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Original Research

Influence of Industrial Transfer on Carbon Emissions in China: a Spatial Spillover Perspective

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Abstract

Industrial transfer has become a breakthrough for regional economic upgrading, while the carbon emissions involved in the industrial transfer are yet to be explored. Based on this, we analyzed the impact of the industrial transfer on carbon emissions for China's 30 provincial-level regions during 2007-2018 using spatial panel econometric models. The results show a significant positive spatial correlation of carbon emissions, whereas the negative spatial correlation of industrial transfer gradually appears, and the local distribution of carbon emissions and industrial transfer is mainly characterized by high-high agglomeration. Furthermore, overall industrial transfer shows significant positive direct and negative indirect effects on carbon emissions. There are negative direct and spatial spillover relationships between industrial transfer and carbon emissions in the industrial transfer-out regions, while the industrial transfer-in regions show a positive effect. The transfer of industries, in particular, does not imply the transfer of carbon emissions; however, the balance of industrial restructuring and technological progress during the industrial transfer process can more effectively control and reduce carbon emissions.

Keywords: carbon emissions, industrial transfer, spatial spillover effect, spatial econometric model, pollution haven

Introduction

Industrial transfer, the process and phenomenon of transferring some industries from developed regions to developing regions driven by regional comparative advantages due to changes in resource supply or product demand, a trend of global economic development [1]. The rapid development of China's economy and the entry into a new normal have pushed industrial transfer gradually from international to domestic, with more emphasis on inter-provincial industrial transfer and upgrading. In 2010, the Guiding Opinions on Undertaking Industrial Transfer in the Central and Western Regions stated the necessity of deepening regional cooperation, promoting the free flow of factors, and realizing the benign interaction between central and western regions. The Ministry of Industry and Information Technology of China 2018 issued a new Directory of Guidance on Industrial Transfer to support qualified regions to actively undertake and develop related industries with high-end links to the global value chain, guide and deepen the regional division

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of labor and cooperation, and strive to build a new pattern of regional industrial development with complementary advantages and harmonious cooperation in the west, northeast, central, and eastern regions.

On the other hand, as the world's largest developing country and the largest carbon-emitting economy, China has made a series of commitments to adapt to climate change and mitigate global warming. In the Paris Agreement, China promised that "the carbon dioxide emission intensity will decrease by 60-65% in 2030 compared with 2005, and carbon emissions will peak around 2030" [2]. In the British Petroleum Corporation (BP) Statistics Yearbook of World Energy 2020, China's carbon dioxide emissions accounted for 27% of the world's total carbon emissions. The carbon dioxide emissions per $10,000 gross domestic product (GDP) were 67,200 tons, which is 1.76 times the world average. China is facing serious energy conservation and emission reduction pressure, and it is urgent to protect the environment and promote sustainable development.

The industrial transfer is an important way to achieve global and regional economic integration and balance regional economic development. Meanwhile, the industrial transfer is also accompanied by a spatial reset of energy consumption and carbon emissions, except for the diffusion of capital, labor, and technology. The research on this issue originated from the concern about the environmental effects of international trade. Ding et al. estimated the carbon emissions embodied in the bilateral trade between China and 68 countries along the Belt and Road routes, and found that China's bilateral trade had extremely little impact on global carbon emissions and there was a possibility of reducing global carbon emissions [3]. Indeed, Yu and Xu verified the negative effect of FDI on industrial CO_2 emissions at the national level [4]. However, Andersson argued that the rising trade with China had become a major contributor to the increase in carbon emissions on the consumption side in developed countries [5]. Additionally, the transfer of carbon emissions occurred between Chinese provinces, and the formulation of carbon reduction policies should take into account the carbon emissions implied in trade [6].

Since 1990, China has been shaped as the world's factory by large-scale industrial transfers from developed countries such as the United States, Britain, and Japan. Along with the booming domestic industries, the transfer of industries within China's regions and between provinces has gradually become the focus of promoting economic growth and realizing industrial optimization and upgrading [7]. Currently, there is no consensus on how to measure industrial transfers, including the direct representation by FDI amount, as well as the exponential measures of the Gini coefficient, Herfindahl index, and location entropy [8-11]. The application of shift-share analysis ensures comprehensive and continuous data acquisition of regional industrial transfer volume [12], compared with the systematic but discontinuous measurement of the input-output analysis [13-14].

Additionally, the issue of China's carbon dioxide emissions has attracted widespread attention. Economic growth, energy consumption, trade, and urbanization are all important factors affecting carbon emissions [15-16]. With the extension of industrial transfer in China, studies on the relationship between industrial transfer, carbon emissions, and environmental pollution are emerging. Some scholars reveal the positive effect of industrial transfer on the environment, and the development of industrial transfer increases carbon emissions between regions. The "pollution haven hypothesis" states that industrial transfer leads to the transfer and diffusion of pollution, exacerbating environmental pressure [17-18]. However, some studies have shown that industrial transfer can reduce carbon emissions and contribute to energy saving and emission reduction goals [19]. In particular, the impact of industrial transfer on the development of a low-carbon economy is not obvious and regionally heterogeneous. It is necessary to optimize industrial allocation and distribution to take responsibility for energy saving and emission reduction [20].

The mobility of production factors and energy resources between different regions makes the industrial development in the surrounding areas affect the local environment, so spatial factors are necessary to be included in the study of the relationship between industrial development and the environment. Overall, regional carbon emissions have significant spatial spillover effects and adjacent convergence [21-22]. Industrial structure upgrading helps to reduce carbon emissions, and there is significant heterogeneity in the spatial spillover effect on carbon emission reduction at the regional level [23], whereas some studies reveal that industrial transfer deepens the spatial correlation between economy, carbon emissions, and environmental quality [24].

Although the impact of industrial transfer on carbon emissions has been widely studied, there is still a need for further research. Firstly, the measurement of industrial transfer variables is often difficult to ensure data continuity and accuracy at the same time, so we use a combination of the shift-share method and input-output analysis to calculate the industrial transfer volumes at the Chinese provincial level. Secondly, most of the literature still focuses on the impact of international industries on carbon emissions, including the transfer from developed to developing countries, as well as industrial transfer activities in an urban agglomeration or a province [25], whereas fewer studies have been conducted at the inter-provincial or intra-regional level. Finally, the application of a simple panel econometric model to identify the influence of carbon emissions ignores spatial effects.

To overcome these limitations and clarify the effects of the industrial transfer on carbon emissions, we use panel data from 30 provinces in China for 2007-2018 to explore the impact of the provincial industrial transfer on carbon emissions with spatial panel econometric models. We apply the shift-share analysis method and the input-output method to define and calculate the industrial transfer volume more comprehensively. The direct impact and spatial spillover effects of the industrial transfer on carbon emissions at the provincial level are analyzed in depth, to provide effective suggestions for the formulation of energy-saving and emission-reduction policies in China.

The marginal contribution of this research to the current literature is reflected in several aspects. First, it extends the application of the pollution haven hypothesis at the inter-provincial level. This paper focuses on the impact of the inter-provincial industrial transfer on carbon emissions, which is different from the research on international trade and the environment. Second, spatial effects are considered to comprehensively analyze the impact of the industrial transfer on the environmental situation in the surrounding areas. Third, many important policy implications can be concluded. The empirical results provide a case study for policymakers to understand the environmental impacts of regional industrial transfer and seek a win-win approach for economic development and environmental protection.

The remaining parts of this paper are organized as follows. The "Material and Methods" section highlights the methodology. The "Results and Discussion" section analyses the empirical results, and the "Conclusions" section summarizes the main findings and provides some suggestions.

Material and Methods

Measurement of Industrial Transfer

To accurately characterize the industrial transfer variable, we accounted for it based on the inflow and outflow of economic activities in each province from the Input-Output Tables of China, but the frequency of data published once every five years lacks continuity. Further, we refer to Cheng and Wei and use the shift-share analysis method to calculate the industrial transfer volume of each province and take it as the main representative indicator [26].

Shift-Share Analysis Method

The shift-share analysis method decomposes the change of the regional economic aggregate in a certain period into share components (or national growth components), structural deviation components, and competitiveness deviation components, and then identifies the industrial sectors with relative competitive advantages in the region, thereby planning the future development direction and adjusting the industrial pattern.

X_{ij} denotes the economic variable of the *i*th industry (or sector) at the beginning of the period in region *j* ($i = 1, 2, \ldots, R$; $j = 1, 2, \ldots, S$), X_{ij}' is the value at the end of the period, then the change of this variable in a period can be expressed as:

$$\Delta X_{ij} = X_{ij}^{'} - X_{ij} = X_{ij} r + X_{ij}\left(r_i - r\right) + X_{ij}\left(r_{ij} - r_i\right) \tag{1}$$

$$r = \frac{\sum_{i=1}^{S}\sum_{j=1}^{R}\left(X_{ij}^{'} - X_{ij}\right)}{\sum_{i=1}^{S}\sum_{j=1}^{R} X_{ij}};\ r_i = \frac{\sum_{j=1}^{R}\left(X_{ij}^{'} - X_{ij}\right)}{\sum_{j=1}^{R} X_{ij}};\ r_{ij} = \frac{X_{ij}^{'} - X_{ij}}{X_{ij}} \tag{2}$$

Where: r is the share of the economic volume added by all industries or sectors to the total economic volume at the beginning of the period, r_i represents the economic growth rate of all industries or sectors, and r_{ij} denotes the economic growth rate at the end of the period relative to the beginning of the period. The share component $X_{ij}r$ indicates the amount that an industry or sector can increase by developing at the growth rate of the country's entire industry or sector; the industrial structure component $X_{ij}(r_i-r)$ is the amount of growth achieved by the difference in growth rates between an industry or sector and the region or the nation. The larger the value, the greater the contribution of the industrial structure to the growth of the total economy. The competitiveness component $X_{ij}(r_{ij}-r_i)$ is equal to the difference between the growth achieved by industry *i* in a region at the actual growth rate and the regional or national growth rate, respectively, and when the value is greater than 0, it indicates that industry *i* in the region is more competitive relative to the overall growth of the country.

Furthermore, we expand the competitiveness component to include the amount of industrial transfer. Industrial transfer in the region lacks competitiveness with the growth of an industry in the region is slower than the average development of the overall regions or the country, and the possibility of transferring outward industry is weak, whereas the growth of industrial transfer out of the region is higher than the whole regional or national average growth. The specific calculation is:

$$\begin{aligned}\sum_{j=1}^{R}\left(X_{ij}^{'} - X_{ij}\right) &= \left[X_{i1}r + X_{i1}\left(r_i - r\right) + X_{i1}\left(r_{i1} - r_i\right)\right] + \left[X_{i2}r + X_{i2}\left(r_i - r\right)\right.\\ &\quad \left.+ X_{i2}\left(r_{i2} - r_i\right)\right] + \ldots + \left[X_{iR}r + X_{iR}\left(r_i - r\right) + X_{iR}\left(r_{iR} - r_i\right)\right]\\ &= \sum_{j=1}^{R}\Delta X_{ij} = \sum_{j=1}^{R} X_{ij}r + \sum_{j=1}^{R} X_{ij}\left(r_i - r\right) + \sum_{j=1}^{R} X_{ij}\left(r_{ij} - r_i\right)\end{aligned} \tag{3}$$

The third term in Equation (3) is the industrial transfer component, and the amount of industrial transfer between regions is represented by *IT*.

$$IT = \sum_{j=1}^{R} X_{ij}\left(r_{ij} - r_i\right) = \left[X_{i1}\left(r_{i1} - r_i\right)\right] + \left[X_{i2}\left(r_{i2} - r_i\right)\right] + \ldots + \left[X_{iR}\left(r_{iR} - r_i\right)\right] \tag{4}$$

Where X is the total industrial output value of each province, which is substituted into Equation (4) to obtain the amount of industrial transfer, where positive values indicate net transfer in and negative values denote net transfer out.

Input-Output Method

The input-output method helps to calculate the direct and indirect energy consumption in economic activities based on the input-output relationships between different sectors and thus identifies the key industries that affect carbon emissions [27]. We apply the non-competitive input-output model excluding imports to measure the amount of industrial transfer driven by final use and export. Total output = final-use output + export-driven output, which is the industrial net transfers, with a negative value representing a net transfer out, and a positive value indicating a net transfer in. The basic form of the interregional input-output table among industries is shown in Table 1.

According to input-output theory, the total output X of a region can be expressed as:

$$X = (I - A)^{-1}(Y + E) \tag{5}$$

$$a_{ij} = \frac{x_{ij}}{X_j}\left(i, j = 1,2,3, \dots, n\right) \tag{6}$$

Where X is the total output matrix, A is the direct consumption coefficient matrix, and the calculation of the elements is as shown in Equation (6); x_{ij} is the direct consumption of the product in section i during the production of section j; X_j is the total direct consumption in the production process of section j; and Y is the final use matrix. The final use of a region is equal to the sum of the final demand for a sector's own products and for other sectors:

$$\begin{pmatrix} X_{11} & \dots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{n1} & \dots & X_{nn} \end{pmatrix} = \begin{pmatrix} I - A_{11} & \dots & -A_{1n} \\ \vdots & \ddots & \vdots \\ -A_{n1} & \dots & I - A_{nn} \end{pmatrix}^{-1} \begin{pmatrix} Y_{11} & \dots & Y_{1n} \\ \vdots & \ddots & \vdots \\ Y_{n1} & \dots & Y_{nn} \end{pmatrix} + \begin{pmatrix} I - A_{11} & \dots & -A_{1n} \\ \vdots & \ddots & \vdots \\ -A_{n1} & \dots & I - A_{nn} \end{pmatrix}^{-1} \begin{pmatrix} E_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & E_n \end{pmatrix} \tag{7}$$

Where the data for final use Y and export E can be directly obtained from the input-output table. We obtain the net transfer volume as well as the industrial transfer volume of each province, driven by consumption and exports, respectively.

Measurement of Carbon Emissions

Carbon emissions were calculated based on eight carbon-containing energy consumption sources. The carbon emissions of each energy source were equal to the consumption of this energy multiplied by their respective carbon emission coefficient (carbon emission coefficient = carbon dioxide emission coefficient/3.67), and the carbon emissions of different energy sources were summed to form the total carbon emissions [28]. The conversion coefficients of eight energy sources to standard coal are shown in Table 2.

Setting of Spatial Weight Matrix

We first set the spatial adjacent weight matrix W_1 to analyze the spatial effects of industrial transfer on carbon emissions:

$$w_{ij} = \begin{cases} 1 & \text{when } i \text{ and } j \text{ are adjacent} \\ 0 & \text{when } i \text{ and } j \text{ are not adjacent} \end{cases} \tag{8}$$

To test the robustness of the model results, we set the spatial distance weight matrix W_2 and the K-nearest neighbor spatial weight matrix W_3.

$$w_{ij} = \begin{cases} 1/d_{ij} & i \neq j \\ 0 & i = j \end{cases} \tag{9}$$

Where d_{ij} denotes the central distance between region i and region j.

The K-nearest neighbor spatial weights matrix W_3 takes the geographically nearest K units as its neighbors, and each unit has K neighbors. We set K = 3.

Exploratory Spatial Data Analysis (ESDA)

The spatial autocorrelation statistic is a common method used in exploratory spatial data analysis (ESDA)

Table 1. Interregional input-output table.

Input \ Output		Intermediate use			Final use				Total output
		Sector 1	…	Sector n	Sector 1	…	Sector n	Export	
Intermediate input	Sector 1	$A_{11}X_{11}$	…	$A_{1n}X_{1n}$	Y_{11}	…	Y_{1n}	E_1	X_1
	…	…	…	…	…	…	…	…	…
	Sector n	$A_{n1}X_{n1}$	…	$A_{nn}X_{nn}$	Y_{n1}	…	Y_{nn}	E_n	X_n
Added value		V_1	…	V_n					
Total input		X_1	…	X_n					

Table 2. Conversion coefficients of various energy sources into standard coal and carbon emission coefficients.

Energy type	Coal	Coke	Crude oil	Gasoline	Kerosene	Diesel oil	Fuel oil	Natural gas	Electricity
Converted to standard coal coefficient	0.7143	0.9714	1.4286	1.4286	1.4714	1.4714	1.4571	1.3300	1.2290
Carbon emission coefficient	1.9003	2.8604	3.0202	3.1705	2.9251	3.0179	3.0959	2.1622	3.4074

Notes: In addition to natural gas and electricity, the unit of other energy conversion into standard coal coefficient is kgce/kg, the unit of carbon dioxide emission coefficient is kg-co_2/kg; the unit of natural gas conversion into standard coal coefficient is kgce/m^3, the unit of carbon dioxide emission coefficient is kg-co_2/m^3; and the unit of electricity conversion into standard coal coefficient is kgce/kwh, the unit of carbon dioxide emission coefficient is kg-co_2/kwh.

to measure the spatial correlation among different regions with Moran's *I* coefficient.

$$Moran's\ \ I_{global} = \frac{N\sum_{i=1}^{N}\sum_{i=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}\sum_{i=1}^{N} w_{ij}} \tag{10}$$

Where *N* is the number of regions; $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, x_i is the observation of region *i*, which is expressed as the carbon emissions and industrial transfer volume of each province in our research; and W_1 is the 0-1 spatial weight matrix. The value of Moran's I_{global} ranges between -1 and 1. A Moran's *I* value of -1 indicates that the variable has a completely negative spatial correlation; when Moran's *I* is equal to 1, the variable has a completely positive spatial correlation; and when Moran's *I* is equal to 0, the variable has no spatial correlation. Finally, we tested the spatial autocorrelation using a standard deviation *z*-value that approximates the standard normal distribution:

$$Z = \frac{|\text{Moran's}\ \ I - E(I)|}{\sigma_I} \tag{11}$$

Where $E(I)$ and σ_I are the mathematical expectation and variance of Moran's *I*, respectively. To explore the spatial correlation characteristics of local regions, we further introduced the local spatial autocorrelation test.

$$Moran's\ \ I_{\text{local}} = \frac{(x_i - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{x})^2}\sum_{j=1}^{N} w_j\,(x_j - \bar{x}) \tag{12}$$

A positive value indicates that the area has a high (low) variable eigenvalue surrounded by a high (low) value, whereas a negative value means that the area with a high (low) variable eigenvalue is accompanied by a low (high) value.

Spatial Panel Econometric Models

The spatial panel econometric model reflects the impact of different factors on carbon emissions, and there are three basic models for spatial panel econometric models: the Spatial Panel Lag Model (SPLM), the Spatial Panel Error Model (SPEM), and the Spatial Panel Durbin Model (SPDM). In the model, carbon emissions are the explained variable, the level of industrial transfer measured by the shift-share analysis method is the core explanatory variable, and the control variables include:

- **Economic development level (*GDP*):** measured by GDP per capita, it is equal to the ratio of GDP to the total annual population. The classical EKC hypothesis verifies an inverted U-shaped curve between environmental quality and economic growth. We include a quadratic term for the economic level to verify the non-linear relationship.
- **Urbanization (*UR*):** = urban population/total population at the end of the year * 100%. Theoretically, the environmental impact of city population size is ultimately determined by the trade-off between economies of scale and congestion effects [29].
- **Financial allocation efficiency (*FE*):** expressed as the proportion of loans to deposit balances from financial institutions. A higher financial allocation efficiency implies a higher likelihood that funds will be invested in green and environmentally friendly industries in the context of high-quality economic development orientation.
- **Industrial structure (*IN*):** IN_1 and IN_2 are the shares of the secondary and tertiary sectors in GDP, respectively.
- **Energy consumption structure (*EC*):** EC_1, EC_2, EC_3, and EC_4 are the ratios of coal, crude oil, natural gas, and electricity consumption to total energy consumption, respectively. Coal and crude oil consumption lead to more carbon emissions compared to natural gas and electric energy consumption.
- **Science and technology investment (*RD*):** = research and experimental development (R&D) expenditure/GDP, high-technology investment is beneficial to improve energy conservation and environmental protection technology and energy use efficiency.
- **Environmental Regulation (*ER*):** = investment in industrial pollution control/GDP.

The SPLM, reflecting the spatial correlation of the explained variable, is expressed as:

$$\ln CE = \rho W \times \ln CE + \beta_1 IT + \beta_2 \ln GDP + \beta_3 \ln^2 GDP + \beta_4 UR + \beta_5 FE + \beta_6 IN_1 + \beta_7 IN_2 + \beta_8 EC_1 + \beta_9 EC_2 + \beta_{10} EC_3 + \beta_{11} EC_4 + \beta_{12} RD + \beta_{13} ER + \varepsilon_{it}, \quad \varepsilon \sim N\left(0, \sigma^2 I\right) \tag{13}$$

Where ε is the error term obeying the standard normal distribution, W is the spatial weight matrix, CE denotes carbon emissions, IT represents industrial transfer degree, lnGDP and ln^2GDP are the logarithms of GDP per capita and GDP per capita square, UR is the urbanization rate, FE is the financial allocation efficiency, IN_1 and IN_2 are the shares of secondary and tertiary industries, respectively, EC_1-EC_4 are the proportions of coal, crude oil, natural gas, and electricity consumption, respectively, RD is science and technology investment, and ER is environmental regulation. ρ is the estimated coefficient of the spatial lag term, β_1-β_{13} are the regression coefficients of the explanatory variables, i represents the region, and t denotes the year.

When the error term is spatially correlated, the SPEM is set to:

$$\ln CE = \beta_1 IT + \beta_2 \ln GDP + \beta_3 \ln^2 GDP + \beta_4 UR + \beta_5 FE + \beta_6 IN_1 + \beta_7 IN_2 + \beta_8 EC_1 + \beta_9 EC_2 + \beta_{10} EC_3 + \beta_{11} EC_4 + \beta_{12} RD + \beta_{13} ER + u_{it}, \quad u_{it} = \lambda W \mu_{it} + \varepsilon_{it}, \varepsilon \sim N\left(0, \sigma^2 I\right) \tag{14}$$

The variables are defined as above. The disturbance term u shows spatial correlation, indicating that the spatial correlation of factors other than the explanatory variables may also affect the explained variable. λ is the estimated coefficient of the spatial error term.

The setting of the SPDM is as follows:

$$\ln CE = \rho W \times \ln CE + \sum_{j=1}^{13} \beta_j X_j + \sum_{j=1}^{13} \varphi_j W * X_j + \varepsilon_{it}, \varepsilon \sim N(0, \sigma^2 I) \tag{15}$$

Where ρ is the estimated coefficient of the spatial lag term of the explained variable. β_j denotes the coefficient of the jth explanatory variable, and φ_j represents the coefficient of the spatial lag term of the jth explanatory variable, j = 1, 2, …, 13, which represents the variables IT, lnGDP, ln^2GDP, UR, FE, IN_1, IN_2, EC_1, EC_2, EC_3, EC_4, RD, and ER, respectively.

Data

The data from 2008 to 2019 is obtained from the China Statistical Yearbook, China Industry Statistical Yearbook, China Energy Statistical Yearbook, China City Statistical Yearbook, and the Statistical Yearbooks of various provinces and cities. Additionally, the input-output data in 2017 was derived from the 2017 Input-Output Tables of China, compiled by the Department of National Accounts of the National Bureau of Statistics. Due to the availability of data before 2007 and the absence of data on some indicators in Tibet, we finally settled on 30 provinces for the study period 2007-2019 with a sample size of 360. The descriptive statistics of variables are shown in Table 3.

Combining the method description and model setting, we show the research idea in Fig. 1 to explore

Table 3. Descriptive statistics of variables.

Variable	Sign	Unit	Max.	Min.	Mean	SD
Carbon emissions	CE	10,000 tons carbon	115261.40	2817.33	38554.74	23435.84
Industrial transfer volume	IT	100,000,000 RMB yuan	2144.77	−2933.70	119.58	496.56
GDP per capita	GDP	10,000 RMB yuan	14.08	0.34	4.42	2.51
Urbanization rate	UR	%	89.61	28.23	54.61	13.42
Financial allocation efficiency	FE	%	114.38	40.85	73.69	12.83
Industrial structure	IN_1	%	61.14	18.07	45.78	8.66
	IN_2	%	90.73	27.70	44.14	9.72
Energy consumption structure	EC_1	%	98.72	4.91	61.76	19.46
	EC_2	%	96.82	0	17.36	16.03
	EC_3	%	4.06	0.01	0.63	0.68
	EC_4	%	25.55	7.72	14.54	3.80
Science and technology investment	RD	%	6.17	0.21	1.50	1.07
Environmental regulation	ER	%	0.99	0.01	0.15	0.13

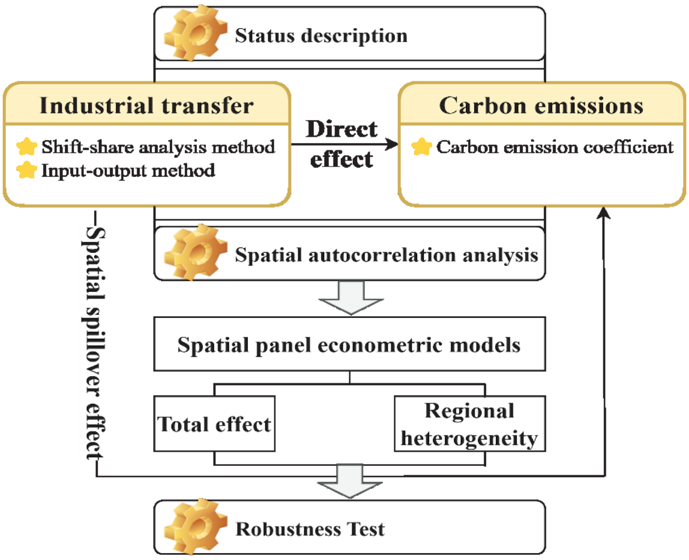

Fig. 1. Technology Route.

the direct and spatial spillover effects of inter-provincial industrial transfer on carbon emissions.

Results and Discussion

In this section, we first show the industrial transfer volume and regional division status under two different methodological calculations, as well as the distribution of provincial carbon emissions. We then test the spatial correlation of the variables and explore the impact of industrial transfer on carbon emissions and regional heterogeneity characteristics at the provincial level using spatial econometric models. Finally, we verify the robustness of the empirical findings.

Status of Provincial Industrial Transfers and Carbon Emissions

Based on the input-output table of China in 2017, the net transfer volume of 30 provinces is calculated, as shown in Fig. 2. In line with China's current stage of pursuing industrial structure optimization and actively promoting the transfer of industrial enterprises to the central and western regions, the trend of industrial transfer in 2017 is characterized by a transfer from the eastern coast, with a strong foundation and a good economic base, to the central and western regions, with relatively weak economies.

In 2017, the transfer out of China's industries exceeded the transfer in of industries by about 134

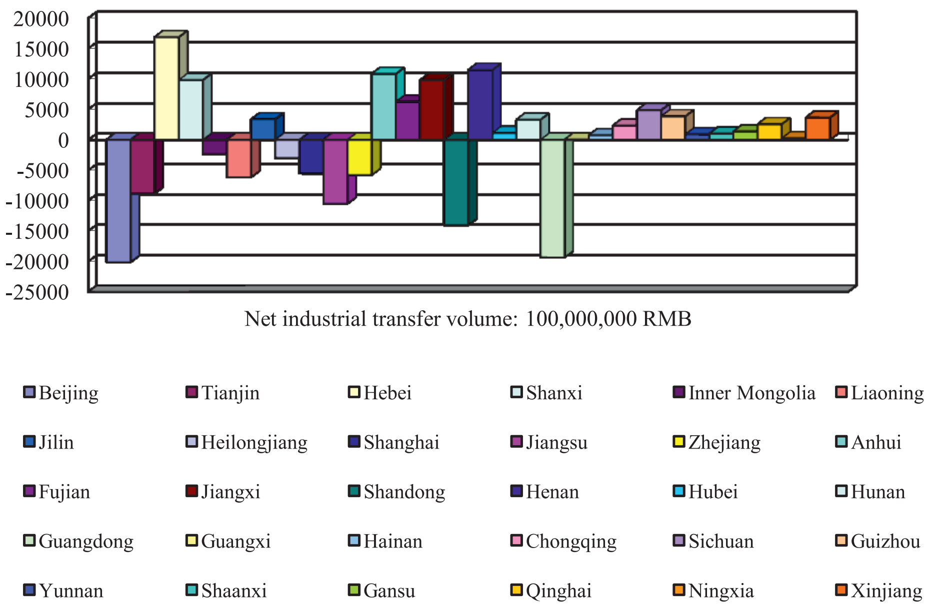

Fig. 2. The net industrial transfer volume of 30 provinces in 2017 under the input-output method.

billion RMB, indicating that there are eliminating and upgrading backward and high energy-consuming sectors and actively transferring out high pollution-intensive industries in the context of de-stocking and de-capacity. Among them, 10 provinces-Beijing, Guangdong, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Shandong, Heilongjiang, and Inner Mongolia-are the major industrial transfer out, while 20 provinces-Hebei, Anhui, Shanxi, Fujian, Shaanxi, and Guizhou-are industrial transfer in. The net industrial transfer out of Beijing accounted for 21% of the total industrial transfer out of the country; the net industrial transfer in Tianjin accounted for 9%; yet the net industrial transfer in Hebei accounted for 18% of the total industrial transfer in the country, undertaking the industrial transfer from Beijing and Tianjin. Similarly, the net industrial transfer out of Guangdong accounted for 20%, transferring a large number of industrial enterprises to Jiangxi, Hunan, and other provinces. The net industrial transfer out of industries in Liaoning accounted for 6%, eliminating several high energy-consuming enterprises such as steel, calcium carbide, and coke.

Alternatively, we applied the shift-share analysis method to measure the industrial transfer volume of 30 provinces from 2007 to 2018 in Fig. 3. Overall, the amount of industrial transfer based on gross industrial output measured under the shift-share analysis method is much lower than the industrial transfer volume based on industry-wide gross output accounting under the input-output method, but the division of industrial transfer out and industrial transfer in provinces remains basically consistent. Specifically, Beijing, Tianjin, and Guangdong were mainly transferred to industries in the early days. With the maturation and transformation of industrial forms, they have been transferred out of heavy pollution and high energy-consuming industries in recent years. Correspondingly, Hebei, Henan, and Fujian have become the main targets of industrial transfer, while Guizhou, Qinghai, and Gansu due to the remote location of the amount of industrial transfer undertaken is relatively small.

Furthermore, we refer to the study of Xu et al. to classify 30 provinces in China into industrial transfer-out, industrial strong transfer-in and industrial weak transfer-in regions [30]. First, the net transfer calculated from the input-output table in 2017 was divided into regions according to the order of negative values (from small to large) followed by positive values (from large to small), with negative values representing transfers out; second, the provincial industrial transfer obtained by applying the shift-share analysis was ranked according to the same method, with the provinces ranked in the top 10, middle 10, and last 10 are industrial transfer out, industrial strong transfer in, and industrial weak transfer in, respectively; third, the differences under the two methods of division are determined in relation to the recent actual development of the provinces. The industrial transfer and the corresponding carbon emission distribution under different partitions are shown in Table 4.

In general, the eastern provinces are mostly industrial transfer-out regions, with the average share of industrial transfer-out regions in the national total transfer volume from 2007 to 2018 being 54.31% and the share of carbon emissions reaching 44.29%. The average share of industrial transfer volume in industrial strong transfer-in regions to the national total industrial transfer volume is 30.41%, and the share of carbon emissions reaches 32.47%, while the western and southwestern provinces are mostly industrial weak transfer-in regions, with an average share of 15.28% of industrial transfer volume and 23.04% of carbon

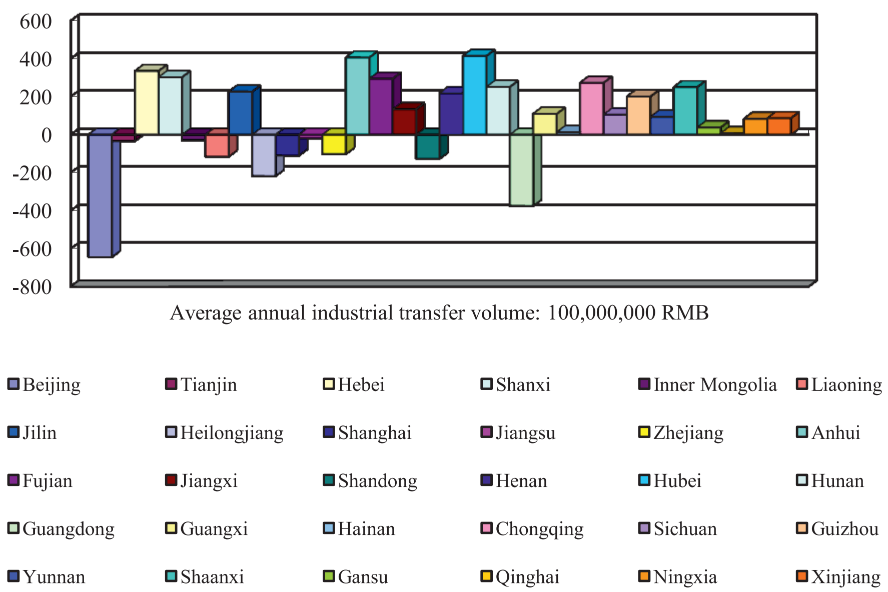

Fig. 3. Average annual industrial transfer volume in 2007–2018 of 30 provinces measured by the shift-share analysis method.

Table 4. Regional division and distribution of industrial transfer.

Division	Average share of industrial transfer volume between 2007 to 2018	Average share of carbon emissions between 2007 to 2018	Province
Industrial transfer-out region	54.31%	44.49%	Beijing, Tianjin, Inner Mongolia, Liaoning, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Shandong, Guangdong
Industrial strong transfer-in region	30.41%	32.47%	Hebei, Shanxi, Jilin, Anhui, Fujian, Henan, Hubei, Hunan, Chongqing, Shannxi
Industrial weak transfer-in region	15.28%	23.04%	Jiangxi, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Gansu, Qinghai, Ningxia, Xinjiang

emissions share. Further, comparing the share of carbon emissions with the share of industrial output value, it is found that the share of carbon emissions in the industrial transfer-out region is lower than the share of industrial transfer volume, while the share of carbon emissions in the industrial strong transfer-in region and the industrial weak transfer-in region is higher than the share of industrial output value, which is related to the high carbon emission characteristics of the region itself or the carbon transfer problem accompanying the industrial transfer-in process, which needs to be further explored.

Spatial Autocorrelation Analysis

We apply Moran's I test to verify the spatial correlation effects of carbon emissions and industrial transfer volume in Table 5. Overall, the Moran's I_{global} coefficients of carbon emissions all exceeded 0.1 and were significant at least at the 10% level except for 2016. There is a positive spatial correlation of provincial carbon emissions. Additionally, the coefficients of the industrial transfer volume from 2007 to 2013 are positive insignificantly. The spatial correlation coefficients in 2014-2016 are greater than 0 at the 1% significance level, yet the values in 2017-2018 are negative and significant at the 5% level, indicating that interprovincial industrial transfers gradually change from positive to negative spatial correlation.

Table 5. Moran's I_{global} test of carbon emissions and industrial transfer.

Year	Carbon emissions		Industrial transfer volume	
	Moran	Z-statistic	Moran	Z-statistic
2007	0.164**	1.801	0.018	0.145
2008	0.152**	1.692	0.274***	2.792
2009	0.144*	1.625	0.086	1.092
2010	0.138*	1.568	0.075*	2.092
2011	0.128*	1.471	0.064***	2.881
2012	0.121*	1.412	0.005	0.353
2013	0.122*	1.420	0.184**	1.989
2014	0.108*	1.294	0.228***	2.375
2015	0.107*	1.285	0.297***	3.015
2016	0.096	1.187	0.258***	3.004
2017	0.109*	1.627	–0.063**	–2.266
2018	0.124*	1.555	–0.011**	–2.222

Notes: ***, **, and * indicate significant at the 1%, 5%, and 10% statistical levels, respectively.

The LISA clustering charts in Fig. 4 show that the spatial agglomeration of industrial transfer occurs in the eastern region, with "high-high" agglomeration. Specifically, the industrial transfer in Shandong, Fujian, Anhui, and Zhejiang is a "high-high" agglomeration in 2018. Sichuan belongs to the "high-low" agglomeration area, and the industrial transfer in the surrounding regions is lower than that of the local. Xinjiang is a "low-low" agglomeration area, and the level of industrial transfer in both the local and the surrounding regions is lower, which is related to the low level of regional economic development, transportation accessibility, and the lack of inter-regional mobility.

Moreover, Table 6 summarizes the provinces with significant local clustering of carbon emissions. Carbon emissions are characterized by "high-high" and "low-high" agglomerations. Shanxi, Shandong, Hebei, Henan, and Anhui belong to the "high-high" agglomeration area, with higher carbon emissions in the local and surrounding areas. In addition, Xinjiang was a "low-low" agglomeration region until 2010. Guangdong was a "high-low" agglomeration region in 2007, 2008, and 2012, with high carbon emissions in Guangdong but low emissions in the surrounding areas.

Empirical Results of Spatial Panel Econometric Models

The spatial correlation test indicates that both provincial carbon emissions and industrial transfers are spatially correlated. Furthermore, Table 7 examines the Moran's I index of residuals in pooled OLS regression and presents the significant spatial correlation of estimated residuals, indicating that spatial econometric analysis can be performed. Moreover, we estimate

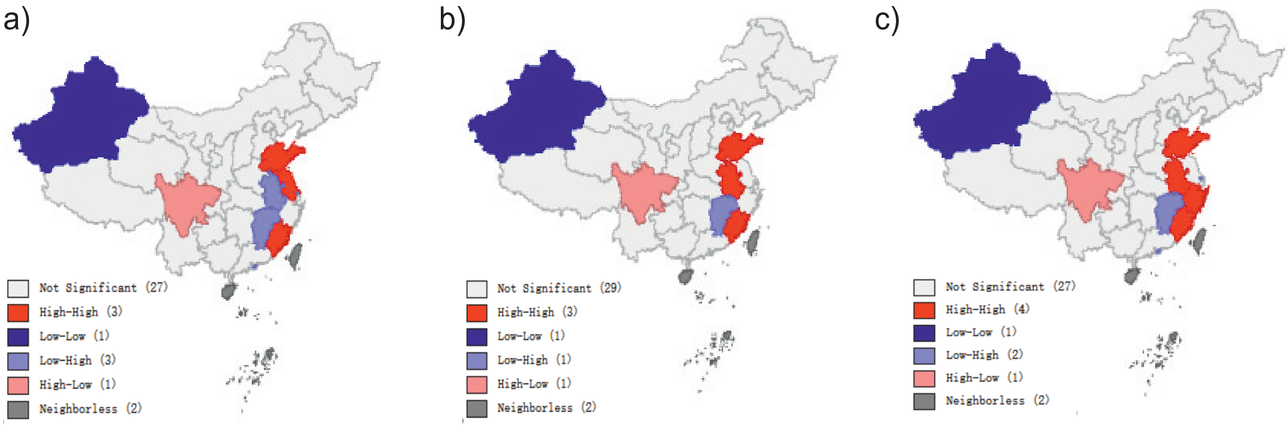

Fig. 4. LISA clustering charts of industrial transfer volumes in 2007, 2013 and 2018. a) LISA clustering chart in 2007, b) LISA clustering chart in 2013, c) LISA clustering chart in 2018.

Table 6. Local agglomeration of carbon emissions in 2007-2018.

Year	"High-High" clustering	"Low-Low" clustering	"Low-High" clustering	"High-Low" clustering
2007-2012	Shanxi, Shandong, Hebei, and Henan	Xinjiang None Xinjiang	Anhui	Guangdong
2013-2018	Shanxi, Shandong, Hebei, Henan, and Anhui	None	None	None

Notes: the listed provinces all have significant agglomeration characteristics, and the provinces not listed indicate that there is no significant local spatial agglomeration.

Table 7. Spatial correlation test results of residuals in pooled OLS model.

Year	Moran's *I*		LM-Error		LM-Lag	
	Test value	P-value	Test value	P-value	Test value	P-value
2007	–0.078***	0.004	0.789***	0.001	0.061**	0.028
2008	–0.046***	0.009	1.052***	0.007	0.871**	0.019
2009	–0.156***	0.001	1.581***	0.009	1.389**	0.036
2010	–0.087***	0.006	0.918***	0.002	1.482**	0.043
2011	–0.130***	0.002	1.325***	0.004	1.735**	0.024
2012	–0.026***	0.004	0.876***	0.005	1.372**	0.031
2013	–0.065**	0.012	0.926***	0.002	0.808**	0.022
2014	–0.285**	0.012	1.348***	0.006	1.030***	0.009
2015	–0.059**	0.041	0.856***	0.009	1.049***	0.005
2016	–0.013**	0.035	0.909**	0.013	1.054**	0.016
2017	–0.048**	0.024	1.062**	0.028	1.356***	0.004
2018	–0.109***	0.003	1.421**	0.027	1.611**	0.031

Notes: ***, **, and * indicate significant at the 1%, 5%, and 10% statistical levels, respectively.

the spatial panel econometric model using the maximum likelihood method. Fixed effects were determined based on the data characteristics and Hausman test. Meanwhile, the LM-Error and LM-Lag statistics in Table 7 are significant at the 5% level, and the results of the log-likelihood estimates (LL) and information criterion (AIC and BIC) tests in Tables 8-10 indicate the suitability and relative optimality of the spatial panel Durbin model with fixed effects.

Impact of Provincial Industrial Transfer on Carbon Emissions

From the estimations of the spatial Durbin panel model under the spatial adjacent weight matrix in Table 8, the spatial lag coefficient ρ of the explained variable is positive at the 1% significance level, which is consistent with the results of the previous ESDA analysis that carbon emissions in the neighboring regions have a significant spatial spillover effect on the local.

Firstly, industrial transfer has a positive effect on carbon emissions at the 1% significance level, and the rise in the level of industrial transfer increases carbon emissions. At present, China's industrial structure is still dominated by secondary industries such as industry and manufacturing, while the tertiary industry is developing rapidly but has not yet surpassed the secondary industry, so the industrial transfer is focused on high pollution-intensive traditional industries, and energy consumption has not been reduced from the root, coupled with the relatively lax environmental regulations and insufficient technological investment in the regions where industries are undertaken, makes inter-regional industrial transfer ineffective in relieving environmental pressure and even leads to the gathering of environmental pollution. Therefore, it should pay more attention to the optimization and upgrading of industrial structures and increase the investment in green technology in the process of industrial transfer.

Secondly, at the 5% significance level, the first and second-term coefficients of per capita GDP are positive, and there is a U-shaped curve between economic growth and carbon emissions, which is contrary to the EKC curve. Economies of scale in the initial stage will reduce carbon emissions, yet the expansion of the economy, population, and industry in the middle and later periods

Table 8. Estimated results under the spatial weight matrix W_1.

Variable	Pooled OLS	SPLM	SPEM	SPDM
cons	12.3408^{***} (23.74)			
IT	–0.0002 (–0.60)	0.7592^{**} (2.51)	0.6677^{**} (2.22)	0.9016^{***} (2.91)
ln*GDP*	0.4931^{***} (3.39)	0.2014^{***} (4.67)	0.1828^{***} (3.76)	0.1907^{***} (3.86)
$\ln^2 GDP$	0.1578^{**} (2.37)	0.0286^{**} (2.24)	0.0393^{***} (2.86)	0.0175^{***} (4.01)
UR	0.1541 (0.96)	0.1597^{***} (4.30)	0.1448^{***} (3.55)	0.1484^{***} (3.65)
FE	-2.4981^{***} (–10.06)	-0.6627^{***} (–9.74)	-0.5954^{***} (–8.01)	-0.5201^{***} (–7.72)
IN_1	–0.6153 (–1.14)	0.0072 (0.06)	0.0556 (0.45)	0.0042 (0.04)
IN_2	-1.9867^{***} (–3.07)	-0.3075^{***} (–2.84)	–0.0445 (–0.36)	-0.2282^{**} (–2.11)
EC_1	0.5226^{***} (3.17)	0.0942^{*} (1.72)	0.1053^{*} (1.91)	0.1518^{***} (3.10)
EC_2	-0.5834^{***} (–3.40)	0.0552 (0.82)	0.0596 (0.88)	0.1316^{**} (2.14)
EC_3	-51.7488^{***} (–11.03)	-8.0668^{***} (–4.13)	-10.7135^{***} (–5.28)	-8.1745^{***} (–4.28)
EC_4	-2.0062^{***} (–2.83)	-0.7982^{**} (–2.41)	-0.8589^{***} (–2.74)	–0.2104 (–0.68)
RD	-11.2599^{**} (–2.36)	–1.6621 (–0.73)	–1.0433 (–0.42)	–1.8132 (–0.80)
ER	-48.1251^{**} (–23.74)	–6.1234 (–1.51)	-7.3341^{*} (–1.87)	–4.3338 (–1.28)
W_1*IT				-0.3566^{***} (–3.10)
W_1*ln*GDP*				0.1795^{***} (2.64)
W_1*$\ln^2 GDP$				-0.1152^{***} (–5.62)

Table 8. Continued.

W_1*UR				0.1438** (2.37)
W_1*FE				0.5434*** (4.23)
W_1*IN_1				0.2965* (1.87)
W_1*IN_2				–0.2414 (–1.33)
W_1*EC_1				0.0591 (0.56)
W_1*EC_2				0.8209*** (5.07)
W_1*EC_3				16.5844*** (4.32)
W_1*EC_4				–0.8208 (–1.35)
W_1*RD				20.9076*** (5.88)
W_1*ER				–13.8173* (–1.92)
ρ		0.4333*** (8.43)	0.5461*** (9.03)	0.2843** (4.19)
σ^2		0.0029*** (13.28)	0.0031*** (12.89)	0.0022*** (13.29)
R^2	0.6213	0.8507	0.8552	0.9157
LL	–192.3362	524.6589	519.1838	585.2531
AIC	412.6723	–1019.3180	–1008.3682	–1114.5063
BIC	467.0778	–961.0263	–950.0764	–1005.6947

Notes: ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively; Z-statistics are in parentheses; LL is the Log-Likelihood estimate, AIC is the Akaike Information Criterion, and BIC is the Bayesian Information Criterion.

will consume large energy resources and generate more carbon emissions. Additionally, at the 1% significance level, urbanization development has a positive effect on carbon emissions, while financial allocation efficiency shows a negative effect on carbon emissions, with each 1% increase in financial allocation efficiency reducing carbon emissions by 0.5201%. The rational allocation of financial resources among industries can exhibit an energy-saving and environmental protection role. The secondary industry has a positive but insignificant effect on carbon emissions, whereas the tertiary industry has a negative effect at the 5% significance level. In terms of the environmental impact of consumption structure, the lower the proportion of coal and crude oil and the higher the share of natural gas consumption, the more beneficial it is to reduce carbon dioxide emissions. The investment in science and technology as well as the improvement in the level of environmental regulation both have positive but insignificant effects on emission reduction.

Finally, considering the spatial effect of the explanatory variables, the coefficient of W_1*IT in SPDM is -0.3566 at the 1% significance level, indicating that industrial transfers have a negative effect on carbon emissions in the surrounding areas, and the industrial transfers in the local area inhibit carbon emissions in the neighboring provinces. The spatial lag coefficients of W_1*lnGDP and W_1*ln^2GDP are 0.1795 and -0.1152 at the 5% significance level, respectively, indicating that economic development has an inverted U-shaped spillover effect on carbon emissions in neighboring provinces. The coefficient of W_1*FE is 0.5434, the improvement of financial allocation efficiency will increase carbon emissions in neighboring provinces, and the uncoordinated financial resource allocation among provinces results in the problem of regional development at the expense of environmental quality in neighboring regions. The coefficient of W_1*IN_2 is -0.2414, indicating that the development of the tertiary industry is also beneficial to the reduction of carbon emissions in neighboring regions; the increase in coal and crude oil consumption has a positive spatial effect, while the increase in the share of electricity consumption can reduce the carbon emissions of the neighboring regions; the coefficient of W_1*RD* is 20.9076, which indicates that the enhance of local science and technology investment level does not significantly reduce the carbon emissions of neighboring regions, and the technical cooperation and sharing between provinces and the collaborative management of the environment should be strengthened. The coefficient of *W*1**ER* is -13.8173, and the improvement of local environmental regulation is also beneficial to carbon emission reduction and environmental protection in neighboring regions.

Table 9. The SPDM empirical results under the spatial weight matrix W_2 and W_3.

Variable	Spatial geographic distance weight matrix W_2		K-nearest neighbor spatial weight matrix W_3	
	Coef.	Z-statistics	Coef.	Z-statistics
IT	0.6596**	2.36	0.6166*	1.84
ln*GDP*	0.0717	1.47	0.0877**	1.97
$\ln^2$*GDP*	0.0289**	2.18	0.0836***	6.16
UR	0.0586***	3.87	0.0697***	3.62
FE	–0.6759***	–10.03	–0.6279***	–9.80
IN_1	0.1981	1.63	0.0122	0.11
IN_2	–0.2163*	–1.74	–0.3027**	–2.48
EC_1	0.1145**	2.14	0.2014***	4.15
EC_2	0.2111***	3.16	0.1138*	1.80
EC_3	–6.6539***	–3.37	–4.4408***	–2.79
EC_4	–0.7043**	–2.19	-0.8501***	–2.73
RD	–0.7559	–0.31	–2.2277	–1.04
ER	–6.1334	–1.59	–2.5709	–0.73
W_1*IT*	–0.0018***	–4.53	–0.2062***	–3.84
W_1ln*GDP*	0.5352***	4.21	0.3669***	6.11
$W_1\ln^2$*GDP*	–0.2722***	–4.74	–0.1586***	–6.89
W_1*UR*	0.3869***	2.66	0.2897***	5.52
W_1*FE*	0.8550***	2.82	0.3932***	3.45
W_1*IN_1	0.6731*	1.72	0.0084	0.05
W_1*IN_2	–0.5477	–1.29	–0.1706	–0.99
W_1*EC_1	0.8009**	2.44	0.0013	0.11
W_1*EC_2	2.2137***	4.50	0.2102***	3.63
W_1*EC_3	12.0115	1.09	1.8472	0.47
W_1*EC_4	–0.0517***	–3.04	–2.9788***	–5.75
W_1*RD*	36.4482***	4.11	10.2572***	2.95
W_1*ER*	–2.5309**	–2.19	–1.8349***	–3.31
ρ	0.2301***	3.65	0.1886***	3.12
σ^2	0.0027***	13.39	0.0024***	13.36
R^2	0.9029		0.9135	
LL	551.9522		574.7716	
AIC	–1047.9041		–1093.5434	
BIC	–944.9284		–984.7323	

Notes: ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

Robustness Test

To test the robustness of the empirical results, we re-estimated the spatial panel econometric model under the spatial geographic distance weight matrix W_2 and K-nearest neighbors spatial weight matrix W_3 in Table 9. The robustness tests are similar to the regression results under the spatial adjacent weight matrix W_1: industrial transfer and urbanization have positive effects on carbon emissions, the optimization of financial allocation efficiency, the industrial, and consumption structures contribute to carbon emission reduction, whereas local

Table 10. Estimations of spatial panel Durbin model in different regions.

Variable	Areas with outward industry transfer		Areas with strong inward industry transfer		Areas with weak inward industry transfer	
	Coef.	Z-statistics	Coef.	Z-statistics	Coef.	Z-statistics
IT	-0.8717^{**}	−2.54	3.1616^{***}	4.76	0.0008^{***}	3.20
$\ln GDP$	0.0811	0.79	0.5237^{***}	6.56	0.1806^{*}	1.92
$\ln^2 GDP$	0.0631^{**}	2.41	-0.0325^{***}	−2.80	0.1576^{***}	4.69
UR	1.1582^{***}	3.96	0.4358^{***}	7.08	-0.5121^{***}	–3.17
FE	-0.1871^{***}	−3.13	0.4785^{***}	5.08	0.4476^{***}	3.44
IN_1	0.3865^{**}	2.56	0.2365^{**}	2.28	0.0445	0.18
IN_2	-0.3898^{***}	–4.38	-0.0543^{***}	–3.30	−0.3556	−1.45
EC_1	0.1527^{***}	3.23	0.1739^{***}	2.70	0.2994^{***}	4.46
EC_2	0.1561	1.43	0.4758^{***}	4.23	0.0290	0.40
EC_3	-5.2088^{***}	−3.92	−6.7629	−1.29	−2.7361	−0.88
EC_4	-1.3642^{***}	−2.68	-2.8753^{***}	−3.91	-1.0745^{**}	−2.21
RD	-8.9593^{***}	−3.49	-3.5275^{***}	−4.76	-2.7603^{***}	−3.50
ER	-8.7972^{***}	−3.28	0.8947^{**}	2.56	−2.5529	−0.63
$W_1{*}IT$	-0.6616^{***}	−3.02	0.3106^{*}	1.90	0.0005^{**}	2.12
$W_1\ln GDP$	-0.1665^{***}	−3.45	−0.0161	−0.14	0.5169^{***}	3.80
$W_1\ln^2 GDP$	0.0718^{**}	2.14	−0.0282	−0.77	-0.1698^{***}	−3.28
$W_1{*}UR$	0.3639	−0.89	−0.0023	−0.03	-0.3238^{**}	−2.04
$W_1{*}FE$	-0.3032^{***}	−4.03	-0.3647^{***}	−3.11	0.3665^{**}	2.18
$W_1{*}IN_1$	−0.0907	−0.52	0.3841^{***}	3.29	0.2614	0.78
$W_1{*}IN_2$	−0.1503	−1.28	-0.3858^{***}	−2.74	−0.4623	−1.45
$W_1{*}EC_1$	0.0534	0.98	0.5108^{***}	6.62	0.2638^{*}	1.91
$W_1{*}EC_2$	0.5082^{***}	3.57	0.3622^{*}	1.77	0.0312	0.21
$W_1{*}EC_3$	−3.5732	−1.27	−7.9398	−1.16	-4.3868^{***}	−4.41
$W_1{*}EC_4$	-0.1039^{**}	−2.02	-3.2825^{***}	−3.58	−0.9983	−1.12
$W_1{*}RD$	−2.0234	−0.65	-10.0714^{***}	−3.25	−3.1984	−0.33
$W_1{*}ER$	-15.4858^{**}	−2.14	2.7608	0.50	−2.9602	−0.36
ρ	-0.2241^{***}	−3.12	0.1683^{***}	4.36	0.2676^{***}	2.63
σ^2	0.0006^{***}	7.71	0.0003^{***}	7.75	0.0018^{***}	7.63
R^2	0.9605		0.9735		0.9616	
LL	278.8542		277.2955		208.5825	
AIC	–501.7084		–498.5913		–361.1652	
BIC	–443.6586		–420.5412		–298.1706	

Notes: ***, **, and * represent significance levels at 1%, 5%, and 10%, respectively.

industrial transfer can significantly decrease carbon emissions in the surrounding areas. This series of empirical results are robust.

Regional Heterogeneity Impact Analysis

According to the division of the areas with the inward and outward industrial transfer, we further analyze the differential effects of the direction and strength of industrial transfer on provincial carbon emissions in Table 10.

Overall, the spatial lag term coefficient of the explained variable in the industrial transfer out region is negative, and the increase of local carbon emissions mitigates the carbon emissions in the surrounding areas, while the spatial lag term coefficient in the industrial transfer in regions is always positive, and the carbon emissions show a positive spatial spillover effect.

In the industrial transfer-out region, the coefficient of industrial transfer *IT* is significantly negative, which indicates that the transfer out of industry improves the local environmental quality; meanwhile, the increase of secondary industry increases carbon emissions at the 1% significance level, while the development of tertiary industry effectively reduces carbon emissions. The efficient flow of economic factors and the improvement of energy resource allocation efficiency in the industrial transfer out area can be realized by transferring marginal industries and eliminating backward production capacity. On the other hand, industrial transfer accelerates the upgrading of industrial structure, and the intensification of secondary industry and the greening of tertiary industry effectively reduce energy consumption. The coefficient of W_1*IT is -0.6616 and has a negative spatial spillover effect on carbon emissions at the 1% significance level, indicating that the transfer of industries to other regions is conducive to suppressing environmental pollution in the surrounding areas and achieving energy conservation and emission reduction in neighboring provinces. Therefore, industrial transfer areas should establish a global synergy optimization perspective, not only to promote local industrial structure optimization and green sustainable development, but also to take into account the economic and ecological benefits brought by industrial transfer to the surrounding areas, and jointly shape a win-win situation for the economy and environment between regions.

In the industrial strong transfer-in region, the estimate of *IT* is as high as 3.1616 at the 1% significance level, which is the largest coefficient among the three divisions, indicating that taking over the transfer of industries from other provinces increases the local carbon emissions. In addition, the coefficient of W_1*IT is 0.3106, and taking over industrial transfer also aggravates the environmental pressure in the surrounding areas.

In the industrial weak transfer-in region, the regression coefficient of industrial transfer on carbon emissions is 0.0008 at the 1% significance level, and the transfer of industries to the central and western regions simultaneously increases the environmental pressure, but the impact intensity is much smaller than that of the strong transfer-in areas. The spatial lag term of industrial transfer is significantly positive at the 5% level, indicating that the industrial development of industrial weak transfer-in region increases the carbon emissions in the neighboring provinces.

In general, the absolute level of industrial transfer in the industrial transfer-out area and the industrial strong transfer-in area is higher than that in the industrial weak transfer-in area. Moreover, the direct and spatial

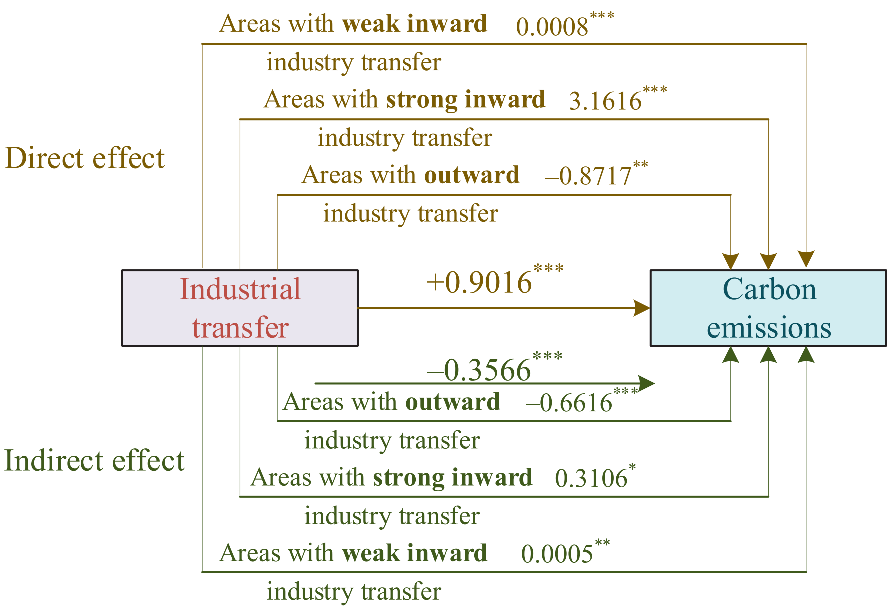

Fig. 5. Summary of the main findings.

spillover effects of the industrial transfer on carbon emissions show that the higher the amount of industrial transfer has the greater impact on carbon emissions. Particularly, the higher the transfer level of the industrial transfer-out area, the more it contributes to carbon emission reduction, while the higher the transfer level of the industrial transfer-in areas, the more carbon emissions are generated.

Furthermore, the direct and spatial spillover effect of industrial transfer on carbon emissions and the regional heterogeneity of these effects are presented in Fig. 5 to clearly grasp the main findings of the empirical study.

Conclusions

In this study, the aim was to assess the impact of the industrial transfer on carbon emissions between 2007 and 2018 in China using spatial panel econometric models. We find that China's industrial transfer activities are concentrated in the economically developed eastern coastal regions, and the carbon emissions in the industrial transfer-our regions are higher than those in the transfer-in regions. There is a significant positive spatial correlation of carbon emissions, while the level of industrial transfer gradually shows a negative spatial correlation, and the local distribution of industrial transfer and carbon emissions is mainly characterized by "high-high" agglomeration. Further, industrial transfer has a significant positive effect on carbon emissions, whereas presents a decreasing effect on carbon emissions in the surrounding areas. Meanwhile, the heterogeneity analysis shows that the industrial transfer in the industrial transfer-out region has negative direct and spatial spillover effects, while the industrial transfer in the industrial transfer-in regions has a positive effect on carbon emissions, and also increases carbon emissions in the neighboring provinces.

Based on the above conclusions, this research puts forward some policy implications:

– Firstly, targeted industrial development, energy conservation, and emission reduction policies are formulated in each province based on their respective endowments. Specifically, the eastern region, with stronger economic strength, should assume greater environmental protection responsibility while promoting coordinated regional economic development, strengthening technological support for environmental protection, and actively guiding industrial enterprises to achieve green and sustainable development. The western region, with abundant resources and strong environmental carrying capacity, should undertake the transfer of industries in an orderly and standardized manner, accelerate the construction of industrial parks in line with local development advantages, and pay particular attention to the protection of the local environment. The government should establish an ecological compensation mechanism to encourage and support energy conservation and environmental protection in various regions.
– Secondly, the central and eastern regions should establish an ecological concept and an overall concept of environmental management in the process of promoting the transfer of industries to the western and southwest regions, and should not develop the economy and relieve environmental pressure based on destroying the environment of other provinces.
– Thirdly, we should promote regional common development in the process of absorbing industrial transfer. Whether an outward or inward industry transfer area, relevant departments should improve their independent innovation ability, increase the development and introduction of environmental protection-related technologies, and promote industrial optimization and upgrading. Meanwhile, the government should strictly regulate pollution-intensive enterprises and expand green and high-quality industries.

Conclusively, the spatial reconfiguration of industries brought about by industrial transfer has changed the inter-provincial carbon emission distribution pattern, which in turn involves problems such as inequitable allocation of emission reduction responsibilities among regions and uneven ecological and environmental management. It is of great practical significance to pay attention to this series of issues implied in the process of industrial transfer, which is also the direction of future research.

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Conflict of Interest

The author declares no conflict of interest.

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