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Industrial Carbon Emissions of China's Regions: A Spatial Econometric Analysis

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Abstract: This paper proposes an extended Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to investigate the factors driving industrial carbon emissions in China. In the first stage, a spatial Durbin model is applied to investigate the determinants of regional industrial carbon emissions. In the second stage, a geographically and temporally weighted regression is applied to investigate temporal and spatial variations in the impacts of these driving factors on the scale and intensity of regional industrial carbon emissions. The empirical results suggest that the provinces with low carbon emissions act as exemplars for those with high carbon emissions and that driving factors impact carbon emission both directly and indirectly. All of the factors were investigated, except energy intensity, energy price, and openness, significantly impact carbon emissions. Overall, the results suggest that spatial correlation, heterogeneity, and spillover effects should be taken into account when formulating policies aiming at reducing industrial carbon emissions. The paper concludes with relevant policy recommendations taking full account of the regional industrial carbon emissions, heterogeneity and spillover.

Keywords: industrial carbon emissions; spatial Durbin panel data model; spatial spillover effects; geographically and temporally weighted regression

1. Introduction

For the past two decades, China has been one of the world's fastest growing economies, with an average annual Gross Domestic Product (GDP) growth rate of 10.4% between 1990 and 2010. This, combined with the fact that China is the world's most populous country, has led to unprecedented growth in energy demand, especially that for fossil fuels. The 2013 *World Energy Outlook* reports that China and India accounted for about 10% of total world energy consumption in 1990 but around 24% in 2010. China's economy rapidly developed between 1990 and 2010, and the country's carbon dioxide emissions more than tripled during this period. By 2010, China's carbon emissions constituted 24% of global emissions. After gains in energy efficiency coupled with deployment of cleaner energy, enabled by economic development, China's carbon intensity (measured in CO_2 emitted per unit of GDP), declined by 15% between 2005 and 2011. Projections indicate that China and India will continue to lead not only future global economic growth but also future growth in energy demand, making up 34% of total world energy consumption in 2040.

Electricity demand is the main driver of China's emissions growth: coal-powered electricity generation was responsible for almost all emissions growth between 1990 and 2010, despite notable improvements in the emissions performance of coal-fired power generating processes. In addition, the demand for large-scale infrastructure investments and Chinese products has grown in tandem with the economy. This has motivated increased energy consumption—mainly of fossil fuels—by the industrial sector, which accounts for around 70% of China's total carbon emissions. The government has recognized the need to prioritize reducing industrial-sector carbon emissions. This is reflected, for example, in the country's 12th Five-Year Plan, which aims to lower CO_2 emissions per unit GDP by 17% between 2010 and 2015. Provincial and local governments are central to implementing this plan, which requires a systematic understanding of China's industrial energy use and CO_2 emissions at sub-national levels. In particular, a spatial understanding—at the provincial and, where possible, local government levels—would help policymakers identify the areas of the greatest energy-saving and emissions-reduction potential.

Most past studies have investigated this issue at the national or aggregate level. The development of spatial econometrics, however, has presented researchers with an opportunity to incorporate spatial dynamics into their analyses of the trends and drivers of China's carbon emissions. Most of these studies empirically test the environmental Kuznets curve (EKC) hypothesis at the regional or industry level. The EKC argument hypothesizes that there is a relationship between various indicators of environmental degradation and economic development measured in terms of income per capita. It argues that initially, environmental degradation rises as a country industrializes; as the country develops economically and is able to invest in combating environmental degradation and the economy shifts from industry to services, however, environmental outcomes improve. Prior work using spatial panel data models has shown that China's regional economic development is spatially correlated with environmental quality [1–7]. By estimating a spatial panel data model with fixed effects, Zhu *et al.* [8] (pp. 65–74) empirically investigated the EKC of China's regional emissions of industrial pollutants. They found that regions' industrial pollutant emissions are strongly correlated and that the spatial panel data model is more robust than the traditional panel model. Wang *et al.* [9] (pp. 818–825) also applied a dynamic spatial panel data model to examine the relationship between China's environmental pollution and its economic growth. The results revealed that environmental pollution is spatially correlated, supporting the hypothesis that the EKC does exist. Yao and Ni [10] (pp. 1432–1438) and Xu and Deng [4] (pp. 30–43) applied spatial panel data models to analyze the relationship between China's carbon intensity and foreign direct investment (FDI). The results showed that FDI decreases China's regional carbon intensity due to FDI's technology spillover effect, which reduces CO_2 emissions and associated carbon intensity. Yu [11] (pp. 93–101) also applied a spatial panel data model to investigate the causes of low energy efficiency. That study found that both increases in total factor productivity (TFP) and changes in industrial structure increased China's energy efficiency, with the former playing a more important role than the latter. Wei *et al.* [12] (pp. 478–488) conducted a comparative study on China's energy efficiency among countries and confirmed China's low energy efficiency. Wei *et al.* [13] (pp. 552–565), Choi *et al.* [14] (pp. 198–208) and Wang *et al.* [7] (pp. 2584–2600) investigated the regional carbon emission efficiency for Chinese Provinces. However, previous studies did not consider the spatial patterns and drivers of carbon emissions for China.

This paper seeks to contribute to the spatial understanding of patterns and drivers of industrial carbon emissions in China. Such analysis is important due to the substantial nature of the cross-regional variation in industrial carbon emissions. As such, for policies aimed at reducing carbon emissions to be effective in China, they must be anchored in a comprehensive understanding of spatial dynamics and reflect the variations in emissions reduction potential across regions. To provide such insights in the form of more effective estimates, this paper applies a spatial econometric model, incorporating both temporal and spatial effects, to investigate the factors influencing regional industrial carbon emissions. Based on the estimations, the paper provides practical and effective policy recommendations for reducing industrial carbon emissions in China.

2. Materials and Methods

2.1. The Extended STIRPAT Model

Ehrlish *et al.* [15] (pp. 1212–1217) were among the pioneers proposing the IPAT (Impact, Population, Affluence, Technology) accounting identity for the impact of human activities on the environment. The IPAT equation, born out of a need to identify sources of human-induced environmental change, posits that interactions between population size, affluence or economic growth, and technological change impact the environment as follows:

$$I = PAT \tag{1}$$

where I represents environmental impact, P is population size, A is affluence or wealth per capita, and T is the technology level. Though simple, the IPAT model emphasizes that environmental degradation (or improvements) result from multiple factors acting together to have a compound effect on the environment. The Intergovernmental Panel on Climate Change (IPCC) has used the IPAT model to assess the contributions of population size, affluence, and technology on greenhouse gas (GHG) emissions. Over time, empirical estimation of the equation has been strengthened by adding additional socio-political and technical factors, thereby improving the equation's predictive power. Some of studies that have used the IPAT equation include Harrison [16], Raskin [17] (pp. 225–233), York [18] (pp. 18–34), Shi [1] (pp. 29–42), Cole [19] (pp. 5–21), and Rosa [20] (pp. 509–512).

The major limitation of the IPAT equation is that, as an accounting identity, it does not allow hypothesis testing because it assumes a proportional functional relationship between the IPAT factors. Based on this limitation, numerous researchers have proposed alternative versions of the equation. Notably, Dietz and Rosa [21] (pp. 277–300) present the IPAT equation in a stochastic manner and propose a Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model. In this approach, carbon emissions are modeled stochastically by regressing them on population, wealth, and technology. The STIRPAT model is expressed as follows:

$$I = aP^{b}A^{c}T^{d}e \tag{2}$$

where a represents the model coefficient; b, c, and d are the coefficients on population, wealth, and technology, respectively; and e is the error term. Environmental pressure is represented by I, population size by P, wealth by A, and technology by T. Taking the natural logarithm of both sides leads to Equation (3).

$$\ln I = \ln a + b\,(\ln P) + c\,(\ln A) + d\,(\ln T) + \ln e \tag{3}$$

The elasticity between the independent variables and the dependent variable is reflected in the coefficients, which express the percentage change in the dependent variable arising from a 1% change in the dependent variable, all else held constant. The STIRPAT model builds on the IPAT equation by making it possible to test hypotheses, allowing estimation of the coefficients and decomposition of the influencing factors, and allowing for the inclusion of other factors. Studies based on the model and its adjustment include Dietz and Rosa [21] (pp. 277–300) and York *et al.* [22] (pp. 351–365).

This paper extends the STIRPAT model to investigate the various impacts of the factors driving regional industrial carbon emissions in China. At the regional industrial level, the level or scale of investment is considered a more important determinant of carbon emissions than is population size. As a result, we place population size with the scale of investment in our model. Additional variables, such as energy consumption structure, energy price, and openness (Openness: measured by the percentage of FDI in total investment by industrial enterprises, unit: %.), are also included. The resulting extended STIRPAT model is expressed as in Equations (4) and (5).

$$\begin{aligned} \ln CS &= \ln a + \beta_1\,(lnSI) + \beta_2\,(lnIE) + \beta_3\,(lnEI) + \beta_4\,(lnECS) + \beta_5\,(lnEP) + \beta_6\,(lnOPEN) + \ln e \\ &= \alpha + \beta_1\,(lnSI) + \beta_2\,(lnIE) + \beta_3\,(lnEI) + \beta_4\,(lnECS) + \beta_5\,(lnEP) + \beta_6\,(lnOPEN) + \varepsilon \end{aligned} \tag{4}$$

$$\begin{aligned}\ln CI &= \ln a + \beta_1 (lnSI) + \beta_2 (lnIE) + \beta_3 (lnEI) + \beta_4 (lnECS) + \beta_5 (lnEP) + \beta_6 (lnOPEN) + \ln e \\ &= \alpha + \beta_1 (lnSI) + \beta_2 (lnIE) + \beta_3 (lnEI) + \beta_4 (lnECS) + \beta_5 (lnEP) + \beta_6 (lnOPEN) + \varepsilon\end{aligned} \quad (5)$$

where *CS* denotes the level or scale of carbon emissions (measured in 10,000 tons of industrial carbon emitted), *CI* is carbon intensity (CO_2 emissions per unit of industrial value-added, measured in tons/10,000 Yuan), *SI* represents the scale of investment (measured by total assets of industrial enterprises above a designated size, in 100 million Yuan), *IE* denotes industrial economic intensity (measured by industrial added-value per employee), *EI* is energy intensity (measured by energy consumption per unit of industrial added-value, in tons of standard coal per 10,000 Yuan), *ECS* is energy consumption structure (measured by the percentage of total energy consumption that is industrial coal consumption), *EP* is energy price (measured by producer price index for manufactured products), and *OPEN* is openness (measured by the percentage of FDI in total investment by industrial enterprises).

2.2. Spatial Econometric Model with Carbon Emissions

Starting from the improved STIRPAT, we build a spatial econometric model by taking into account the fact that carbon emissions are heterogeneous and spatially correlated among regions and industries. As highlighted in Equations (4) and (5), the two dependent variables used in the analysis are industrial: the level of carbon emissions and carbon intensity. The spatial panel data econometric model, which integrates spatial econometrics (spatial effects) and panel data (time effects), this paper utilizes a space and time fixed-effects in a spatial econometric framework. This makes spatial econometric analysis more efficient. The spatial panel data econometric model includes three basic models: the spatial lag panel data model, the spatial error panel data model, and the spatial Durbin panel data model. These models are discussed in detail below.

2.2.1. Spatial Lag Panel Data Model (SLPDM)

The spatial lag panel data model (SLPDM) used in the paper is represented as follows:

$$\begin{aligned}\ln CS_{it} &= \delta \sum_{j=1}^{N} w_{ij}\ln CS_{it} + \ln a + \beta_1 (lnSI_{it}) + \beta_2 (lnIE_{it}) + \beta_3 (lnEI_{it}) + \beta_4 (lnECS_{it}) + \beta_5 (lnEP_{it}) \\ &\quad + \beta_6 (lnOPEN_{it}) + \mu_i + \lambda_t + \ln e_{it} \\ &= \delta \sum_{j=1}^{N} w_{ij}\ln CS_{it} + \alpha + \beta_1 (lnSI_{it}) + \beta_2 (lnIE_{it}) + \beta_3 (lnEI_{it}) + \beta_4 (lnECS_{it}) + \beta_5 (lnEP_{it}) \\ &\quad + \beta_6 (lnOPEN_{it}) + \mu_i + \lambda_t + \varepsilon_{it}\end{aligned} \quad (6)$$

$$\begin{aligned}\ln CI_{it} &= \delta \sum_{j=1}^{N} w_{ij}\ln CI_{it} + \ln a + \beta_1 (lnSI_{it}) + \beta_2 (lnIE_{it}) + \beta_3 (lnEI_{it}) + \beta_4 (lnECS_{it}) + \beta_5 (lnEP_{it}) \\ &\quad + \beta_6 (lnOPEN_{it}) + \mu_i + \lambda_t + \ln e_{it} \\ &= \delta \sum_{j=1}^{N} w_{ij}\ln CI_{it} + \alpha + \beta_1 (\ln SI_{it}) + \beta_2 (\ln IE_{it}) + \beta_3 (lnEI_{it}) + \beta_4 (lnECS_{it}) + \beta_5 (lnEP_{it}) \\ &\quad + \beta_6 (lnOPEN_{it}) + \mu_i + \lambda_t + \varepsilon_{it}\end{aligned} \quad (7)$$

where CS_{it} and CI_{it} denote industrial carbon emissions scale and intensity of the region i at time t, respectively. $\sum w_{ij}\ln CS_{it}$ and $\sum w_{ij}\ln CI_{it}$ represent the spatial correlation between $\ln CS_{it}$ and $\ln CI_{it}$ of region i and that of its adjacent regions. $\ln SI_{it}$, $\ln IE_{it}$, $\ln EI_{it}$, $\ln ECS_{it}$, $\ln EP_{it}$, and $\ln OPEN_{it}$ are independent variables corresponding to region I at time $t.\delta$ is the spatial auto-correlation index, w_{ij} is an element of the spatial weight matrix representing the spatial relations between regions i and j, α is the constant term, the βs are coefficients to be estimated, μ_i is the individual (region) fixed effect and λ_t is the time fixed effect.

2.2.2. Spatial Error Panel Data Model (SEPDM)

The spatial error panel data model (SEPDM) is specified as follows:

$$\begin{aligned}
\ln CS_{it} &= \ln a+\beta_1\,(lnSI_{it})+\beta_2\,(lnIE_{it})+\beta_3\,(lnEI_{it})+\beta_4\,(lnECS_{it})+\beta_5\,(lnEP_{it})+\beta_6\,(lnOPEN_{it}) \\
&\quad +\mu_i+\lambda_t+\ln e_{it} \\
&= \alpha+\beta_1\,(\ln SI_{it})+\beta_2\,(\ln IE_{it})+\beta_3\,(\ln EI_{it})+\beta_4\,(lnECS_{it})+\beta_5\,(lnEP_{it})+\beta_6\,(lnOPEN_{it}) \\
&\quad +\mu_i+\lambda_t+\varnothing_{it} \\
\varnothing_{it} &= \rho\sum_{j=1}^{N} w_{ij}\varnothing_{it}+\varepsilon_{it}
\end{aligned} \tag{8}$$

$$\begin{aligned}
\ln CI_{It} &= \ln a+\beta_1\,(lnSI_{it})+\beta_2\,(lnIE_{it})+\beta_3\,(lnEI_{it})+\beta_4\,(lnECS_{it})+\beta_5\,(lnEP_{it})+\beta_6\,(lnOPEN_{it}) \\
&\quad +\mu_i+\lambda_t+\ln e_{it} \\
&= \alpha+\beta_1\,(\ln SI_{it})+\beta_2\,(\ln IE_{it})+\beta_3\,(\ln EI_{it})+\beta_4\,(lnECS_{it})+\beta_5\,(lnEP_{it})+\beta_6\,(lnOPEN_{it}) \\
&\quad +\mu_i+\lambda_t+\varnothing_{it} \\
\varnothing_{it} &= \rho\sum_{j=1}^{N} w_{ij}\varnothing_{it}+\varepsilon_{it}
\end{aligned} \tag{9}$$

where $\ln CS_{it}$, $\ln CI_{it}$, α, β, μ_i, λ_t, ε_{it}, $\ln SI_{it}$, $\ln IE_{it}$, $\ln EI_{it}$, $\ln ECS_{it}$, $\ln EP_{it}$, and $\ln OPEN_{it}$ are defined as in Equations (6) and (7). φ_{it} denotes spatial error auto-correlation, and ρ is the spatial auto-correlation index.

2.2.3. Spatial Durbin Panel Date Model (SDPDM)

The spatial Durbin panel data model (SDPDM) is specified as follows:

$$\begin{aligned}
\ln CS_{it} &= \delta\sum_{j=1}^{N} w_{ij}\ln CS_{it}+\ln a+\beta_1\,(lnSI_{it})+\beta_2\,(lnIE_{it})+\beta_3\,(lnEI_{it})+\beta_4\,(lnECS_{it})+\beta_5\,(lnEP_{it}) \\
&\quad +\beta_6\,(lnOPEN_{it})+\theta_1\sum_{j=1}^{N} w_{ij}\ln SI_{iJt}+\theta_2\sum_{j=1}^{N} w_{ij}\ln IE_{iJt}+\theta_3\sum_{j=1}^{N} w_{ij}\ln EI_{iJt} \\
&\quad +\theta_4\sum_{j=1}^{N} w_{ij}\ln ECS_{iJt}+\theta_5\sum_{j=1}^{N} w_{ij}\ln EP_{ijt}+\theta_6\sum_{j=1}^{N} w_{ij}\ln OPEN_{ijt}+\mu_i+\lambda_t+\ln e_{it} \\
&= \delta\sum_{j=1}^{N} w_{ij}\ln CS_{it}+\ln a+\beta_1\,(lnSI_{it})+\beta_2\,(lnIE_{it})+\beta_3\,(lnEI_{it})+\beta_4\,(lnECS_{it})+\beta_5\,(lnEP_{it}) \\
&\quad +\beta_6\,(lnOPEN_{it})+\theta_1\sum_{j=1}^{N} w_{ij}\ln SI_{iJt}+\theta_2\sum_{j=1}^{N} w_{ij}\ln IE_{iJt}+\theta_3\sum_{j=1}^{N} w_{ij}\ln EI_{iJt} \\
&\quad +\theta_4\sum_{j=1}^{N} w_{ij}\ln ECS_{iJt}+\theta_5\sum_{j=1}^{N} w_{ij}\ln EP_{ijt}+\theta_6\sum_{j=1}^{N} w_{ij}\ln OPEN_{ijt}+\mu_i+\lambda_t+\varepsilon_{it}
\end{aligned} \tag{10}$$

$$\begin{aligned}
\ln CI_{it} &= \delta\sum_{j=1}^{N} w_{ij}\ln CS_{it}+\ln a+\beta_1\,(lnSI_{it})+\beta_2\,(lnIE_{it})+\beta_3\,(lnEI_{it})+\beta_4\,(lnECS_{it}) \\
&\quad +\beta_5\,(lnEP_{it})+\beta_6\,(lnOPEN_{it})+\theta_1\sum_{j=1}^{N} w_{ij}\ln SI_{iJt}+\theta_2\sum_{j=1}^{N} w_{ij}\ln IE_{iJt} \\
&\quad +\theta_3\sum_{j=1}^{N} w_{ij}\ln EI_{iJt}+\theta_4\sum_{j=1}^{N} w_{ij}\ln ECS_{iJt}+\theta_5\sum_{j=1}^{N} w_{ij}\ln EP_{ijt} \\
&\quad +\theta_6\sum_{j=1}^{N} w_{ij}\ln OPEN_{ijt}+\mu_i+\lambda_t+\ln e_{it} \\
&= \delta\sum_{j=1}^{N} w_{ij}\ln CS_{it}+\ln a+\beta_1\,(lnSI_{it})+\beta_2\,(lnIE_{it}) \\
&\quad +\beta_3\,(lnEI_{it})+\beta_4\,(lnECS_{it})+\beta_5\,(lnEP_{it})+\beta_6\,(lnOPEN_{it}) \\
&\quad +\theta_1\sum_{j=1}^{N} w_{ij}\ln SI_{iJt}+\theta_2\sum_{j=1}^{N} w_{ij}\ln IE_{iJt}+\theta_3\sum_{j=1}^{N} w_{ij}\ln EI_{iJt} \\
&\quad +\theta_4\sum_{j=1}^{N} w_{ij}\ln ECS_{iJt}+\theta_5\sum_{j=1}^{N} w_{ij}\ln EP_{ijt}+\theta_6\sum_{j=1}^{N} w_{ij}\ln OPEN_{ijt}+\mu_i \\
&\quad +\lambda_t+\varepsilon_{it}
\end{aligned} \tag{11}$$

where $\ln SI_{it}$, $\ln IE_{it}$, $\ln EI_{it}$, $\ln ECS_{it}$, $\ln EP_{it}$, $\ln OPEN_{it}$, α, μ_i, λ_t are defined as in Equations (6) and (7). θ is a vector of coefficients to be estimated. We test the joint hypotheses H_0: $\theta = 0$ and H_0: $\theta + \delta\beta = 0$; rejection of the hypotheses indicates that the SDPDM fits the data optimally.

Our extension of the STIRPAT model not only allows examination of the impacts of the above-mentioned independent variables on the scale and intensity of a region's industrial carbon emissions but also makes it possible to examine the impacts of the adjacent regions' independent variables on a given region's industrial carbon emissions scale and intensity. It also allows measurement of the impact of the adjacent region's carbon emissions scale and intensity on a given region's industrial carbon emissions scale and intensity.

2.2.4. Spatial Weight Matrix

A spatial weight matrix must be constructed to reflect the spatial correlation among regions, and an appropriate spatial weight matrix is essential for obtaining a sound spatial econometric result. We opt for both geographic and economic spatial weight matrixes. The former is constructed via the inverse distance method.

$$W^{GS}{}_{ij} = \begin{cases} \dfrac{1}{d_{ij}{}^{\alpha}} & i \neq j \\ 0 & i = j \end{cases} \tag{12}$$

where d_{ij} is the distance between regions i and j, which is calculated using their longitudes and latitudes.

The economic spatial weight matrix W^* is a product of W and the economic weight matrix, E.

$$E_{ij} = \begin{cases} \dfrac{1}{\left|\overline{G}_i - \overline{G}_i\right|^{\alpha} + m} & i \neq j \\ 0 & i = j \end{cases} \qquad \overline{G}_i = \frac{1}{5}\sum_{t=2006}^{2010} G_{it} \tag{13}$$

where G_{it} denotes per capita industrial value-added, representing the actual industrial output per capita of region i at time t (Deflated by the price index in 2006). Thus, W^* incorporates economic development into the weight matrix.

Regional industrial carbon emissions are obtained from energy types via the stable carbon emissions factors for electricity and thermo, such as raw coal, washed coal, other washed coal, briquette, coke, coke oven gas, other gases, other coking products, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, refinery gas, other petroleum products, and natural gas. The data is from *China Energy Statistical Yearbook 2007–2011* [23].

3. Empirical Investigation

3.1. Model Specification

Two Lagrange Multiplier tests (LM-Lag and LM-Error tests) are applied to choose which model of those described in Sections 3.1–3 best fits the data. In classical panel data models, there are four options for fixed effects, namely individual fixed effects, time fixed effects, individual and time fixed effects, and no fixed effects. We test these four options via the LM test. Tables 1 and 2 show the LM test statistics for Models 1 and 2, with dependent variables Log (CS) and Log (CI), respectively.

Table 1 shows that in Model 1 the LM statistic for the spatial error model with time fixed effects is significant at the 5% level. The LM statistics for the spatial lag model under no spatial effects and time fixed effects are significant (Table 2). Thus, the hypothesis that spatial correlation does not exist is rejected. In addition, the likelihood ratio (LR) tests reject the hypotheses that individual fixed effects and time fixed effects do not exist, indicating that the individual and time fixed effect model outperforms its alternatives. We further determine which model (SLPDM, SEPDM, or SDPDM) best fits the data using Wald and LR tests.

Table 1. LM test for Model 1 (dependent variable: Log (*CS*)).

Variable	Pooled OLS	Individual Fixed Effects	Time Fixed Effect	Individual and Time Fixed Effect
Constant	−5.6650 *** (−5.2619)	–	–	–
Log(SI)	1.1638 *** (28.2449)	0.8632 *** (30.1539)	1.1750 *** (29.4582)	1.0276 *** (9.4509)
Log(IE)	0.4286 *** (4.1127)	0.0181 (0.3679)	0.5213 *** (4.9142)	0.0247 (0.4977)
Log(EI)	1.1953 *** (13.7546)	0.8343 *** (22.9815)	1.1824 *** (14.1376)	0.8428 *** (23.1001)
Log(ECS)	0.5700 *** (6.2444)	0.0313 (1.1421)	0.6205 *** (6.9625)	0.0639 ** (2.3508)
Log(EP)	0.8240 ** (2.1345)	0.1033 ** (2.4452)	2.1933 *** (2.9781)	−0.0040 (−0.0492)
Log(OPEN)	0.0857 ** (1.9728)	−0.0176 (−1.1628)	0.1130 *** (2.6721)	−0.0157 (−1.0903)
σ^2	0.0163	0.0002	0.0148	0.0001
R^2	0.8821	0.9201	0.8914	0.8447
Adjusted R^2	0.8771	0.9173	0.8877	0.8393
Durbin-Watson	2.1067	1.8217	2.2265	2.0198
Log-likelihood	99.3054	438.8255	106.1706	450.8258
LM spatial Lag	0.0480 (0.827)	0.1109 (0.739)	0.0084 (0.927)	0.3449 (0.557)
Robust LM spatial Lag	0.4311 (0.511)	0.0212 (0.884)	1.4950 (0.221)	2.2990 (0.129)
LM spatial error	2.9681 (0.085)	0.8291 (0.363)	5.1309 (0.024)	1.3763 (0.241)
Robust LM spatial error	3.3513 (0.067)	0.7394 (0.390)	6.6176 (0.010)	3.3304 (0.068)
Joint test of significance LR	Fixed-effects	Statistics	df	P-value
	Individual-fixed effects	689.3104	30	0.0000
	Time-fixed effects	24.0007	5	0.0002

Note: t or z-values are in the parentheses. P-values in the parentheses under the coefficients of the LM tests. * represents significance at 10%, ** 5%, and *** 1% respectively.

Table 2. LM test for Model 2 (dependent variable: Log (*CI*)).

Variable	Pooled OLS	Individual Fixed Effects	Time Fixed Effect	Individual and Time Fixed Effects
Constant	−1.5254 *** (−2.8568)	–	–	–
Log(SI)	0.0705 *** (3.4491)	−0.1369 *** (−4.7811)	0.0771 *** (3.7957)	0.0277 (0.2544)
Log(IE)	0.1595 ***(3.0865)	0.0182 (0.3685)	0.1973 *** (3.6527)	0.0247 (0.4986)
Log(EI)	1.1555 ***(26.8095)	0.8343 *** (22.9802)	1.1596 ***(27.2301)	0.8428 ***(23.0986)
Log(ECS)	0.1957 ***(4.3232)	0.0314 (1.1439)	0.2158 *** (4.7543)	0.0640 ** (2.3528)
Log(EP)	0.2765(1.4439)	0.1033 ** (2.4443)	0.2896 (0.7723)	−0.0041 (−0.0498)
Log(OPEN)	0.0063 (0.2940)	−0.0175 (−1.1607)	0.0103 (0.4765)	−0.0157 (−1.0880)
σ^2	0.0040	0.0002	0.0038	0.0001
R^2	0.9411	0.9309	0.9418	0.8007
Adjusted R^2	0.9386	0.9285	0.9398	0.7937
Durbin-Watson	2.0015	1.8220	2.0977	2.0200
Log-likelihood	204.4955	438.8169	207.4130	450.8174
LM spatial Lag	7.9070 (0.005)	2.6476 (0.104)	9.1879 (0.002)	1.3206 (0.250)
Robust LM spatial Lag	9.3611 (0.002)	1.8238 (0.177)	9.6301 (0.002)	5.3170 (0.021)
LM spatial error	0.0046 (0.946)	0.8303 (0.362)	0.1920 (0.661)	1.3742 (0.241)
Robust LM spatial error	1.4587 (0.227)	0.0065 (0.936)	0.6342 (0.426)	5.3706 (0.020)
Joint test of significance (LR)	Fixed-effects	Statistics	df	P-value
	Individual fixed effects	486.8087	30	0.0000
	Time fixed effects	24.0011	5	0.0002

Note: t or z-values are in the parentheses. P-values in the parentheses under the coefficients of the LM tests. * represents significance at 10%, ** 5%, and *** 1% respectively.

3.2. Industrial Carbon Emissions SDPDM

Three Durbin models are considered: (1) individual and time fixed effects (*Model 3*); (2) both time and individual effects, with bias correction borrowed from (*Model 4*) [23]; and (3) individual random effect and time fixed effect (*Model 5*). The estimation results using Log (*CS*) and Log (*CI*) as dependent variables are reported in Tables 3 and 4 respectively. In Model3 and Model 4, the coefficients of *SI*, *IE*, *EI*, *ECS*, *EP*, *OPEN*, and σ^2 changed slightly after bias correction, and the coefficients of the spatially lagged dependent and independent variables are also sensitive to bias correction. Thus, bias correction is necessary for the spatial Durbin model with both individual and time fixed effects. The SDPDM has two hypotheses: H_0: $\theta = 0$ and H_0: $\theta + \delta\beta = 0$; rejection of both indicates that the SDPDM fits the data best. Both Wald and LR tests reject the two hypotheses, suggesting that neither the SLPDM nor the SEPDM is appropriate. We thus opt for the SDPDM. Meanwhile, the Hausman test lends support to Model 4, the coefficients in Model 4 align with our expectations, and its goodness of fit is greater than those of the alternatives.

Table 3. Spatial Durbin model with both individual and time fixed effect (dependent variable: Log (CS)).

Variables	Individual and Time Fixed Effect	Individual and Time Fixed Effect (Bias Corrected)	Individual Random Effect and Time Fixed Effect
*W**Log(CS)	−0.0930 (−0.9547)	−0.0484 (−0.4917)	−0.0810 (−0.8257)
Log(SI)	1.1804 *** (11.0696)	1.1860 *** (9.7884)	1.1141 *** (17.0034)
Log(IE)	0.0679 (1.4516)	0.0695 (1.3071)	0.0612 (1.1652)
Log(EI)	0.7823 *** (21.5919)	0.7809 *** (18.9591)	0.8461 *** (22.5372)
Log(ECS)	0.0557 ** (2.1734)	0.0561 * (1.9237)	0.0530 * (1.8354)
Log(EP)	−0.0100 (−0.1353)	−0.0078 (−0.0931)	−0.0133 (−0.1565)
Log(OPEN)	−0.0062 (−0.4694)	−0.0061 (−0.4066)	−0.0127 (−0.8649)
*W**Log(SI)	−0.6954 ** (−2.5700)	−0.7466 ** (−2.4707)	0.0194 (0.1272)
*W**Log(IE)	−0.2031 ** (−2.3151)	−0.2069 ** (−2.0754)	−0.1202 (−1.2563)
*W**Log(EI)	0.1863 * (1.8330)	0.1502 (1.3894)	0.1395 (1.2992)
*W**Log(ECS)	−0.1110 ** (−1.9561)	−0.1142 * (−1.7711)	−0.1014 (−1.5774)
*W**Log(EP)	−0.1751 (−1.2580)	−0.1734 (−1.0952)	−0.2302 (−1.4528)
*W**Log(OPEN)	0.0088 (0.5443)	0.0094 (0.5144)	0.0088 (0.4831)
teta	–	–	0.0369 *** (5.4795)
σ^2	0.0001	0.0002	0.0002
R^2	0.9991	0.9991	0.9988
Square correlation coefficient	0.8713	0.8714	0.8237
Log likelihood	465.4752	465.4752	345.2436
Wald test spatial Lag	31.9461 (0.000)	24.0161 (0.000)	14.8409 (0.0215)
LR test spatial Lag	28.9664 (0.000)	28.9664 (0.000)	NA
Wald test spatial error	30.7361 (0.000)	24.1035 (0.000)	14.7719 (0.0221)
LR test spatial error	27.7109 (0.000)	27.7109 (0.000)	NA
Hausman test	Statistics	df	P-value
	23.7970	13	0.0330

Note: t or z-values are in the parentheses. P-values in the parentheses under the coefficients of the LM and Wald tests. * represents significance at 10%, ** 5%, and *** 1% respectively.

Table 4. Spatial Durbin model with both individual and time fixed effect (dependent variable: Log (CI)).

Variables	Individual and Time Fixed Effect	Individual and Time Fixed Effect (Bias Corrected)	Individual Random Effect and Time Fixed Effect
*W**Log(CI)	−0.0920 (−0.9407)	−0.0470 (−0.4761)	−0.0520 (−0.5448)
Log(SI)	0.1805 * (1.6928)	0.1861 (1.5360)	−0.0061 (−0.1588)
Log(IE)	0.0680 (1.4530)	0.0696 (1.3086)	0.0457 (0.8805)
Log(EI)	0.7823 *** (21.5900)	0.7809 *** (18.9574)	0.8992 *** (25.4063)
Log(ECS)	0.0558 ** (2.1757)	0.0562 * (1.9259)	0.0559 * (1.9479)
Log(EP)	−0.0099 (−0.1343)	−0.0077 (−0.0920)	−0.0068 (−0.0778)
Log(OPEN)	−0.0061 (−0.4668)	−0.0060 (−0.4043)	−0.0236 (−1.6327)
*W**Log(SI)	−0.7884 *** (−3.1937)	−0.7950 *** (−2.8319)	0.0076 (0.1216)
*W**Log(IE)	−0.2033 ** (−2.3175)	−0.2072 ** (−2.0778)	−0.0896 (−0.9588)
*W**Log(EI)	0.1854 * (1.8193)	0.1489 (1.3753)	0.1037 (0.9703)
*W**Log(ECS)	−0.1113 ** (−1.9599)	−0.1145 * (−1.7750)	−0.1056 * (−1.6609)
*W**Log(EP)	−0.1750 (−1.2573)	−0.1733 (−1.0945)	−0.2225 (−1.3693)
*W**Log(OPEN)	0.0088 (0.5440)	0.0094 (0.5144)	0.0018 (0.0974)
teta	–	–	0.0778 *** (5.4872)
σ^2	0.0001	0.0002	0.0002
R^2	0.9982	0.9982	0.9974
Square correlation coefficient	0.8348	0.8350	0.9270
Log likelihood	465.4691	465.4691	363.4027
Wald test spatial Lag	30.3274 (0.000)	22.6643 (0.000)	10.4796 (0.1059)
LR test spatial Lag	28.0752 (0.000)	28.0752 (0.000)	NA
Wald test spatial error	30.7411 (0.000)	24.1089 (0.000)	11.0656 (0.0864)
LR test spatial error	27.7196 (0.000)	27.7196 (0.000)	NA
Hausman test	Statistics	df.	P-value
	27.5757	13	0.0104

Note: t or z-values are in the parentheses. P-values in the parentheses under the coefficients of the LM and Wald tests. * represents significance at 10%, ** 5%, and *** 1% respectively.

3.2.1. Discussion

Since Model 4 fits the data best, we discuss only the results of Model 4, as shown in the third columns of Tables 3 and 4 respectively, for the two dependent variables. The coefficients on most of the independent variables are significant and have the expected signs. The coefficients for the spatially lagged dependent variables are negative and insignificant in both models (line 2, column 3 in Tables 3 and 4), indicating that carbon emissions are correlated among regions. A region's industrial carbon emissions are estimated to decrease by 0.05% if its neighboring regions' scale and intensity of industrial carbon emissions increase by 1%. This indicates that under the Chinese government's 11th Five-Year Plan, the provinces managed to optimize industrial structures, innovate in industrial technology, and encourage energy savings and reduced emissions in industrial enterprises. Since the successful provinces 'exemplary achievements play an important role in adjusting economic structures nationwide, strategic planning of regional industrial carbon emissions is necessary to further optimize the industrial structure and reduce industrial carbon emissions. Below we discuss the impacts of the independent variables on regional industrial carbon emissions.

3.2.2. Scale of Investment

The significant and positive coefficients on *SI* (line 3, Table 3) suggest that industrial investment contributes considerably to China's carbon emissions. The reason is that the dramatically increased energy consumption of the fast-expanding industrial sector has led to rapid growth in carbon emissions. Table 4 shows that *SI* positively impacts carbon intensity, but the relationship is statistically insignificant, suggesting that an increase in *SI* does not boost China's industrial carbon emissions intensity. Given the emissions reduction target of the industrial sector, it should take full responsibility for saving energy and reducing emissions, as it consumes the most energy and resources while emitting the most pollutants. The provinces have set targets for energy consumption per unit of industrial value-added, which is intended to lead to reduced industrial carbon emissions intensity. The coefficient on the spatially lagged variable *W**Log (*SI*) significantly and positively impacts both the level and intensity of carbon emissions, suggesting that there are carbon emissions spillover effects from the level of investment. As provinces prioritize industrial carbon emissions reductions, investments flow to low-carbon industrial enterprises.

3.2.3. Industrial Economy

China is in an era of rapid industrialization, causing swift growth of both its industrial economy and its CO_2 emissions. The positive but insignificant impacts of industrial value-added per unit of labor (*IE*) on the level and intensity of carbon emissions, as found in this estimation, suggest that China's growth in industrial production is not the main driver of carbon emissions growth. Although industrial energy consumption and industrial carbon emissions are increasing, industrial carbon emissions intensity is decreasing. Thus, carbon emissions reductions are unlikely to be achieved by controlling industrial development but rather by adjusting the structure of industrial energy consumption, optimizing industrial structure, and following a low-carbon development path. The negative and significant coefficient on the spatially lagged variable *W**Log (*IE*) shows that the industrial economy in one region can affect carbon emissions of other regions through spillover effects. This is explained by the fact that the adjacent provinces compete to develop low-carbon industries. These resource-saving and environmentally friendly industries are aimed at creating a sustainable and low-carbon economy.

3.2.4. Energy Intensity

Decreased industrial energy intensity arises mainly from technological innovation, which affects both the scale and intensity of industrial carbon emissions. We found a significant and positive impact of energy intensity (*EI)* on carbon emissions levels and intensity, indicating that the industrial low-carbon technologies are advancing and energy consumption per unit of industrial value-added is decreasing. This is beneficial for lowering carbon emissions and aligns with expectations. Recently, with the progress of industrial technologies, optimization of industrial structures, and efforts at energy savings and emissions reductions, China's industrial sector energy intensity is decreasing. This lowering of energy intensity is an important strategy for reducing China's industrial carbon emissions. No spatial spillover effects of energy intensity on carbon emissions are found: the coefficient on *W**Log (*EI*) is positive but insignificant. This is because carbon emissions technology is hard to imitate across regions. The development of carbon emissions-reduction technologies is largely influenced by economic development and innovation capability of a given region. The large differences in research capabilities across regions block diffusion of these technologies.

3.2.5. Energy Consumption Structure

The rapid development of China's industrial economy has created need to optimize its industry consumption structure to slow long-term growth in carbon emissions. However, given resource constraints, a coal-intensive energy consumption structure is likely to remain in place for a long time. In this model estimation, energy consumption structure has a positive and significant effect on both the scale and intensity of carbon emissions, indicating that an increase in the coal intensity of total energy consumption has a negative effect on industrial carbon emissions reductions. Thus, increasing the ratio of non-fossil energies, such as wind, nuclear, and solar, to total energy consumption will support a reduction in the scale and intensity of carbon emissions. Furthermore, energy consumption structure has a spillover effect: the coefficient on *W**Log (ECS) has a negative and significant impact on the intensity of carbon emissions. This spillover is due to competition among adjacent regions to save energy and reduce emissions. All provinces are trying to optimize their industrial energy consumption structures and develop green technologies, such as non-fossil energies, so measures should be taken to let the availability of new and renewable energy types play an important role in adjusting the structure of industrial energy consumption.

3.2.6. Energy Price

In this paper, the energy price refers to the producer price index for manufactured products. In theory, factor prices are negatively correlated with factor demands. The energy price has a negative but insignificant effect on carbon emissions levels and intensity, indicating that the role of energy prices in shaping China's industrial carbon emissions is statistically insignificant. To meet the increasing industrial demand for energy (and accompanying growth in carbon emissions), China needs to scale upmarket supervision and inspection and enforce a price-forming mechanism for important energy types, such as electricity and gas. Under such a mechanism, energy prices can act as signals of energy demand and supply. When energy price in one region increases, producers in that region would be expected to purchase energy from adjacent regions, causing increases in total carbon emissions. However, we find no evidence that spillover effects exist for energy prices, probably because the release of regional energy price information is inefficient. When energy prices rise in the region, especially regions that rely on industrial development, it will purchase energy from the neighboring regions, resulting a slightly increase of industrial carbon emissions. Therefore, China should improve and perfect the price information release system and stabilize social expectations.

3.2.7. Openness

Accelerating urbanization has pushed up energy consumption and CO_2 emissions. In recent years, the need for a low-carbon economy has necessitated importing advanced technologies from abroad, and these foreign imports are also expected to be environmentally sustainable. Thus, openness should decrease carbon emissions. However, this hypothesis is rejected in the estimation results: the coefficient on *OPEN* is negative but insignificant, as is that on *W**Log (*OPEN*), suggesting that *OPEN* does not have spillover effects. It shows that the changes of opening level in China has a limited negative effect on China's industrial carbon emissions, but the rise in opening level can still help to reduce carbon emissions which make it of great significance. China buy low carbon technology and clean energy from abroad, and attract low carbon foreign investment. FDI technology spillover effect can reduce China's carbon emissions scale and intensity. These methods both play a positive role in reduce China's carbon emissions scale and intensity. In the Durbin Model which use natural logarithm Log *(CS)* (CS: carbon emission scale) and Log *(CI)* (CI: carbon emission intensity) as the explanatory variable, the opening level spatial lag estimated coefficient is negative, but it is not significant. This indicating that there is a limited spatial spillover effect of opening level. The reason is mainly reflected in the spillover effect of competition between neighboring regions, while they open the gate to the world. Regions have accelerated the pace of industrial opening, this laid a solid foundation for China to stick to the low-carbon economic development.

3.3. Spillover Effect of Regional Industrial Carbon Emissions

It is common to use point estimates from one or more spatial regressions to test the existence of spillover effects. Lesage and Pace [2] (pp. 19–44), however, argue that using point estimates from multiple spatial regressions will bias prediction of spillover effects. They further decompose spillover effects into direct and indirect effects.

The SDPDM model Equation (13) can be rearranged as Equations (14) and (15).

$$\begin{gathered} Y_{it} = \delta \sum_{j=1}^{N} Y_{it} + \alpha + \sum_{i=1}^{m} \beta_i X_{it} + \sum_{J=1}^{N} w_{ij} X_{ijt} \theta + \mu_i + \lambda_t + \varepsilon_{it} \\ Y_{it} = \delta W Y_{it} + X_{it} \beta + W X_{it} \theta + + \mu_i + \lambda_t + \varepsilon_{it} \end{gathered} \tag{14}$$

$$\begin{aligned} Y_{it} &= (I-\delta W)^{-1}(X_{it}\beta + WX_{it}\theta) + (I-\delta W)^{-1}\mu_i \\ &+ (I-\delta W)^{-1}\lambda_t + (I-\delta W)^{-1}\varepsilon_{it} \end{aligned} \tag{15}$$

where Y_{it} is the dependent variable for region i at time t, X_{it} is a vector of independent variables of region i at time t, α is the constant term, θ is similar to β, which is a $K \times 1$ vector of coefficients, μ_i is an individual-fixed effect, and λ_t is a time-fixed effect. Taking partial derivatives of the k^{th} independent variable X on both sides, we obtain:

$$\begin{bmatrix} \frac{\partial Y}{\partial \chi_{ik}} & \frac{\partial Y}{\partial \chi_{Nk}} \end{bmatrix} = \begin{bmatrix} \frac{\partial y_1}{\partial \chi_{ik}} & \frac{\partial y_1}{\partial \chi_{ik}} \\ \frac{\partial y_N}{\partial \chi_{ik}} & \frac{\partial y_N}{\partial \chi_{ik}} \end{bmatrix} = (I-\delta W)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_k & w_{2N}\theta_k \\ w_N\theta_k & w_{N2}\theta_k & \beta_k \end{bmatrix} \tag{16}$$

where W_{ij} is the (i, j) element of the matrix W. The direct effect is defined as the sum of the diagonal elements in the right matrix while the indirect effect is defined as the average of all the non-diagonal elements (Lesage and Pace, 2009). Identifying the direct and indirect effects via this method has drawbacks in that calculating $(I-\delta W)^{-1}$ is time-consuming. To solve this, Lesage and Pace [2] (pp. 19–44) propose another method, specified in Equation (17).

$$(I-\delta W)^{-1} = I + \delta W + \delta^2 W^2 + \delta^3 W^3 \tag{17}$$

The models estimating the direct and indirect effects in Equation (16) are denoted as Method 1 and Method 2 using Equation (17). Table 5 displays the direct and indirect effects estimated through Method 1, for Model 4 with Log (*CS*) as the dependent variable. The results differ slightly between Method 1 and Method 2, but all variables have direct and indirect effects. *SI*, *EI*, and *ECS* positively and significantly impact the scale of carbon emissions, while *IE*, *EP*, and *OPEN* insignificantly impact it, although their signs are as expected.

Table 6 displays the direct and indirect effect estimates for Model 4 with Log (*CI*) as the dependent variable. The results do not differ from the Model 1 results. All variables have direct and indirect effects, direct effects of *EI* and *ECS* on intensity of industrial carbon emissions are positive, and the direct effects of *SI*, *IE*, *EP*, and *OPEN* are all insignificant, although the signs are as expected. On the other hand, *SI*, *IE*, and *ECS* have significant indirect effects. We can thus argue that spillover effects do exist. Spillover effects imply that the independent variables affect the dependent variable via the spatially lagged variables. The differences indirect and indirect effects are substantial for all the control variables, indicating that failing to explicitly model the spatial correlation would lead to estimation bias.

Table 5. Direct, indirect and total effects of Spatial Durbin model (Method1, dependent variable: Log (*CS*)).

Variable	Direct Effect	Indirect Effect	Total Effect
Log(SI)	1.2012 *** (9.8339)	−0.7645 *** (−2.6558)	0.4367 (1.3678)
Log(IE)	0.0700 (1.3308)	−0.2086 ** (−2.1793)	−0.1386 (−1.4935)
Log(EI)	0.7803 *** (18.5641)	0.1058 (1.4353)	0.8861 *** (11.4843)
Log(ECS)	0.0576 ** (1.9643)	−0.1193 ** (−1.8808)	−0.0616 (−0.9326)
Log(EP)	−0.0106 (−0.1193)	−0.1709 (−1.1175)	−0.1815 (−1.0960)
Log(OPEN)	−0.0057 (−0.3914)	0.0094 (0.5229)	0.0037 (0.1572)

Note: * represents significance at 10%, ** 5%, and *** 1% respectively.

Table 6. Direct, indirect and total effects of Spatial Durbin model (Method1, dependent variable: Log (*CI*)).

Variable	Direct Effect	Indirect Effect	Total Effect
Log(SI)	0.1975 (1.6262)	−0.7795 *** (−2.9212)	−0.5820 ** (−1.9978)
Log(IE)	0.0717 (1.3607)	−0.2048 ** (−2.0105)	−0.1331 (−1.3790)
Log(EI)	0.7790 *** (18.7878)	0.1094 (1.4981)	0.8884 *** (11.7796)
Log(ECS)	0.0576 ** (1.9648)	−0.1138 * (−1.7426)	−0.0562 (−0.8170)
Log(EP)	−0.0033 (−0.0382)	−0.1658 (−1.0350)	−0.1692 (−1.0068)
Log(OPEN)	−0.0061 (−0.4183)	0.0098 (0.5407)	0.0037 (0.1646)

Note: * represents significance at 10%, ** 5%, and *** 1% respectively.

4. Conclusions

In this paper, an expanded Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model was conceptualized to investigate the factors driving regional industrial carbon emissions in China. Based on provincial panel data from 2006 to 2010, a spatial Durbin model was applied to test the impacts of these contributing factors on the scale and intensity of industrial carbon emissions, examine the spatial correlation of industrial carbon emissions among provinces, and consider the determinants' potential spillover effects. In addition, a geographically was applied to investigate the regional heterogeneity in the impacts of the driving factors on the scale and intensity of industrial carbon emissions. The main conclusions from these analyses are as follows.

First, most of the driving factors significantly impact the scale and intensity of carbon emissions, and their signs align with expectations. The coefficients on the spatially lagged dependent variables are estimated to be negative but insignificant, suggesting that industrial carbon emissions are highly correlated among regions. As a result, the exemplar role of the low-carbon-emissions provinces is of great importance in fostering nationwide low-carbon economy.

Second, the driving factors impact carbon emission both directly and indirectly. Considering the indirect effects, all of the variables except for energy intensity, energy price, and openness have significant indirect effects. We can thus argue that spillover effects do exist: the independent variables affect the dependent variable via the spatially lagged variables. Using the transitional panel data model, which assumes the indirect effect to be zero, will bias the estimation. The differences in the direct and indirect effects of the control variables are substantial, indicating that ignoring spatial correlation would lead to estimation bias.

Third, the impacts of the influencing factors and their spillover effects vary across provinces. The results show substantial variation in the coefficients on the spatially lagged dependent variables of the control variables. The driving factors' influences on industrial carbon emissions and their spillover effects suggest that regional industrial spatial correlation, heterogeneity, and externalities must be taken into account during policy formulation. Considering the fact that industrial carbon emissions differ across regions, we propose the following strategies to reduce industrial carbon emissions: (1) a moderate increase in investment in low-carbon industries; (2) optimization of the structure of industrial energy consumption; (3) optimization of industrial structures; (4) innovation in industrial technology; and (5) effective coordination of planning related to regional industrial carbon emissions.

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