structural Upgrade of Human Capital. *Popul. Econ.* **2020**, *2*, 87–101. [CrossRef]
41. Bano, S.; Zhao, Y.; Ahmad, A.; Wang, S.; Liu, Y. Identifying the impacts of human capital on carbon emissions in Pakistan. *J. Clean. Prod.* **2018**, *183*, 1082–1092. [CrossRef]
42. Li, X.; Ullah, S. Caring for the environment: How CO_2 emissions respond to human capital in BRICS economies? *Environ. Sci. Pollut. Res.* **2022**, *29*, 18036–18046. [CrossRef] [PubMed]
43. Sharifi, F.; Birt, A.G.; Gu, C.; Shelton, J.; Farzaneh, R.; Zietsman, J.; Fraser, A.; Chester, M. Regional CO_2 impact assessment of road infrastructure improvements. *Transp. Res. Part D Transp. Environ.* **2021**, *90*, 102638. [CrossRef]
44. Kang, Z.-Y.; Li, K.; Qu, J. The path of technological progress for China's low-carbon development: Evidence from three urban agglomerations. *J. Clean. Prod.* **2018**, *178*, 644–654. [CrossRef]
45. Li, R.; Lin, L.; Jiang, L.; Liu, Y.; Lee, C.-C. Does technology advancement reduce aggregate carbon dioxide emissions? Evidence from 66 countries with panel threshold regression model. *Environ. Sci. Pollut. Res.* **2021**, *28*, 19710–19725. [CrossRef] [PubMed]
46. Zhang, B.; Li, H. Promoting the deep integration of Internet and manufacturing industry: Mechanism and path of innovation based on "Internet plus". *Econ. Manag. Res.* **2017**, *38*, 87–96. [CrossRef]
47. Yu, X.; Wu, Z.; Zheng, H.; Li, M.; Tan, T. How urban agglomeration improve the emission efficiency: A spatial econometric analysis of the Yangtze River Delta urban agglomeration in China. *J. Environ. Manag.* **2020**, *260*, 110061. [CrossRef]
48. Huang, Q.; Hu, Y.; Luo, L. Spatial analysis of carbon dioxide emissions from producer services: An empirical analysis based on panel data from China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 53293–53305. [CrossRef]
49. Zhang, Z.; Wu, D. Regional integration, opening up and industrial agglomeration development: A case study of the Yangtze River economic belt. *Sci. Technol. Prog. Countermeas.* **2018**, *35*, 39–46. [CrossRef]
50. Andersson, F.N. International trade and carbon emissions: The role of Chinese institutional and policy reforms. *J. Environ. Manag.* **2018**, *205*, 29–39. [CrossRef]
51. Wang, L.; Su, C.-W.; Ali, S.; Chang, H.-L. How China is fostering sustainable growth: The interplay of green investment and production-based emission. *Environ. Sci. Pollut. Res.* **2020**, *27*, 39607–39618. [CrossRef]
52. Khan, Y.; Hassan, T.; Kirikkaleli, D.; Xiuqin, Z.; Shukai, C. The impact of economic policy uncertainty on carbon emissions: Evaluating the role of foreign capital investment and renewable energy in East Asian economies. *Environ. Sci. Pollut. Res.* **2022**, *29*, 18527–18545. [CrossRef] [PubMed]
53. Lin, C. Research on the Impact Mechanism of China's Producer Services FDI on Manufacturing Efficiency. Master's Thesis, Guizhou University, Guiyang, China, 2020. [CrossRef]
54. Wang, Z.; Gao, L.; Wei, Z.; Majeed, A.; Alam, I. How FDI and technology innovation mitigate CO_2 emissions in high-tech industries: Evidence from province-level data of China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 4641–4653. [CrossRef] [PubMed]
55. Sun, F.; Han, J.; Wang, X. Analysis on Driving factors of coordinated development of ecology and industry in Beijing Tianjin Hebei ecological conservation area. *Agric. Resour. Reg. China* **2018**, *39*, 68–76. [CrossRef]
56. Zhang, Y. Transformation and upgrading of China's carbon reduction policy system. *Tianjin Soc. Sci.* **2022**, *3*, 90–99. [CrossRef]

57. Wu, H.; Xu, L.; Ren, S.; Hao, Y.; Yan, G. How do energy consumption and environmental regulation affect carbon emissions in China? New evidence from a dynamic threshold panel model. *Resour. Policy* **2020**, *67*, 101678. [CrossRef]
58. Song, L.; Zhou, X. How does industrial policy affect manufacturing carbon emission? Evidence from Chinese provincial sub-sectoral data. *Environ. Sci. Pollut. Res.* **2021**, *28*, 61608–61622. [CrossRef] [PubMed]
59. Wang, Y. Research on the Influence of the Coupling Coordination of the Logistics Industry and Manufacturing Industry on the Upgrading of the Manufacturing Industry. *IEEE Access* **2022**, *10*, 30189–30201. [CrossRef]
60. Huang, B.; Wu, B.; Barry, M. Geographically and Temporally Weighted Regression for Spatio—Temperal Modeling of House Prices. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 383–401. [CrossRef]
61. Bai, D.; Dong, Q.; Khan, S.A.R.; Chen, Y.; Wang, D.; Yang, L. Spatial analysis of logistics ecological efficiency and its driving factors in China: Based on super-SBM-undesirable and spatial Dubin models. *Environ. Sci. Pollut. Res.* **2021**, *29*, 10138–10156. [CrossRef]
62. Long, R.; Ouyang, H.; Guo, H. Super-slack-based measuring data envelopment analysis on the spatial–temporal patterns of logistics ecological efficiency using global Malmquist Index model. *Environ. Technol. Innov.* **2020**, *18*, 100770. [CrossRef]
63. Gong, X. Coupling Coordination Evaluation and Spatial Differentiation Analysis of Manufacturing Industry and Logistics Industry in China. *Resour. Dev. Mark.* **2018**, *34*, 242–248. [CrossRef]
64. Su, T.; Zhang, L.; Zhaom, X. The impact of the coupling of manufacturing and logistics on the productivity of manufacturing enterprises – from the perspective of industrial symbiosis. *Ind. Eng. Manag.* **2020**, *25*, 42–49. [CrossRef]
65. Chen, C.; Chen, J.; Gu, J. The study on the evolution of interactive development between manufacturing and logistics industry in china. *J. Shandong Univ. (Philos. Soc. Sci.)* **2020**, *2*, 73–81. [CrossRef]
66. Xu, J.Z.; Wang, M.M.; Guan, J. Study on the mechanism of energy consumption carbon emission and green innovation efficiency from the perspective of dynamic endogenous—An Empirical Analysis Based on China's equipment manufacturing industry. *Manag. Rev.* **2019**, *31*, 81–93. [CrossRef]
67. Zhang, S.; Wang, J.; Zheng, W. Analysis on temporal and spatial differences of carbon emissions and driving factors in transportation in China. *J. Environ. Sci.* **2017**, *37*, 4787–4797. [CrossRef]
68. Zheng, W.L.; Wang, J.; Zhang, S. Analysis on carbon emission decoupling effect and driving factors of environmental pollution in China's transportation industry. *Chem. Eng. Trans.* **2018**, *66*, 637–642. [CrossRef]
69. Zhang, J. Estimation of China's provincial capital stock (1952–2004) with applications. *J. Chin. Econ. Bus. Stud.* **2008**, *6*, 177–196. [CrossRef]
70. Zhang, H.; Zhou, N. Analysis on the coordinated development of manufacturing and service industries and its influencing factors. *Stat. Decis.* **2019**, *35*, 86–90. [CrossRef]
71. Démurger, S. Infrastructure development and economic growth: An explanation for regional disparities in China? *J. Comp. Econ.* **2000**, *29*, 95–117. [CrossRef]
72. Sang, R.; Han, C.; Li, X. How export market competition affects enterprise productivity: An analysis from the perspective of product allocation. *Ind. Econ. Res.* **2018**, *96*, 45–57. [CrossRef]
73. Dai, X.; Wang, R. "The Belt and Road" initiative and foreign direct investment: Analysis on the mechanism of "five links". *Financ. Res.* **2022**, *48*, 79–93. [CrossRef]
74. Liang, W.; Sun, H.; Liu, H. The Coordinated Development of New Urbanization and Logistics in China—Taking the Yangtze River Economic Belt as an Example. Modern Finance and Economics. *J. Tianjin Univ. Financ. Econ.* **2018**, *38*, 69–80. [CrossRef]
75. Cong, J. Research on the impact of carbon emission of Chinese urban form under the vision of carbon neutrality–Based on the data analysis of 289 prefecture level cities. *Guizhou Soc. Sci.* **2021**, *9*, 125–134. [CrossRef]
76. Li, X. Research on Industrial Structure and Productivity Changes of Manufacturing Industry in the Yangtze River Delta under Energy and Environmental Constraints. Ph.D. Thesis, Nanjing University of Aeronautics and Astronautics, Nanjing, China, 2018.
77. Chen, J.; Zhang, S.; Pan, L. Research on the Characteristics of City Size Distribution in China – Analysis Based on Census Data from 2010 to 2019. *Ind. Econ. Rev.* **2022**, *1*, 185–200. [CrossRef]
78. Huang, L. Research on Environmental Regulation, Industrial Agglomeration and Urban Industrial Green Development Efficiency of the Yangtze River Economic Belt. Ph.D. Thesis, Wuhan University, Wuhan, China, 2019. [CrossRef]
79. Lv, Q. Evaluation of Industrial Green Growth Efficiency of the Three Urban Agglomerations in the Yangtze River Economic Belt and Research on Its Influencing Factors. Master's Thesis, Chongqing Technology and Business University, Chongqing, China, 2021. [CrossRef]