 doi:10.20944/preprints202206.0314.v1

Article

Heterogeneous Dynamic Correlation Research Among Industrial Structure Distortion, Two-way FDI, and Carbon emission intensity

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Abstract: In this paper, industrial structure distortion, two-way FDI and carbon emission intensity are brought into a unified research framework, and based on China's panel data from 2011 to 2020, empirical tests are conducted employing Exploratory Spatial Data Analysis (ESDA), spatial econometric model and intermediary effect test. The results show the following. Firstly, China's industrial structure distortion index shows a downward trend. The industrial structure distortion index is the highest in the west, followed by the middle, and the lowest in the East. Secondly, the relationship between carbon emission intensity and economic development shows a "decoupling" effect and keeps decreasing year by year. The spatial disparity is remarkable, showing the pattern of "the east leading, the middle catching up and the west lagging ". At the provincial level, except in Xinjiang province, the carbon emission intensity of other provinces showed different degrees of decline. In terms of spatial distribution, the polarization characteristics of carbon emission intensity are significant, and the traditional spatial distribution pattern has been broken. Thirdly, there is a positive spatial correlation between China's industrial structure distortion, two-way FDI and carbon emission intensity. The distortion of industrial structure will not only lead to the increase of local carbon emission intensity but also produce reverse spillover to adjacent areas. IFDI and OFDI provide a strong driving force for the decline of carbon emission intensity. IFDI promotes the decline of carbon emission intensity in adjacent areas, while OFDI will increase the carbon emission intensity in surrounding areas. The interaction of IFDI and OFDI can significantly reduce the carbon emission intensity of local and adjacent areas. Fourthly, the results of intermediary effect analysis show that two-way FDI is the two channels of industrial structure distortion affecting carbon emission intensity. Industrial structure distortion can affect the transmission mechanism of carbon emission intensity by affecting two-way FDI.

Keywords: two-way FDI; structural distortion; ecological civilization construction; spatial econometrics; carbon emission intensity

1. Introduction

As the largest energy consuming country in the world, China's long-term implementation of the inclined development policy with economic growth as the priority and rapid industrial system construction has accelerated the pace of China's modernization to a certain extent, but it has also caused great damage to the ecological environment [1]. With the rapid development of industry, China's energy consumption has always maintained a strong growth demand, which not only affects its industrial development and energy supply but also profoundly affects the global carbon emission pattern [2].

Given the current severe situation of carbon emission reduction, Chinese leaders made an important commitment at the Paris Summit that China will reach a carbon peak in 2030 and achieve carbon neutrality before 2060[3]. As to how to achieve carbon emission reduction, the academic circles generally believe that industrial structure adjustment, energy consumption structure transformation, and technological progress are the three major ways to promote energy conservation and emission reduction, among which industrial structure adjustment is the most important support point to achieve carbon emission reduction. However, at present, the economic development and industrial structure of different provinces, municipalities, and autonomous regions in China are highly out of balance, which leads to significant differences in carbon emission levels in different regions [4]. Therefore, how to adapt to local conditions and implementing feasible industrial development policies in each province is of great significance for achieving the "double carbon" goal.

Since China acceded to WTO, China's industrial development has entered the "fast lane" and actively participated in international competition and trade cooperation as an investor [5]. China's inward Foreign Direct Investment (IFDI) and Outward Foreign Direct Investment (OFDI) have increased year by year, becoming a large two-way FDI cross-border country, which has played a key role in promoting China's rapid economic growth [6].

However, due to the imbalance of economic development among different regions in China, the shortcomings of infrastructure construction, and the allocation deviation caused by the distortion of factor markets, the economic development is excessively driven by energy factors, thus diluting the positive effect of two-way FDI in boosting economic development [7]. Furthermore, excessive, and inefficient energy input also increases energy consumption intensity and carbon emission reduction pressure year by year. Under the background of economic globalization and marketization, the dynamic contradiction between industrial transformation and low-carbon development has become increasingly prominent.

Industry structure determines energy utilization efficiency and energy consumption structure, while energy consumption is closely related to carbon emissions [8]. Therefore, industrial structure adjustment is considered an important breakthrough point to reduce carbon emissions. The distortion of industrial structure is an irrational state of industrial structure, which is characterized by low efficiency in resource allocation and market regulation. So, does the distortion of industrial structure lead to the increase in carbon emission intensity? In the current international environment, can actively "going out" and "bringing in" reduce carbon emission intensity? Does the distortion of the industrial structure have a conduction effect between two-way FDI and carbon emission intensity? If the above hypothesis is verified, what is the degree of impact? The effective answers to the above questions are of great practical significance for realizing "carbon peak" and "carbon neutralization", promoting the rationalization of industrial structure and accelerating the reform of the ecological civilization system.

The main contributions of this study are as follows. Firstly, in the past, most studies only noticed the positive effect of industrial structure, but seldom mentioned the negative effect. This paper innovatively put forward a new concept of industrial structure distortion and used it as a breakthrough point to explore the impact of two-way FDI on carbon emission intensity. Secondly, different from considering the influence of IFDI and OFDI on carbon emissions as an isolated single action, this paper only studies the mechanism of the relationship between IFDI and carbon emissions or OFDI and carbon emissions. This paper brings IFDI and OFDI into the same research framework to systematically analyze their influence on China's carbon emission intensity, making the conclusion more scientific. Thirdly, regarding the influence of two-way FDI and carbon emission intensity, most scholars use the threshold model and intermediary effect model to explore the mechanism, but inevitably ignore the spatial law of the research samples. Therefore, this paper breaks through the traditional practice, examines its evolution law from the spatial perspective, and expands the existing research.

Given the above analysis, this paper brings the distortion of industrial structure, two-way FDI, and carbon emission intensity into the unified research framework. Firstly, based on the national panel data from 2011 to 2020, this paper calculates the carbon emission intensity of each province. Secondly, combined with exploratory spatial analysis (ESDA) and a spatial econometric model, this paper analyzes the spatial evolution characteristics of industrial structure distortion, two-way FDI, and carbon emission intensity. Thirdly, to clarify the mechanism of industrial structure distortion on carbon emissions, this study also sets two-way FDI as an intermediary variable for the empirical test. Finally, the paper determines the key factors affecting carbon emission intensity and expects to provide targeted suggestions for China's carbon emission reduction from the perspective of regional coordination with the help of the spatial measurement method.

This paper adopts the following structural arrangements: the second part combs the literature review and theoretical hypotheses; The third part introduces the research methods; The fourth part makes an empirical test; The fifth part is the conclusion and enlightenment.

2. Literature Review

The research on the relationship between IFDI and carbon emission intensity has a long history, and most of them focuses on the host country. The earliest international research on foreign investment and ecological problems can be traced back to the hypothesis of "pollution shelter" put forward by Copeland and Taylor [9]. Copeland and Taylor believed that under the high degree of free trade, due to the differences in the intensity of regional environmental policies, developed countries may move pollution-intensive industries across regions to developing countries, increasing the carbon emission intensity of the host country. Omri et al [10] and Millimet and Roy [11] scholars have all confirmed this hypothesis that IFDI leads to a reduction of pollution in the home country, while the pollution emissions in the foreign capital inflow country will increase relatively. On the contrary, Reppelin-Hill [12] put forward the hypothesis of a "pollution halo", and found that enterprises in developed countries are subject to higher environmental regulatory standards. While crowding out inefficient enterprises, changing industrial structure, and improving productivity and energy efficiency, foreign direct investment can promote the technological progress of the host country through horizontal, forward, and backward linkages of enterprises, stimulating the spillover effect of ecological innovation and reducing carbon emission intensity. Liang [13] believed that IFDI will promote the upgrading of the industrial structure of the host country, realize industrial upgrading, and improve environmental quality. With the acceleration of market-oriented reform, Zheng, and Sheng [14] pointed out that the mature factor markets and product transactions are conducive to the impact of IFDI on China's carbon dioxide emissions. However, due to the unsynchronized market development in different regions, the impact of IFDI on the carbon emission environment is different.

Because OFDI's research on carbon emission intensity is still in the initial stage, most of the research focuses on the economic environment and environmental level. On the one hand, from the economic level, Ozawa [15], Pan, et al. [16], and Yao et al. [17] respectively demonstrated the impact of foreign direct investment on the home country's economy from the aspects of industrial structure upgrading, reverse technology spillover, and agglomeration effect.

On the other hand, from the perspective of the environment, the main viewpoints can be divided into four angles. The first point is that OFDI can reduce the carbon emission intensity of the home country. Xin and Zhang [18] took economic development as the starting point, simulated the environmental effects of OFDI improvement on the home country with the help of scale, structure, and technology transmission mechanism, and affirmed that OFDI has a positive role in reducing carbon emissions. Gong and Liu [19] found that OFDI can weaken the carbon emission intensity of the home country through the scale effect by constructing the simultaneous equation model. Pan et al. [16] verified that OFDI could not promote carbon emission reduction in the home country through the spatial spillover effect and the System GMM model. The third point is that OFDI has a comprehensive effect on the carbon emission intensity of the home country. Based on the dynamic panel model, sung et al. [20] concluded that OFDI aggravates the environmental pollution of the home country in terms of the economic scale, but in terms of industrial structure and technical level, OFDI can improve the environmental quality, the positive effect is generally greater than the negative effect, and OFDI can promote the improvement of the overall environmental quality. The fourth point is the relationship between uncertainty and nonlinearity of OFDI in environmental governance. Hao et al. [21] proved that the impact of OFDI on environmental pollution in the home country has an "inverted U-shape".

3. Research Hypothesis

Theoretically, when the free flow of factors is hindered, the economy will be distorted and imperfect, which will inevitably lead to low efficiency and inefficiency of resource allocation [22]. As far as the distortion of industrial structure is concerned, the opposite is that the industrial structure is reasonable. Rationality roughly includes two aspects: one is the rational allocation of production factors among different departments, and the other is that production factors can be fully "reflected in the market". Therefore, if we analyze the degree of industrial structure distortion, we should discuss it from two aspects: market distortion and factor allocation deviation. Product market distortion is caused by trade barriers, price controls, and export subsidies. When this difference is reflected in different departments, it will worsen the overall allocation efficiency of resources. In the allocation of production factors, Ando and Nassar [23] found through the non-competitive equilibrium model that the transfer rate of production factors among various departments is equal. When production resources can be effectively allocated, the industrial structure is the best. When there is a deviation between output and employment in an economic sector, the equilibrium between industries is broken, and other sectors have a reverse deviation, resulting in the distortion of the factor market. In the industrial sector, due to the relative increase in labor price caused by industrial distortion, producers often choose to use the capital for labor substitution to achieve the established output and reduce costs. This often leads to excessive energy consumption, resulting in increased carbon emissions. When industrial investment is much higher than agricultural investment, the total energy consumption intensity obtained by different industrial sectors must deteriorate.

Theoretically, when the free flow of factors is hindered, the economic state can be distorted and imperfect, resulting in the inefficient allocation of resources [24]. The opposite of the distortion of industrial structure is the rationality of industrial structure, which includes the following two aspects. The first point is the rational allocation of production factors among different departments [25]. The second point is that all factors of production can be fully "reflected in the market". Therefore, the analysis of industrial structure distortion should be discussed from two aspects: factor allocation deviation and market distortion [26]. Market distortion is the unreasonable relative price of products caused by trade barriers, price control, and export subsidies. When this difference is reflected in different sectors, it worsens the overall efficiency of resource allocation and leads to increased carbon emissions.

In factor allocation, Ando and Nassar [23] argued that the rate at which factors of production are transferred between sectors is equal and that the industrial structure is optimal when productive resources can be allocated efficiently. However, when there are deviations in output and employment in one sector of the economy and the equilibrium between industries is broken, the other sectors deviate in the opposite direction, creating factor market distortions that lead to increased energy intensity in the production process. In the industrial sector, where labor prices are relatively elevated as a result of industrial distortions, producers often choose to use capital laborious substitution to achieve a given output and reduce costs. However, this often results in excessive consumption of energy, which increases carbon emissions, and in the current reality where investment in the industry is much higher than investment in agriculture, the summed energy consumption intensity obtained by the different industrial sectors must deteriorate.

Based on this, this paper puts forward the first hypothesis:

Hypothesis 1（H1）: *Distortions in the industrial structure can lead to market distortions and factor misallocation, resulting in increased aggregate energy consumption and increased carbon emissions intensity.*

The interaction between IFDI and OFDI has a tuning effect on the economic development of a country or region and has an impact on carbon emissions. Specifically, when the government reduces the environmental constraints and attracts foreign investment through low cost, this kind of IFDI promotes the rapid development of processing and manufacturing industries, and then expands production and produces economies of scale, which stimulate the significant growth of the regional economy, but at the same time, it also means a large amount of energy consumption. In a word, economic development can increase carbon emission intensity at the same time. However, IFDI crowds out some inefficient and low-quality domestic enterprises and transfers advanced technology to China through technology spillovers, to promote the upgrading of industrial structure and improve energy utilization efficiency and innovation ability, which is consistent with the hypothesis of the "pollution halo"[27].

From an OFDI perspective, long-term growth in OFDI can effectively shift excess capacity and achieve a reduction in fixed costs, leading to a reduction in carbon emissions intensity. Market-driven OFDI seeks overseas markets and locates production investments, driving profit growth while diverting pollution emissions. Technology-driven OFDI can help home countries seek advanced technologies and promote their industrial structure towards new industries to improve energy efficiency and reduce emissions and curb carbon intensity [28]. By going global, resource-driven enterprises can, on the one hand, alleviate resource constraints in their home countries and reduce their dependence on overseas resources, and, on the other hand, through international cooperation with resource-rich countries and regions, help their home countries to improve energy efficiency and optimize the structure of energy use, which has a positive effect on reducing carbon emission intensity.

Overall, the impact of two-way FDI on carbon emissions intensity is complex. As two-way FDI interaction accelerates, China's global value chain position improves, promoting the two-way flow of production factors and significant technological innovation spillovers, which will effectively reduce carbon emissions intensity. This leads to the second hypothesis of this paper.

Hypothesis 2（H2）: *The coordinated development of two-way FDI significantly inhibits the increase in carbon intensity, and the positive effect of technological innovation outweighs the negative effect of environmental pollution.*

From the perspective of industrial structure distortions affecting IFDI and hence regional carbon emissions, industrial structure distortions make lower labor costs and attract more IFDI inflows, which are mostly labor-intensive and resource-seeking enterprises. Lower production costs also make the technology leader lose its original advantage, leading to a "race to the bottom" among enterprises and inhibiting the development and upgrading of environmental technology [29]. Such IFDI flows into the market mainly in exchange for low factor prices, so it is difficult to expect such foreign-funded enterprises to produce technology spillovers and structural transformation.

From the perspective of industrial structure distortions affecting OFDI and hence regional carbon intensity. On the other hand, distortions in the industrial structure can cause the price of production factors used by manufacturing enterprises to deviate from the equilibrium price, generating a cost advantage that is reflected in export trade. Although it promotes the international competitiveness of enterprises and the scale of their exports, making them highly profitable, it also results in a lack of incentive for enterprises to face risky and costly R&D activities, preferring to manufacture traditional industrial products and leading to higher carbon emission intensity [30].

On the other hand, because of the need of pursuing economic development and improving political achievements, local governments prefer enterprises with a short production cycle and quick economic results [31]. As a result, enterprises tend to choose to enter government-supported industries in pursuit of cheaper factors of production, which further forces industrial structure distortions increasing the lock-in effect on the sloppy development model. That is, in an environment with an inadequate market exit mechanism, energy-intensive enterprises continue to survive by their cost advantage, increasing the carbon intensity of export manufacturing. In short, industrial structure distortions can have an impact on regional carbon emissions intensity through two-way FDI.

Based on the above analysis, a third hypothesis was formulated.

Hypothesis 3（H3）: *Two-way FDI exerts a significant mediating effect between industrial structural distortions and carbon emissions intensity.*

4. Research Methods and Data

4.1. Research method

4.1.1. Carbon Emission Intensity Measurement

The main methods for measuring carbon emissions are the life cycle assessment [32] the material balance approach, the carbon footprint estimation approach [33], and the carbon emission coefficient method. In this paper, we select eight types of energy consumption from the China Energy Statistical Yearbook: various types of coke, coal, crude oil, diesel, paraffin, fuel oil, gasoline, and natural gas, and include the carbon dioxide produced by their combustion in the emission inventory, and calculate the carbon emissions of 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) in China from 2011 to 2020. According to the standard coal conversion factor and carbon emission factor published by IPCC (Table 1), the measurement equation is as follows.

$$CE_i = \sum_{i=1}^{n} CE_i = \sum_{i=1}^{n} E_i \times NCV_i \times CEF_i \qquad (1)$$

In equation (1), CE_i is the carbon dioxide emissions from fossil energy source *i*. E_i is the consumption of energy source *i*. NCV_i and CEF_i are the average low-level heating value and emission factor of fuel *i*, respectively. The carbon intensity (CI) of the province is obtained by dividing the total carbon dioxide emissions measured by equation (1) with the GDP expressed in constant 2005 prices.

Table 1. The average low calorific value of energy and carbon dioxide emission coefficient.

	Coke	Coal	Crude oil	Diesel oil	Kerosene	Fuel oil	Gasoline	Gas
NCV	283,435	20,908	41,816	43,070	43,070	41,816	43,070	38,931
CEF	107,000	95,333	73,300	74,100	71,500	77,400	70,000	56,100

4.1.2. Measurement of Industrial Structure Distortions

At this stage, research on distortions has mainly focused on firm-level distortions, and some studies have classified them as product market distortions and factor market distortions, but few studies have addressed the industrial structure level.

Drawing on Ando and Nassar [23] this paper uses Euclidean distances to measure the degree of distortion in industrial structure, starting from the output and employment shares between sectors in disequilibrium, as follows.

$$D_i = \frac{L_i}{\sum_k L_k} - \frac{VA_i}{\sum_k VA_k}, \qquad D = \sqrt{\sum_i d_i^2} \qquad (2)$$

In equation (2), d_i represents the distance between output share and employment share, and d denotes the Euclidean distance between value added and employment share of the economy. VA_i and L_i represent value added and employment in each industrial sector i respectively.

The model has the following advantages. Firstly, it can correct the measurement deviation caused by the time series development difference between regions. Secondly, this model considers the importance of different departments. Thirdly, the numerical distribution is reasonable, that is $-1 \leqslant d_i \leqslant 1$, $0 \leqslant d \leqslant \sqrt{N}$,and the total effect of distortion of the three industrial sectors is equal to 0.

4.1.3. Spatial Correlation Test

The spatial correlation between variables is the basis for establishing a spatial regression model. The correlation description of variables in different spaces should be tested. This paper uses Moran's I to explore whether there is a spatial correlation between two-way FDI, industrial structure distortion, and carbon emissions. The equation is as follows.

$$Moran's\ \mathrm{I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (3)$$

In equation (3), I am Moran's I index, y_i is the observed value of region i, $\bar{Y}$ is the arithmetic mean of carbon emissions from all provinces,n is the number of provinces and W_{ij} is the spatial adjacency matrix. Moran's, I index takes values in the range [-1,1], with an I value greater than zero indicating a positive spatial correlation. A value of I closer to 1 indicates a strong spatial correlation, a value of I less than 0 indicates a negative spatial correlation, and a value of I closer to -1 indicates a strong spatial discrepancy. When I equal zero, it indicates a random distribution.

4.1.4. Spatial Econometric Model

Two-way FDI and industrial structure distortion are not unique economic phenomena in a region, and their causes may be spatially related. When there are economic differences in different regions, especially labor remuneration differences, production factors will flow not only between different industries within the region but also between different regions. At this time, there may be a spatial correlation between two-way FDI and industrial structure distortion. This paper further constructs a spatial econometric model to capture the spillover of two-way FDI and industrial structure distortion on carbon emissions from the two dimensions of space and time sequence, as follows:

The spatial autoregressive model (SAR) only considers the spatial correlation of the explained variables.

$$\ln CI_{i,t} = \rho W \ln CI_{j,i} + \beta_i X_i + \mu_i + \eta_i + \varepsilon_{i,t} \quad (4)$$

Where, lnCI is the logarithm of carbon emission intensity of region i at time t, ρ is the spatial autocorrelation coefficient, W is the spatial weight matrix, Xi is the explanatory variable, μ_i, η_i are individual fixed effect and time fixed effect models respectively, $\varepsilon_{i,t}$ is random interference term.

The spatial autocorrelation model (SAC) considers the spatial correlation between the error term and the explained variable.

$$\ln CI_{i,t} = \rho W \ln CI_{j,t} + \beta_i X + \mu_i + \eta_i + v_{i,t}$$
$$v_{i,t} = \lambda W v_{i,t} + \varepsilon_{i,t} \quad (5)$$

Where: λ is the spatial autocorrelation coefficient, and the meaning of other variables remains unchanged.

The Spatial Dubin model (SDM) considers the lag factor of dependent variables and the spatial effect of different factors on explanatory variables.

$$\ln CI_{i,t} = \rho W \ln CI_{j,t} + \beta_i X_i + WX_{i,t}\gamma + \mu_i + \eta_t + \varphi_{i,t} \quad (6)$$

Where: γ is the spatial autoregressive coefficient of the independent variable, ϱ is the spatial autoregressive coefficient of and dependent variables, and the meaning of other variables remains unchanged.

4.1.5. Intermediary Effect Model

To further verify hypothesis 3 and investigate whether the distortion of industrial structure will have an impact on carbon emission intensity through two-way FDI, an intermediary effect test procedure is constructed for the stepwise regression test.

$$CI_{i,t} = \gamma_0 + \gamma_1 CI_{i,t-1} + \gamma_2 D_{i,t} + \gamma_3 X_{i,t} + v_i + \varepsilon_{i,t} \quad (7)$$

$$IFDI_{it} = \alpha_0 + \alpha_1 IFDI_{it-1} + \alpha_2 D_{it} + \alpha_3 X_{it} + \upsilon_i + v_i + \varepsilon_{it} \quad (8)$$

$$OFDI_{it} = b_0 + b_1 OFDI_{it-1} + b_2 D_{it} + b_3 X_{it} + \upsilon_i + v_i + \varepsilon_{it} \quad (9)$$

$$CI_{it} = \lambda_0 + \lambda_1 CI_{it-1} + \lambda_2 D_{it-1} + \lambda_3 IFDI_{it} + \lambda_4 OFDI_{it} + \lambda_5 X_{it} + \upsilon_i + v_i + \varepsilon_{it} \quad (10)$$

Where, equation (7) represents the total effect of industrial structure distortion (*d*) on carbon emission intensity (CI), expressed in λ_2. Measure the total effect; Equations (8) and (9) respectively represent the impact of industrial structure distortion on intermediate variables (IFDI) and (OFDI), to investigate the impact of industrial structure distortion on China's two-way FDI respectively; In equation (10) λ_2 measure the direct effect of industrial structure distortion on carbon emission intensity. If equations (8) and (9) are respectively brought into (10), the coefficient product is obtained $\lambda_3\alpha_2$ and $\lambda_4 b_2$ represent the intermediary effect of IFDI and OFDI respectively, that is, the distortion of industrial structure will affect the degree of carbon emission intensity by affecting IFDI and OFDI.

4.2. Index Selection and Data Source

4.2.1. Variable Selection

Explained variable. Carbon emission intensity (CI) is calculated by dividing the total carbon emission calculated by equation (1) and GDP expressed at a constant price in 2005.

Core explanatory variables. Industrial structure distortion index (d), expressed as the square root of the sum of squares of the deviation between employment share and output share of all local departments. Two-way FDI is represented by foreign direct investment (IFDI) and foreign direct investment (OFDI).

Control variables. To reduce the bias of regression results caused by the omission of explanatory variables, this paper refers to the existing research results (Yin et al., 2015), and selects the following as control variables.

Energy structure (Ener). Select the proportion of energy consumption converted into standard coal in the actual GDP to measure.

Environmental regulation (ER). Select the proportion of total investment in environmental pollution control in GDP to measure the impact of environmental regulation on carbon emissions. The impact of environmental regulation on carbon emissions should be two-way. On the one hand, appropriate environmental regulation can promote the upgrading of enterprise production structure, achieve high energy efficiency and innovation ability, and effectively reduce carbon emissions. On the other hand, the setting of environmental regulation is too high. To reduce pollution emissions, enterprises will increase production costs. With the loss of profits, enterprises will choose to expand production, aggravate energy consumption, and increase carbon emissions.

Therefore, the expected coefficient of environmental regulation is uncertain and can be used as a control variable. Economic development level (PGRP). Select per capita GDP as an economic measurement index for the empirical test. On the one hand, the improvement of economic development aggravates energy consumption and leads to an increase in carbon emissions. On the other hand, when the "turning point of the Environmental Kuznets Curve" is reached, the enthusiasm of the public to participate in environmental protection and the awareness of environmental protection are enhanced in economically developed areas, to promote the decoupling of economic development and carbon emission.

Technology input (R&D). Select the proportion of the actual R&D expenditure of each province in GDP to measure. Technological progress can improve the innovation ability of enterprises, promote the upgrading of industrial structure, and reduce the ineffective allocation of factors caused by the distortion effect. The higher the technological level, the higher the energy efficiency, and the lower the carbon emission and the level of economic development.

Urbanization rate (urban). Considering the obvious differences in administrative division area and population scale in different provinces, to enhance the contrast between indicators, the proportion of the urban population in the total population is selected to measure the urbanization rate.

4.2.2. Data Sources

To reduce the regression deviation caused by data omission, based on fully considering the availability and operability of data, the author excludes Tibet, Hong Kong, Macao, and Taiwan, and combs and cleans the relevant data of 30 provinces (cities and autonomous regions) from 2011 to 2020. The data comes from the website of the National Bureau of Statistics, China Statistical Yearbook, China Science and technology statistical yearbook, China energy statistical yearbook, and China Environmental Statistical Yearbook, and the invalid data are identified and eliminated with the help of SPSS 22.0. Logarithmic processing is used to eliminate the influence of heteroscedasticity and multicollinearity on the regression results. For some missing data, trend prediction and interpolation are used to supplement. The descriptive statistics of variables are shown in Table (2).

Table 2. Descriptive statistics of variables.

variable	observations	mean value	standard deviation	minimum value	Maximum
CI	300	0.971	0.707	0.151	3.922
D	300	0.336	0.139	0.033	0.670
IFDI	300	21453.4	35142.8	67.619	22438.3
OFDI	300	7164.43	18631.25	0.068	15431.44
ENER	300	69.427	28.523	4.917	155.761
ER	300	34.634	7.436	24.576	52.765
PGRP	300	1.376	0.834	0.412	4.697
R&D	300	15.134	9.427	1.564	78.477
URBAN	300	0.056	0.069	0.002	0.412

5. Empirical Test and Result Analysis

5.1. Temporal and Spatial Evolution of Carbon Emission Intensity in China

5.1.1. Temporal Characteristics of Carbon Emission Intensity in China

According to table 3, overall, in terms of period, the national carbon emission intensity has been "decoupled" from economic growth, basically maintaining an average annual decline of about 4.2%. There are significant group differences. The overall change trend of the eastern, central, and western regions is consistent with that of the whole country, but their intensity changes show a pattern of "the eastern region leads, the central region catches up, and the western region lags ". In terms of subregions, the decline rate

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of carbon emission intensity of provinces and cities from 2011 to 2020 can be divided into five groups (Table 4). Beijing's carbon intensity decreased by 55.90%, leading the country; Chongqing, followed by Chongqing, took multiple measures to promote the deep integration of pollution reduction and carbon reduction through innovative ways such as "carbon sink +" and climate change investment and financing pilot. The proportion of carbon intensity reduction during the study period was 54.39%. The carbon intensity of Tianjin, Sichuan, Guizhou, and Yunnan decreased by more than 50%. The carbon intensity of Hebei, Jilin, Fujian, Henan, Hubei, Hunan, Guangdong, Guangxi, Gansu, and other provinces decreased by 35% ~ 50%; Inner Mongolia, Liaoning, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Shandong, Shaanxi, Hainan, Qinghai, and Ningxia. The decline of carbon intensity in Shanxi is in the proportion range of 5% ~ 20%. Xinjiang's carbon emission intensity showed an increasing trend, with an increased ratio of 12.70%.

On the one hand, it benefits from the strong implementation of the national overall acceleration of green and low-carbon development and energy conservation and emission reduction policies, and the formulation of strict and effective total energy consumption control targets. It is also closely related to the continuous strengthening of the sense of responsibility of governments at all levels, a deep understanding of the severe situation of ecological protection, and actively promoting the upgrading of local energy-related industrial structures.

Table 3. Carbon emission intensity values of China's provinces from 2011 to 2020.

Region	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	0.322	0.281	0.253	0.208	0.193	0.168	0.164	0.162	0.158	0.142
Tianjin	0.608	0.534	0.479	0.423	0.382	0.329	0.311	0.314	0.309	0.302
Hebei	1.352	1.258	1.149	1.037	0.953	0.894	0.824	0.823	0.818	0.816
Shanxi	2.554	2.513	2.358	2.314	2.224	0.219	2.248	2.243	2.247	2.246
Inner Mongolia	2.153	2.043	1.795	1.716	1.583	1.496	1.506	1.488	1.476	1.473
Liaoning	1.183	1.122	0.984	0.937	0.894	0.913	0.896	0.892	0.887	0.882
Jilin	0.987	0.886	0.769	0.725	0.651	0.626	0.584	0.557	0.561	0.553
Heilongjiang	0.963	0.911	0.823	0.784	0.767	0.755	0.738	0.691	0.688	0.652
Shanghai	0.437	0.426	0.414	0.386	0.372	0.354	0.339	0.327	0.317	0.309
Jiangsu	0.524	0.519	0.503	0.495	0.461	0.454	0.387	0.364	0.351	0.346
Zhejiang	0.517	0.462	0.422	0.394	0.382	0.367	0.378	0.356	0.352	0.341
Anhui	0.844	0.786	0.763	0.731	0.722	0.668	0.609	0.583	0.587	0.552
Fujian	0.534	0.471	0.409	0.426	0.368	0.337	0.317	0.313	0.309	0.313
Jiangxi	0.646	0.592	0.562	0.524	0.514	0.476	0.433	0.418	0.426	0.408
Shandong	0.871	0.834	0.749	0.712	0.698	0.705	0.661	0.642	0.639	0.635
Henan	0.871	0.752	0.686	0.637	0.574	0.534	0.471	0.482	0.459	0.462
Hubei	0.822	0.831	0.786	0.584	0.509	0.458	0.434	0.446	0.427	0.421
Hunan	0.662	0.594	0.583	0.554	0.501	0.461	0.428	0.386	0.377	0.359
Guangdong	0.421	0.376	0.354	0.335	0.317	0.296	0.281	0.276	0.281	0.264
Guangxi	0.726	0.687	0.631	0.585	0.527	0.486	0.472	0.466	0.471	0.453
Hainan	0.949	0.927	0.759	0.765	0.743	0.722	0.667	0.643	0.638	0.622
Chongqing	0.649	0.551	0.433	0.408	0.378	0.341	0.322	0.304	0.296	0.286
Sichuan	0.635	0.557	0.543	0.507	0.459	0.381	0.346	0.321	0.309	0.297
Guizhou	1.866	1.742	1.723	1.384	1.247	1.224	1.068	1.104	0.983	0.922
Yunnan	1.097	0.976	0.811	0.718	0.624	0.583	0.557	0.543	0.546	0.529
Shaanxi	1.223	1.243	1.183	1.133	1.043	1.003	0.943	0.951	0.937	0.926
Gansu	1.537	1.402	1.316	1.218	1.113	0.984	0.967	0.944	0.950	0.935
Qinghai	1.213	1.293	1.283	1.093	0.923	1.003	0.893	0.901	0.887	0.874
Ningxia	3.947	3.797	3.677	3.467	3.327	3.047	3.497	3.312	2.976	2.972
Xinjiang	1.898	1.958	2.018	2.038	1.887	1.895	2.012	2.113	2.027	2.139

 doi:10.20944/preprints202206.0314.v1

Table 4. The reduction ratio of carbon emission intensity of China's provinces from 2011 to 2020.

Order number	proportion	province
1	＞50	Beijing (55.90%), Tianjin (50.33%), Chongqing (54.39%), Sichuan (53.22%), Guizhou (50.59%), Yunnan (51.78%)
2	(35% ,50%]	Hebei (39.64%), Jilin (43.97%), Fujian (41.38%), Henan (46.96%), Hubei (48.78%), Hunan (45.77%), Guangdong (37.29%), Guangxi (37.60%), Gansu (39.17%)
3	(20% ,35%]	Inner Mongolia (31.58%), Liaoning (25.44%), Heilongjiang (32.29%), Shanghai (29.23%), Jiangsu (33.97%), Zhejiang (34.04%), Anhui (34.60%), Shandong (27.09%), Shaanxi (24.28%), Hainan (34.46%), Qinghai (27.94%), Ningxia (24.70%)
4	(5% ,20%]	Shanxi (12.06%)
5	≤5%	Xinjiang (-12.70%)

5.1.2. Spatial Characteristics of Carbon Emission Intensity in China

With the support of ArcGIS software, the natural discontinuity method is used to render the spatial distribution of China's carbon emission intensity in 2011 and 2020 to investigate the spatial differentiation of China's carbon emission intensity, as shown in Figure 1.

Overall, from 2011 to 2020, the national carbon emission intensity decreased significantly, the low-carbon emission intensity regions gradually shifted to the north, the carbon emission intensity of the Yangtze River economic belt and North China withdrew from the medium carbon emission intensity regions, and the difference between the north and the South gradually increased. From the perspective of the spatial distribution of "low carbon emission" around the country in 2011, it shows a "high carbon emission intensity" in the middle. High-value areas are mainly distributed in Shanxi, Inner Mongolia, and Ningxia, and the median area is concentrated in the north and Anhui, Hubei, Hainan, Guizhou, and Yunnan. And formed a concentrated and continuous “regional block” distribution characteristic, and it is speculated that there is a spatial correlation between carbon emission intensity.

With time, the regional heterogeneity of China's carbon emission intensity will become more prominent in 2020, showing a "cascade" spatial change of "high in the northwest and low in the Southeast", forming a spatial pattern of carbon emission intensity with Shanxi and Ningxia as high-value areas and significant "decoupling" effect of carbon emission in the central region. It is worth noting that low-value areas are widely distributed in most areas south of the Yangtze River. The carbon emission intensity of all provinces in the Yangtze River economic belt has decreased significantly, the polarization characteristics are significant, and the difference in carbon emission intensity between the north and the South has increased, indicating that the traditional spatial development pattern has been broken.

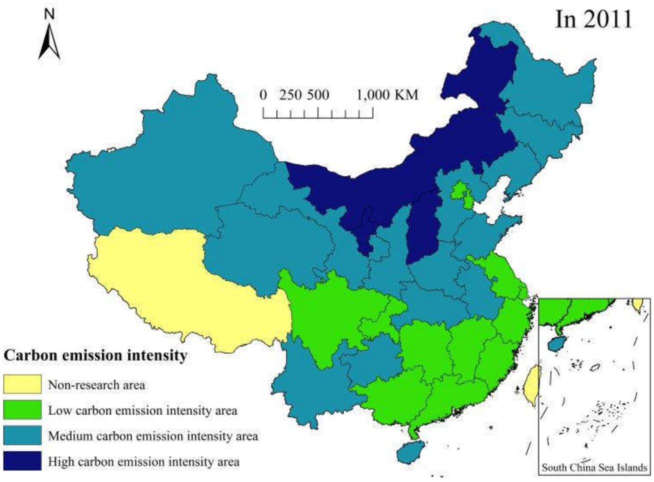

Figure 1. Spatial distribution of China's carbon emission intensity in 2011 and 2020.

5.2. Industrial Structure Distortion Index

According to the classification standard of the National Bureau of Statistics, 30 provinces and cities are divided into three regions in the East, middle and West, and the average value of the industrial structure distortion index of each region and the country from 2011 to 2020 is calculated according to equation (2). See Figure 2 for details. Overall, the national industrial structure distortion index shows an obvious downward trend, which shows that with the improvement of marketization, the continuous improvement of innovation ability, the rational allocation of production factors among different departments, and the vigorous implementation of measures such as capacity removal and inventory reduction, the production capacity structure is continuously optimized to promote the rationalization of industrial structure.

In terms of subregions, the industrial structure distortion index of the western region is the highest, followed by the central region, and the industrial structure distortion index of the eastern region is the lowest during the research period. The reason is that the economic development of the western region still depends on the traditional "three high enterprises", the industrial foundation is weak, and the investment in technology R&D is insufficient, which makes the emerging industries still in the embryonic stage and fall into a "low-level cycle", resulting in the disharmony between the existing resource allocation and the desired resource allocation. To promote economic growth, the central region government intervened in the price formation and allocation of factor markets such as capital, labor, and land.

Although the growth target was achieved in the short term, it caused an imbalance in the industrial structure in the long run. At the same time, the distortion of industrial structure will also lead to the depression of labor price and the rapid growth of labor-intensive industries, The ratio of the output value structure of capital intensive and labor-intensive industries has expanded, which further hinders the optimization of industrial structure. Due to the developed economy and sound factor market-oriented pricing mechanism, the eastern region can promote the rational allocation of production factors, high innovation ability, promote the improvement of productivity, accelerate the elimination of backward production capacity, change the traditional economic growth model, and improve the acceptable level of industrial structure.

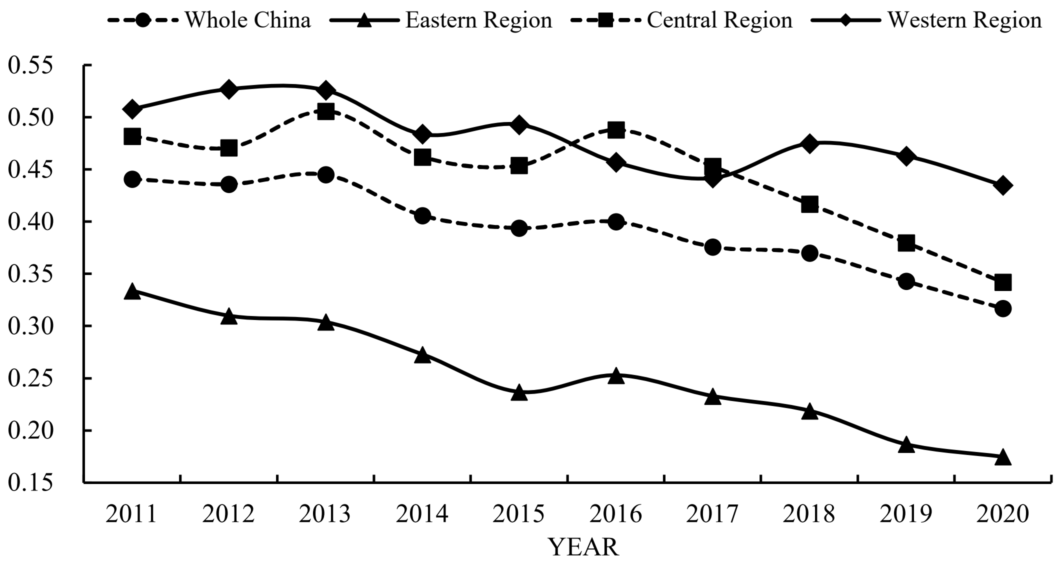

Figure 2. China's industrial structure distortion index from 2011 to 2020.

5.3. Spatial Correlation Test Results

The comparison of temporal and spatial distribution can only simply analyze the evolution trend of carbon emission intensity, but can't describe the internal evolution law. To further explore the correlation characteristics between industrial structure distortion, two-way FDI and carbon emission intensity, Moran's I index in each province in different years is calculated according to equation (3). The results are shown in Table 5.

The Moran's *I* indices for carbon emissions intensity, industrial structure distortion, and two-way FDI over the period 2011-2020 are all positive, with most passing the significance test at the 1% level and a small number passing the significance test at the 5% and 10% levels. There was a significant positive correlation and positive agglomeration in spatial distribution. The spatial effect between variables should be fully considered when constructing the influencing factor model. In addition, Moran's *I* value changes in wave shape during the study period, and the fluctuation range in individual years is large, indicating that there is volatility agglomeration among different provinces, and the nearest neighbor effect is obvious.

Table 5. Global Moran's I calculation results from 2011 to 2020.

Year	CI		D		IFDI		OFDI	
aa	Moran's *I*	*P-value*	Moran's *I*	*P-value*	Moran's *I*	*P-value*	Moran's *I*	*P-value*
2011	0.338***	0.000	0.454**	0.014	0.337**	0.028	0.217***	0.000
2012	0.308***	0.000	0.477**	0.012	0.308**	0.044	0.155***	0.003
2013	0.319***	0.000	0.529***	0.000	0.341**	0.001	0.049**	0.016
2014	0.308***	0.000	0.531***	0.000	0.352***	0.000	0.106*	0.059
2015	0.297***	0.000	0.510***	0.001	0.375***	0.000	0.066*	0.089
2016	0.273***	0.001	0.516***	0.000	0.324**	0.038	0.183***	0.001
2017	0.281***	0.000	0.456**	0.014	0.331**	0.031	0.202***	0.000
2018	0.263***	0.002	0.416**	0.021	0.409***	0.000	0.177***	0.002
2019	0.266***	0.002	0.490***	0.006	0.305**	0.046	0.241***	0.000
2020	0.235***	0.004	0.458***	0.009	0.367***	0.000	0.148***	0.004

Notes: *, ** and *** Denote statistical significance at the 10%, 5% and 1% levels, respectively.

5.4. Spatial Econometric Empirical Test

5.4.1. Model Selection

Considering that the factors affecting carbon emission intensity are complex, the traditional OLS model, spatial autoregressive model, spatial autocorrelation model, and spatial multi-objective model are constructed for spatial econometric regression. Based on ignoring the spatial correlation, the statistical results of the houseman rejected the original hypothesis of the random effect model at a 1% significance level. Considering the individual heterogeneity of provinces and cities in the sample, the AC-FE, SAR-FE, and SDM-FE models are tested based on the time-space dual fixed effect regression model. In Table 6, LR is significant at the statistical level of 1%, rejecting the original assumption that the coefficients of the spatial lag explanatory variable are equal to 0, that is, the SDM model can't be simplified to the SAR model. According to the further test of AIC, BIC, and log-likelihood values, the SDM model has smaller values and is a better fit than the sac model. Therefore, this paper finally selects the estimation results of the SDM model to illustrate the impact of various factors on carbon emission intensity.

Table 6. Model selection test.

Model selection	Null Hypothesis		*LR* test	*P value*	
SDM-FE vs SAR-FE	The coefficients of all spatial lag explanatory variables are 0		X^2=9.2	0.009***	
SAC-FE vs SDM-FE	observations	Value of log-likelihood	Degree of freedom	*AIC*	*BIC*
SAC-FE	300	488.95	12	-953.88	-904.57
SDM-FE	300	484.94	10	-947.89	-907.72

5.4.2. Regression Result Analysis

According to the regression results, table 7 shows that the regression coefficient of industrial structure distortion is 0.284, and through the significance test of 1%, it shows that the failure of market regulation and the deviation of production factor allocation caused by industrial structure distortion leads to the output share much higher than the employment share, and its essence is the substitution of capital for the labor force. This substitution leads to low energy efficiency, and the capital-driven economic growth model lags the rate of aggregate energy consumption, resulting in the overall increase in carbon emission intensity, which verifies hypothesis 1. The regression coefficient of China's foreign direct investment is -0.045, and the 5% significance test supports the "pollution halo" hypothesis to a certain extent, that is, IFDI inhibits the increase of carbon emission intensity.

The above shows that the cost of environmental protection is not the only factor that needs to be considered for enterprises transferred through foreign investment. Labor, infrastructure and policy subsidies are all considered. At the same time, foreign enterprises promote the progress of environmental protection technology in developing countries and reduce pollution emissions through the "demonstration effect" and "spillover effect".

The regression coefficient of foreign direct investment is -0.036, and it has passed the significance test of 1%. To a certain extent, it reflects that with the improvement of the potential of China's global value chain. On the one hand, "gradient" OFDI can promote the upgrading of China's industrial structure, digest backward production capacity, help improve resource mismatch, make production factors flow to sectors with higher marginal reporting, and promote the realization of carbon emission reduction. On the other hand, "reverse gradient" OFDI can give birth to the reverse spillover effect of technology and indirectly reduce the carbon emissions of home countries, which is consistent with the research conclusions of Hao et al.[35].

The interaction terms of IFDI and OFDI are negative and pass the significance test at the level of 5%, indicating that there is an obvious complementary effect of two-way FDI among China's provinces, and this effect will effectively promote the improvement of enterprise green technology innovation level and reduce carbon emission intensity, which is consistent with the research conclusions of Feng et al.[36] and others, and verifies hypothesis 2.

By analyzing the control variables, the regression coefficient of energy structure to carbon emission intensity is 0.134, and through the significance test of 5%, it shows that the energy structure dominated by coal will lead to serious environmental pollution. At the same time, high energy consumption will aggravate the distortion of industrial structure and increase the intensity of carbon emission. The regression coefficient of environmental regulation on carbon emission intensity is 1.613, but it is not significant, but it supports the "green paradox" hypothesis to a certain extent, that is, the implementation of environmental regulation intensifies carbon emission. The reason may be that the article selects market incentive regulation tools as the proxy variable. After paying high pollution control investment, enterprises usually choose to expand production to make up for the loss of profits, in addition, the insufficient development of clean energy has restrained the decline of carbon emission intensity. The regression coefficient of economic development level on carbon emission is -0.645, and through the 5% significance test, combined with the EKC hypothesis, with China's rapid economic growth and crossing a certain threshold, there will be a dividend period of carbon emission reduction. The regression coefficient of technology input on carbon emission is negative and passes the significance test of 5%, and the carbon emission intensity will be reduced by 0.136% for every 1% increase in technology input, indicating that the progress of low-carbon technology and the development and use of new energy have significantly controlled the increase of carbon emission from the source of production. The regression coefficient of urbanization rate carbon emission is -0.136, and through the significance test of 5%, it shows that urbanization forms agglomeration effect and scale effect by increasing population density and promotes the formation of agglomeration economy such as infrastructure sharing, service value sharing and knowledge spillover, improves production efficiency, reduces pollution and energy consumption, and promotes the reduction of carbon emission intensity.

Table 7. Spatial econometric regression results.

Influence factor	OLS	SAR	SAC	SDM
Model	(1)	(2)	(3)	(4)
ln*D*	0.810***	0.189***	0.205***	0.284***
ln*IFDI*	-1.691***	-0.027**	-0.028**	-0.045**
ln*OFDI*	1.212**	0.027***	0.026***	-0.036***
ln*ENER*	-5.191*	0.148**	0.144**	0.134**
ln*ER*	-0.129*	0.314*	1.217*	1.613
ln*PGRP*	-0.097***	-0.501**	-0.586**	-0.645**
ln*R&D*	-1.506**	-0.134**	0.125**	-0.136**
ln*URBAN*	0.023***	-0.354***	-0.485***	-0.442***
ln*IFDI*×ln*OFDI*	-0.561**	-0.364**	-0.257*	-0.154**
ln*D*·*W*	-	-	-	0.045
ln*IFDI*·*W*	-	-	-	-0.036**
ln*OFDI*·*W*	-	-	-	0.047
Spatialρ	-	0.159***	0.155*	0.165***
Log-likelihood	-	483.7741	484.3731	488.3451
R^2		0.431	0.354	0.591
Individual effect	control	control	control	control
time effect	control	control	control	control
observations	300	300	300	300

It can be seen from Table 7 that the spatial lag parameter ϱ of spatial Durbin model is positive. It shows that the local carbon emission intensity will be affected by neighboring areas. According to LeSage and Pace[36], in the spatial regression model, the direct effect, indirect effect, and total effect of explanatory variables can respectively reflect the influence degree of each variable on the local area, adjacent areas, and the whole country. In this paper, each index is decomposed, as shown in Table 8.

From the perspective of industrial structure distortion, its direct and indirect effects on China's carbon emission intensity are significantly positive. The distortion of industrial structure not only reduces the efficiency of local resource allocation and intensifies the intensity of energy consumption, but also has a significant adverse effect on the decline of carbon emission intensity in adjacent areas through indirect effects. Specifically, an increase of 1% in the distortion of industrial structure in other regions will increase the local carbon emission intensity by 0.037%.

From the perspective of foreign direct investment, its direct and indirect effects on China's carbon emission intensity are significantly negative at the level of 10% and 5% respectively. Under the long-term investment-driven development model, the government attracts foreign capital through tax relief and other policies. When it enters, it will promote the spillover effect. Foreign-funded enterprises from developed countries have higher innovation abilities. Domestic enterprises can reduce the fixed and variable costs of technology research and development through the "shared product" of inter-industry technical knowledge, promoting technological progress to reduce carbon emission and consumption intensity.

From the perspective of foreign direct investment, the direct impact of OFDI on local carbon emission intensity is negative and fails to pass the significance test. However, to a certain extent, with the acceleration of China's economic development and to protect its ecology, Chinese enterprises carry out OFDI, although inhibiting innovation and development to a certain extent, they also transfer some "three high" industries overseas, alleviate domestic competition and reduce pollution emissions, to promote the reduction of carbon emission intensity. The spillover effect of foreign direct investment is positive and has passed the significance test of 5%, which reflects that with the increase of the intensity of OFDI, the difficulty of technology transfer and innovation development increases, coupled with the limited absorption capacity of domestic reverse technological innovation, the weakening of innovation drive, "negative externalities of the environment" are beginning to appear, and the uncoordinated joint prevention and control policies among the governments of adjacent regions, Lead to the transfer of carbon emissions nearby, resulting in the increase of carbon emission intensity in surrounding areas.

From the perspective of the interaction between IFDI and OFDI, the direct and indirect impact of the interactive development of China's two-way FDI on carbon emission intensity is negative, which can significantly reduce carbon emission intensity. On the one hand, the rapid development of IFDI drives economic growth, contributes to the increase of OFDI, promotes the development of reverse technological innovation to a certain extent, and directly promotes the reduction of local carbon emissions. On the other hand, OFDI strongly supports IFDI. In the process of China's foreign investment, it can not only transfer excess capacity but also promote economic development. With the rise of the enterprise economy, the requirements for the IFDI access threshold will increase. In the long run, this will help to play a positive role in the decline of carbon emission intensity in surrounding areas through the cross-regional flow of technicians and technology spillover.

Table 8. Decomposition of spatial Doberman effect.

Influence factor	Direct effect	Indirect effect	Total effect
ln*D*	0.053*	0.037**	0.090**
ln*IFDI*	-0.030*	-0.015**	-0.045
ln*OFDI*	-0.027	0.016**	-0.009*
ln*ENER*	0.114***	0.041***	0.155**
ln*ER*	-0.026*	0.035*	0.009*
ln*PGRP*	-0.553	-0.350*	-0.903
ln*R&D*	-0.121*	-0.091**	-0.212*
ln*URBAN*	0.394***	-0.273**	0.121**
ln*IFDI*×ln*OFDI*	-0.134**	-0.125	-0.259*

6. Intermediary Effect Test

The previous paper theoretically analyses the transmission mechanism of industrial structural distortions on China's carbon intensity based on the perspective of two-way FDI. To test the theoretical hypothesis proposed in this paper and to check whether two-way FDI plays a mediating role, the article chooses a mediating effect model for testing, and the results are shown in Table 9.

The results in column (1) show that the estimated coefficient of industrial structural distortion is 0.086, which significantly contributes to the increase in China's carbon emission intensity and the waste of resources and ecological damage caused by structural distortion, which puts serious pressure on China's pollution control. Column (2) shows that the estimated coefficient of industrial structure distortion (D) is 0.142, indicating that industrial structure distortion has contributed to the increase of China's IFDI level. Under the dual pressure of maintaining growth and promoting employment, local governments compete to formulate preferential policies on the supply and price of production factors, which intensifies the distortion of industrial structure, and this distortion will significantly reduce the environmental management costs of enterprises. The results in column (3) show that the estimated coefficient of industrial structure distortion is -0.131, indicating that industrial structure distortion will inhibit the development of OFDI in China. The

 doi:10.20944/preprints202206.0314.v1

reason is that industrial structure distortion will help enterprises turn their factor cost advantages into export advantages, promote the growth of their export scale and export competitiveness, and attract more enterprises to invest abroad. At the same time, industrial structure distortion will keep some overcapacity enterprises alive, and to transfer these backward production capacities, the government will encourage overseas investment, resulting in a significant increase in the level of OFDI.

According to the intermediary effect test procedure, further test whether two-way FDI plays the role of an intermediary variable. Two-way FDI has added into the regression equation that industrial structure distortion affects carbon emission intensity. The results show that the regression coefficients of individual effect and overall effect both pass the significance test. Based on verifying the previous test process, it is further shown that two-way FDI is the two channels through which industrial structure distortion affects carbon emission intensity, that is, the transmission mechanism of industrial structure distortion affects carbon emission intensity by affecting two-way FDI. In model (4), the intermediary variable of two-way FDI is added, and the significant relationship between industrial structure distortion and carbon emission intensity has not changed. However, the coefficient in the model (4) is smaller than that in the model (1), which indicates that the influence of industrial structure distortion on carbon emission intensity has weakened, and two-way FDI plays a partial intermediary role between them, to some extent, "covering up" the negative influence of industrial structure distortion on carbon emission intensity, which verifies hypothesis 3.

Table 9. Test results of mediating effect.

	CI	**IFDI**	**OFDI**		**CI**	
	(1)	**(2)**	**(3)**		**(4)**	
D	0.086***	0.142**	-0.131***	0.214***	0.236**	0.219***
IFDI				-0.087***		0.206***
OFDI					0.194***	0.198***
Constant term	-0.614***	-0.514***	0.376**	0.434***	-0.529***	0.716***
control variable	Yes	Yes	Yes	Yes	Yes	Yes
time effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2680	0.2755	0.1372	0.2031	0.1835	0.2239
N	300	300	300	300	300	300

7. Conclusion and Discussion

With the deepening of China's economic system reform and the acceleration of the "going global" process, the impact of industrial structure distortion and two-way FDI on carbon emission intensity has become increasingly prominent. Based on relevant theories, this paper brings two-way FDI, industrial structure distortion, and carbon emission intensity into the same research framework, and makes an empirical test based on the panel data of 30 provinces in China from 2011 to 2020, to deeply explore the impact of two-way FDI and industrial structure distortion on carbon emission intensity from both theoretical and empirical aspects.

The main conclusions include the following aspects. Firstly, overall, thanks to the improvement of marketization, the rational allocation of production factors, and the continuous optimization of industrial structure, the industrial structure distortion index of

China showed a downward trend from 2011 to 2020. By region, because the central and western regions lag the eastern regions in terms of economic development level, innovation ability, and rational allocation of labor resources, the industrial structure distortion index in the western region is the highest, followed by the central region and the lowest in the eastern region. Second, China's carbon emission intensity is "decoupled" from its economic development, and keeps declining year by year. However, the intensity decline shows a heterogeneous distribution pattern of "the east is leading, the middle is catching up, and the west is lagging ". On the provincial scale, except in Xinjiang, the carbon emission intensity of other provinces has declined to various degrees. In terms of spatial distribution, the carbon emission intensity has changed from a distribution pattern of "high in the middle and low around" to a "cascade" pattern of "high in the northwest and low in the southeast". The polarization characteristics are remarkable, and the traditional spatial distribution pattern has been broken. Thirdly, there is a positive spatial correlation between China's industrial structure distortion, two-way FDI and carbon emission intensity, and there is fluctuation agglomeration among provinces. The distortion of industrial structure leads to the deviation of factor allocation and the failure of market regulation, which not only leads to the increase of local carbon emission intensity but also produces a reverse spillover effect, which increases the carbon emission intensity of the surrounding areas. IFDI and OFDI provide a powerful driving force for the reduction of carbon emission intensity. IFDI promotes the decrease of carbon emission intensity in neighboring areas, while OFDI will increase the carbon emission intensity in surrounding areas. The interaction between IFDI and OFDI can significantly reduce the carbon emission intensity of local and neighboring areas. Fourthly, the overall test of intermediary effect shows that two-way FDI is two channels through which industrial structure distortion affects carbon emission intensity. Industrial structure distortion can affect the transmission mechanism of carbon emission intensity by affecting two-way FDI.

According to the above research conclusions, this paper puts forward the following policy suggestions. First, it is suggested to continue to promote the optimization of industrial structure and reduce carbon emission intensity. The government should attach importance to the optimization and adjustment of industrial structure, issue relevant policy documents to promote economic growth, improve the quality and growth rate, eliminate backward production capacity, promote the development of innovative, green, and low-carbon industrial clusters, and continue to promote the decoupling of economic growth from carbon emissions. Optimize the spatial development pattern of industrial structures. For the central and western regions with slightly backward economic development, relevant policy documents should be issued, support for emerging industries should be strengthened, capital investment should be increased, regional development differences should be narrowed, industrial structure distortion should be reduced, and "resonance with the optimization and upgrading of national industrial structure" should be realized. Secondly, it is suggested that IFDI should be guided to develop in high-tech, low-carbon emission reduction, and other fields. Establish a reasonable performance evaluation system, highlight the unified and coordinated evaluation of economic development and environmental protection, and encourage local governments to pay more attention to quality in the process of attracting investment. Improve environmental protection-related policies, gradually abolish the "super-national treatment" of foreign-funded enterprises, improve the entry threshold of high-carbon industries, and reduce the tolerance of foreign-funded enterprises for environmental pollution. Introduce high-quality foreign capital, promote the coordinated development of resources, environment, and economy, pay attention to the "benchmarking" of foreign-funded enterprises, give full play to the "pollution halo" effect of IFDI, drive domestic green low-carbon technology innovation, and achieve carbon emission reduction. Third, it is suggested to speed up the transformation of foreign economic development mode and give full play to the reverse innovation effect. In the process of "going global", we should pay attention to reverse gradient investment in developed economies, increase investment in technology and research industries, and reduce OFDI's activities of seeking markets and resources. Make full use of overseas enterprises' advantages of being close to the source of technical resources, track advanced technology, learn green technology, knowledge, and management experience, and promote domestic enterprises to carry out environmental innovation, produce green products and reduce domestic carbon emission intensity. Fourthly, it is suggested to pay attention to the rational layout and guidance of two-way FDI and promote the interactive and coordinated development of two-way FDI. The empirical results show that IFDI will significantly affect the carbon emission intensity. At present, China's IFDI is still seeking resources. Therefore, it is necessary to formulate corresponding investment policies, take energy conservation and emission reduction as a reference factor to adjust the investment structure, increase investment in green environmental protection industries, and promote China's green transformation and development. At the same time, China's OFDI should pay attention to investing in the research and technology industries of other countries, and make full use of OFDI's reverse technology spillover effect to reduce the technical effect of domestic carbon emissions, to promote the in-depth development of the low-carbon economy.

Author Contributions: This paper is a collaborative work of all the authors. In formal analysis, JS together with LY and GH executed the experimental work. Additional characterization was performed by JS. This paper was drafted by ST and further edited by LY and JS. All authors contributed to the article revision and have both read and approved the submitted version.

Funding: This research was funded by The National Social Science Fund of China, grant number 19BJY085.

Institutional Review Board Statement: The authors declare that they have no known competing financial interests or personal relationships that seem to affect the work reported in this article. We declare that we have no human participants, human data, or human tissues.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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