

## Research Article

# The Spatial Spillover Effect of Environmental Regulation and Technological Innovation on Industrial Carbon Productivity in China: A Two-Dimensional Structural Heterogeneity Analysis

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Environmental regulation and technological innovation are two crucial factors for improving industrial carbon productivity. However, prior research ignored the spatial spillover effects of these factors, and heterogeneity caused by industrialization level and resource dependence did not acquire attention either. Thus, we use the STIRPAT model and spatial panel Durbin model to study the spatial spillover effects of two independent variables. Then, a two-dimensional structural heterogeneity analysis is conducted according to the industrialization level and resource dependence. The results are as follows: improving environmental regulation and technological innovation is good for industrial carbon productivity. Simultaneously, there are obvious regional differences under two-dimensional structural heterogeneity. From the perspective of space, industrial carbon productivity has high spatial autocorrelation, and it can be enhanced through local environmental legislation, as well as technological innovation. Environmental regulation's spatial spillover impact inhibits the improvement of industrial carbon productivity in surrounding provinces, resulting in a pollution haven effect. However, there is no evident regional spillover effect of technological innovation. Therefore, we provided new perspectives from spatial spillover and structural heterogeneity to optimize low-carbon policies.

## 1. Introduction

As a large amount of greenhouse gas emissions has been produced, global warming has caused frequent occurrences of extreme weather. Therefore, alleviating global climate change and reducing greenhouse gas emissions have become urgent issues. To mitigate climate change, China regarded carbon neutrality as an important part of ecological progress and promised to reach carbon neutrality by 2060. However, according to data released by the International Energy Agency [1], nearly 60 percent of global emissions were from China in 2016, and the industrial sector is the main source, consuming 67.9 percent of China's energy and emitting 83.1 percent of carbon dioxide [2]. Thus, reducing industrial carbon emissions is crucial to achieving China's commitment, and a big challenge for China is how to reduce industrial carbon dioxide emissions while achieving

sustainable economic development. Exactly, industrial carbon productivity is the embodiment of CO<sub>2</sub> reduction and economic growth. Improving carbon productivity reflects an important effort to achieve China's commitment to carbon reduction and global climate change strategy.

Carbon productivity, the ratio of GDP output to carbon dioxide, was put forward by Kaya and Yokobori [3]. Considering the high pollution attribute of industrial industry, it is extended as the output level of industrial added value per unit of industrial carbon dioxide, which refers to industrial carbon productivity [4]. To improve industrial carbon productivity, it is necessary to explore its influencing factors. Porter's hypothesis, a classical theory, exactly gave us an appropriate framework to analyze such an issue. Porter's hypothesis describes the relationship between environmental regulation, technological innovation, and enterprises' productivity [4]. It is considered that environmental

regulation gives a driving force to technological innovation and finally improves the productivity of enterprises. However, due to the existence of industrial pollutants, such as CO<sub>2</sub>, how to improve green total factor productivity (GTTP) of enterprises has been a new topic under Porter's hypothesis framework. Many researches have discussed the effect of environmental regulation on GTTP [5, 6]. The result shows that, in the long run, environmental regulation would achieve the win-win goal for enterprise competitiveness and environmental protection. And technological innovation is also regarded as a driven factor of GTTP in some regions [7–9]. Therefore, we bring environmental regulation, technological innovation, and industrial carbon productivity into a framework, studying its impact mechanism to reduce industrial carbon emissions and promote high-quality industrial development. In addition, due to the imbalances of industrialization level and resource endowment, environmental regulation and technological innovation might generate different effects in different regions [10, 11]. With the continuous propulsion of industrialization, there is an obvious phenomenon that industrial development in some provinces mainly relies on natural resources. This may induce industry structure change and economic agglomeration [12, 13], and the economic agglomeration will accelerate carbon emissions in turn [14]. Therefore, we further explored two-dimensional structural heterogeneity caused by industrialization level and resource dependence when studying the driving factors. Meanwhile, the influence of two independent variables on industrial carbon productivity may spill over to the surrounding areas. Based on such consideration, we dug into the spatial agglomeration characteristics and spatial spillover effects of them.

The contributions of this study are as follows. First, according to Porter's hypothesis, this paper integrated environmental regulation, technological innovation, and industrial carbon productivity into a framework to analyze their relationship. And when analyzing spatial spillover effects, we adopted an improved STIRPAT model and Spatial Durbin model to carry through. Secondly, three different spatial matrices are creatively used to ensure robustness when discussing spatial spillover effects. Finally, to investigate the heterogeneity, 30 provinces in China are divided into four quadrants based on the two-dimensional structural heterogeneity analysis of industrialization level and resource dependence.

The rest of the sections are as follows: literature about industrial carbon productivity, environmental regulation, and technological innovation is reviewed in Section 2. Section 3 states the econometric model, index of variables, and data source. Section 4 presents the empirical analysis and related discussions. Section 5 gives a conclusion for the paper and offers some suggestions.

## 2. Literature Review

We mainly review the literature from the following three aspects. Firstly, as for the relationship between environmental regulation and industrial carbon productivity, we summarized three conclusions: (1) environmental regulation stimulates carbon productivity, which was the innovation

compensation effect. Environmental regulation with appropriate intensity can induce the driving force of technological innovation, cover the compliance cost caused by environmental regulation, and finally realize the double dividend of economy and environment. For example, Wu et al. [15] believed that environmental regulation effectively restricted and controlled the growth of carbon emissions in central and eastern China. Li et al. [16] found that the disclosure of pollution information transparency index (PITI) has significantly improved the environmental quality of Chinese cities. Yang et al. [17] discussed that carbon trading policies can effectively reduce carbon emissions at a provincial level in China. (2) Environmental regulation decreased carbon productivity, namely, compliance cost effect. For example, Jensen et al. [18] found that declaring climate policy would stimulate energy demand and accelerate carbon emission. Zhang et al. [19] confirmed that because of local fiscal decentralization, environmental regulation policies did not work to reduce carbon emission. (3) There is not only a linear relationship between them. Many factors will change the effect of environmental regulation, and carbon productivity will give a different response to it [20]. For instance, Munasinghe [21] pointed out that appropriate environmental regulation would reduce the radius of the inverted U-shaped curve and even reach the peak earlier. Yin et al. [22] also found that if conducting stricter environmental regulations, the inflection point of carbon emissions might be achieved forward. They all believed that enhancing environmental regulation was helpful to reach the peak of carbon emission in advance. But the impact of environmental regulations on industrial carbon productivity did not receive much attention.

Secondly, there are the following views about technological innovation and industrial carbon productivity: (1) To improve carbon productivity, technological innovation might be the key. Li et al. [23] believe that technology gradually plays a dominant role in the growth of total factor industrial carbon productivity. Long et al. [24] verified that technological progress significantly improved industrial carbon productivity. Cheng et al. [25] showed that technological innovation can effectively reduce carbon emissions with significant heterogeneity and asymmetry. (2) Technological innovation may reduce carbon productivity. The rebound effect of energy explains that technological innovation may not reduce carbon emissions. The reason is that technological innovation will increase productivity. To replace labor and capital investment in production activities, increased productivity may lead to more energy consumption and carbon emissions [26]. Mizobuchi [27] extended the research of Brännlund et al. [28] and calculated the rebound effect with Japanese household data, concluding that the rebound range was about 27%. Lin and Du [29] confirmed that, in China, the rebound effect of energy was between 30% and 40%. Most researches about the rebound effect take carbon emission as the main object, while little attention is paid to industrial carbon productivity.

Thirdly, we notice the effect of resource dependence and industrialization level on industrial carbon productivity. Auty and Mikesell [30] first proposed the concept of resource curse

when they studied economic development in countries with more mines. Compared with countries owning a few resources, the countries with abundant natural resources tended to develop slowly. Many scholars verified and confirmed the existence of the resource curse [31]. Some studies even pointed out that abundant natural resources (especially oil) harmed manufacturing and limited its prospect of economic growth [32, 33]. In China, different provinces have diverse resource endowments. Some provinces have formed an economic model relying on the comparative advantages of mineral resources. As a result of economies of scale, learning effect, coordination effect, adaptive effect, and vested interests, resource-based provinces have formed path dependence [34]. Such provinces constantly insist on the inherent development mode and maintain the high-carbon development path with high energy consumption. Thus, regions with high resource dependence have significantly different impacts on carbon productivity compared with other regions. Government departments will formulate policies to regulate the economic activities of mining enterprises and adopt stricter environmental regulations in mining areas with rich resources to protect the ecological environment, maintain ecological balance, and improve industrial carbon productivity. Additionally, different conditions of economic development will cause different driving forces on the industrialization level in each region. The improvement of the industrialization level will increase air pollutants [35]. Therefore, the level of industrialization has an impact on the formulation of regional environmental regulations and the evolution of technological innovation. Obviously, the eastern part of China has a higher level of industrialization, more flexible environmental regulation policies, and more active technological innovation. Therefore, regional differences in industrialization level may affect the development level of environmental regulation and technological innovation, leading to differences in industrial carbon productivity. In a word, the degree of resource dependence and industrialization in different regions produces heterogeneity for environmental regulation and technological innovation. And they may further cause a heterogeneous impact on industrial carbon productivity.

To sum up, many scholars have conducted fruitful studies on environmental regulation, technological innovation, and carbon emissions. However, there are still some shortcomings. Firstly, many works of literature only pay attention to a single target of environmental regulation, without considering economic and carbon reduction targets

simultaneously. Most of them only verify the impact of environmental regulation on carbon intensity or total factor productivity, rather than industrial carbon productivity. Secondly, existing literature mostly adopts the geographical administrative division method to consider regional heterogeneity. Few studies consider the heterogeneous effects of industrialization levels and resource dependence on industrial carbon productivity in different regions. Finally, to estimate the spatial spillover effect, most studies choose a geographic adjacency matrix, instead of geographical distance matrices based on the inverse of the highway mileage or its squared. And fewer papers verify the robustness of the results through multiple spatial weight matrices.

### 3. Methodology and Data

**3.1. STIRPAT Model.** To sum up, many scholars have conducted fruitful studies on environmental regulation, technological innovation, and carbon emissions. However, there are still some shortcomings. Firstly, many works of York et al. [36] proposed the STIRPAT model, and this paper introduced environmental regulation into it so that we can explore environmental regulation, technological innovation, and industrial carbon productivity [37]. The improved STIRPAT model is formula (1).

$$\ln \text{ICP}_{it} = \alpha_0 + \beta_1 \ln \text{ERI}_{it} + \beta_2 \ln T_{it} + \gamma \text{Contr}_{it} + \eta_i + \lambda_t + \varepsilon_{it}. \quad (1)$$

As shown in model (1), the dependent variable  $\ln \text{ICP}$  is industrial carbon productivity.  $\ln \text{ERI}$  stands for environmental regulation and  $\ln T$  stands for technological innovation. Subscript  $i$  refers to provinces, and  $t$  represents year.  $\beta_1$  and  $\beta_2$  are the coefficients of environmental regulation and technological innovation, respectively.  $\text{Contr}$  refers to control variables, which specifically are foreign direct investment level (FDI), the structure of energy consumption (ECS), and population size ( $\ln \text{PS}$ ).  $\varepsilon$  denotes error term,  $\eta$  represents individual effects, and  $\lambda$  denotes time effects.

**3.2. Spatial Durbin Model.** To explore the spatial spillover effect, we add spatial weight matrices based on model (1) to construct a spatial panel Durbin model as shown in model (2).

$$\begin{aligned} \ln \text{ICP}_{it} = & \alpha_0 + \rho \sum_{j=1}^n W_{ij} \ln \text{ICP}_{it} + \gamma_1 \sum_{j=1}^n W_{ij} \ln \text{ERI}_{it} + \gamma_2 \sum_{j=1}^n W_{ij} \ln T_{it} \\ & + \beta_1 \ln \text{ERI}_{it} + \beta_2 \ln T_{it} + \gamma_3 \sum_{j=1}^n W_{ij} \text{Contr} + \gamma \text{Contr}_{it} + \eta_i + \lambda_t + \varepsilon_{it}, \end{aligned} \quad (2)$$

where  $\rho$  is the spatial autoregressive coefficient of  $\ln \text{ICP}$ .  $\gamma_1$  and  $\gamma_2$  are the spatial lag coefficients of independent variables, respectively.  $W_{ij}$  represents the spatial weight matrix which is constructed in three ways. A binary contiguity

matrix is built following the principle of the geographic adjacent relation ( $W_1$ ). Another method of establishing spatial weight matrix is based on geographical distance according to the reciprocal of highway mileage between

provincial capitals ( $W_2$ ). Moreover, we further build the inverse squared distance matrix using highway mileage ( $W_3$ ) for robustness. The specific forms of the three matrices are as follows, where  $d_{ij}$  is the highway mileage between provincial capitals  $i$  and  $j$ :

$$W_1 = \begin{cases} 0, & \text{if } i \text{ and } j \text{ are adjacent,} \\ 1, & \text{if } i \text{ and } j \text{ are not adjacent,} \end{cases} \quad (3)$$

$$W_2 = \begin{cases} \frac{1}{d_{ij}^2}, & i \neq j, \\ 0, & i = j, \end{cases} \quad (4)$$

$$W_3 = \begin{cases} \frac{1}{d_{ij}^2}, & i \neq j, \\ 0, & i = j. \end{cases} \quad (5)$$

It should be noted that a spatial regression model based on point estimation will generate bias [38]. Due to spatial correlation, coefficient estimates of explanatory variables do not represent true spillover effects. But we can use the partial derivative method to obtain its direct effect and indirect effect. Therefore, the SDM model can be converted into formula (6), and the partial differential equation matrix of explanatory variables is shown as formula (7) [39].

$$Y_t = (1 - \rho W)^{-1} (\beta X_t + \phi W X)^{-1} + (1 - \rho W)^{-1} \varepsilon_t, \quad (6)$$

$$\frac{\partial Y}{\partial X_{it}} \cdots \frac{\partial Y}{\partial X_{Nt}} = (1 - \rho W)^{-1} \begin{bmatrix} \beta_k & W_{12}\lambda_k & \cdots & W_{1N}\lambda_k \\ W_{21}\lambda_k & \beta_k & \cdots & W_{2N}\lambda_k \\ \cdots & \cdots & \ddots & \vdots \\ W_{N1}\lambda_k & W_{N2}\lambda_k & \cdots & \beta_k \end{bmatrix}. \quad (7)$$

**3.3. Index of Variables.** Industrial carbon productivity (ICP): we measured it through the ratio of industrial added value to industrial carbon dioxide emissions. However, China's central government does not currently publish direct data on carbon dioxide emissions. Thus, it needs to be calculated through the physical consumption of the energy mix. The calculation method is formula (8), which contains nine energy sources such as raw coal, kerosene, crude oil, gasoline, diesel, fuel oil, coke, natural gas, and electricity.

$$CE_{i,t} = \sum_{r=1}^9 En_{i,r,t} \times S_r \times F_r \times \frac{44}{12}, \quad (8)$$

where  $CE_{i,t}$  indicates the industrial  $CO_2$  emissions of province  $i$  in year  $t$ .  $En_{i,r,t}$  denotes the energy consumption and the energy type is  $r$ .  $S_r$  stands for the reference coefficient of all energy standard coals provided in China Energy Statistical Yearbook [40] (Table 1).  $F_r$  is the carbon emission coefficient of China published by the Chinese Academy of Sciences (Table 2) [41]. Finally, the regional industrial  $CO_2$  emissions are calculated in units of 10,000 tons.

**Environmental regulation intensity (ERI):** currently, there is no uniform standard to measure environmental regulation. It is more common to regard the expenditure of pollution treatment and control for unit output, policy quantities, pollutant emissions, and per capita income as indicators of environmental regulation [42]. Dasgupta et al. [43] proposed that the national income level was highly correlated with environmental regulation. Through the correlation coefficient, Xu [44] tested that the severity of environmental regulations is endogenously determined by income level. Thus, in this study, we choose per capita disposable income to measure environmental regulation.

**Technological innovation (TE):** as a key to achieving carbon peak and carbon neutrality in China, technological

innovation is important for high-quality economic development. Existing studies usually adopt the number of patents as an indicator to stand for technical level and technological innovation ability [45]. Considering the availability of data, effective invention patents of industrial enterprises above designated size are used to measure technological innovation.

**Foreign direct investment (FDI):** using the ratio of actual utilization of foreign direct investment to GDP, foreign direct investment in each province was measured. The actual utilization of foreign direct investment is converted from dollars to RMB according to the exchange rate.

**Population size (PS):** the population size is considered to be constant in a short time. Thus, the population size is taken as the control variable, and the number of populations in each province is regarded as its indicator. Meanwhile, to avoid the heteroscedasticity problem, the population is processed in a logarithm.

**Energy consumption structure (ECS):** it is measured by the proportion of coal consumption in total energy consumption. It directly reflects carbon content in each energy. Calculating formulas are as follows:

$$CC = En_{1,i,t} \times S_1, \quad (9)$$

$$EC = \sum_{r=1}^9 En_{r,i,t} \times S_r, \quad (10)$$

where  $CC$  is coal consumption,  $EC$  is the total energy consumption, and the sign of various energy consumption of each province is  $En_{i,r,t}$ .  $S_r$  is the standard coal conversion coefficient of each kind of energy source.  $r = 1$  means that the energy variety is raw coal. According to equations (9) and

TABLE 1: The standard coal conversion coefficient of energy mix.

Energy mix	Convert units	The standard coal conversion coefficient
Raw coal	ton	0.7143
Gasoline	ton	1.4714
Fuel oil	ton	1.4286
Coke	ton	0.9714
Kerosene	ton	1.4714
Natural gas	104 m <sup>3</sup>	13.3
Crude oil	ton	1.4286
Diesel	ton	1.4571
Electricity	104 kw·h	1.229

TABLE 2: Carbon emission coefficient of energy mix.

Energy mix	Convert units	Carbon emission coefficient
Raw coal	ton	0.7476
Coke	ton	0.1128
Crude oil	ton	0.5854
Gasoline	ton	0.5532
Kerosene	ton	0.3416
Diesel	ton	0.5913
Fuel oil	ton	0.6176
Natural gas	10 <sup>4</sup> m <sup>3</sup>	0.4479
Electricity	10 <sup>4</sup> kw·h	2.2132

(10), a calculation formula of the energy consumption structure could be derived as shown in the following:

$$ECS = \frac{En_{1,it} \times S_1}{\sum_{r=1}^9 En_{r,it} \times S_r}. \quad (11)$$

**3.4. Data Source.** In this paper, data of 30 provinces and autonomous regions in 2004–2016 are all collected from yearbooks and databases. But because of the availability of data, Taiwan, Hong Kong, Macao, and Tibet are excluded from our sample. Per capita disposable income of residents, industrial added value, GDP in each province, and the population size are collected in the China Statistical Yearbook (2005–2017) [46]. Energy consumption structure and the CO<sub>2</sub> emission are calculated according to 9 kinds of energy in China Energy Statistical Yearbook (2005–2017) [47]. Effective invention patents of industrial enterprises are in the Science and Technology Statistical Yearbook of China (2005–2017) [48]. Actual utilization of foreign direct investment is taken from Wind Database.

## 4. Empirical Result

**4.1. The Trend of Industrial Carbon Productivity Change.** Figure 1 depicts the developing trend of GDP and industrial carbon productivity in China. Obviously, from 2004 to 2016, industrial carbon productivity generally shows a steady rising trend. And it increased from 67,716 yuan/ton to 142,271 yuan/ton with an increased rate of 110%. However, the trend of industrial carbon productivity is flat from 2008 to 2009. And after that, there is a sharp increase. We inferred that it may be accounted for by the global crisis. From 2014

to 2016, China's economic growth is stable, but the growing trend of industrial carbon productivity slows down. Beijing, Tianjin, Shanghai, Guangdong, and other economically developed provinces show a significant increasing trend, while Heilongjiang, Yunnan, Ningxia, and Xinjiang provinces decrease. It is noteworthy that the industrial carbon productivity in 2016 is higher than in 2004 in Shanxi, Inner Mongolia, Liaoning, Hainan, Gansu, and Qinghai provinces. But in recent years, it has been decreasing obviously. The decline of industrial carbon productivity in these provinces is probably influenced by resource dependence and industrialization levels.

**4.2. Results of the Nonspace Panel Model.** Variance Inflation Factor (VIF) analysis, one index to exemplifying multicollinearity between variables, is required before estimating regression coefficients (Table 3). Table 3 shows that VIF values of all variables range from 1.1 to 5.58, with an average of 2.95. All the VIF values of each variable are smaller than 10, which indicates that there is no multicollinearity between variables.

Based on the econometric model (5), we conduct empirical tests using different methods. As shown in Table 4, the outcome of the Hausman test shows that we need to reject the null hypothesis, which means that, in our study, a fixed-effects model is more appropriate. According to the Bayesian Information Criterion (BIC), we find that the value of BIC in column (2) is smaller. It means that the explanatory power of column (2) is fitting better. Besides, the core explanatory variables of column (2) are significant at a 1% significance level. Therefore, we select the individual fixed effect model to analyze and explain the results.

When only considering the effect of two independent variables, environmental regulation and technological innovation are both significantly positive. It can be concluded that environmental regulation positively relates to industrial carbon productivity, which is similar to technological innovation. The results show that environmental regulation and technological innovation have strong positive effects on industrial carbon productivity. After adding control variables one by one, we can get the same conclusion. But the influence of environmental regulation is greater than technological innovation by comparing the coefficient of two variables. Specifically, for every 1% increase in environmental regulation intensity, the dependent variable will increase by 0.512%. While if technological innovation increases by 1%, industrial carbon productivity will only increase by 0.0795%. This implies that the current level of technological innovation does not have an effective promotion effect on industrial carbon productivity. Hence, stringent environmental regulation contributes more to the improvement of industrial carbon productivity than other means. But as an important way for sustainable development, technological innovation cannot be ignored. For control variables, FDI is significantly positive at the 1% significance level, while ECS is significantly negative. This means that we should expand foreign direct investment to improve industrial carbon productivity and get off overreliance on coal consumption as soon as possible.

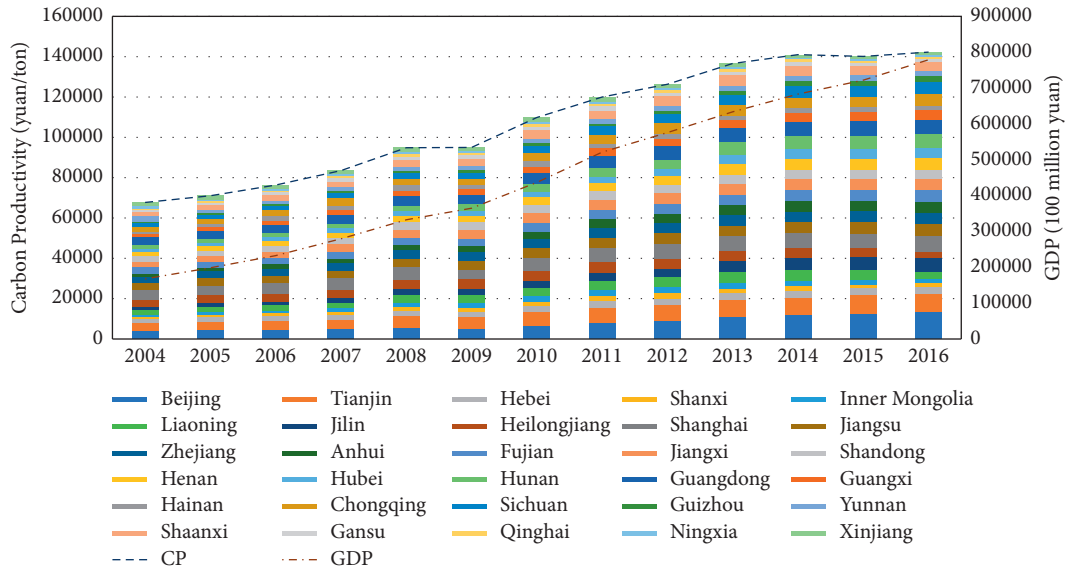


FIGURE 1: The trend of industrial carbon productivity and GDP in China.

TABLE 3: Variance inflation factor analysis of the variables.

Variable	LnTE	LnERI	LnPS	ECS	FDI	Mean VIF
VIF	5.58	3.98	2.67	1.42	1.10	2.95

#### 4.3. Two-Dimensional Structural Heterogeneity Analysis.

The term resource-based industry has been focused on and used widely in recent years, but there is not a uniform definition for it. At present, the resource-based industry in a narrow sense refers to the mining of minerals and the primary processing of minerals [5]. Considering the availability of data, we determined 11 resource-based industries according to the narrow concept mentioned above as shown in Table 5. Based on the existing research, we measure each province's resource dependence through the proportion of resource-based industrial employees in all industrial employees. If the proportion is more than 40%, the province will be defined as a province with high resource dependence. Figure 2 shows the proportion of resource-based industrial employees in all industrial employees in 2015 in each province. And Hebei, Shanxi, Heilongjiang, Guizhou, Gansu, Yunnan, Ningxia, Shaanxi, Inner Mongolia, Qinghai, and Xinjiang provinces can be assigned to provinces with high resource dependence.

Besides, per capita GDP, industrialization rate (the ratio of industrial added value to GDP), industrial structure, employment structure, and urbanization rate are international indicators for measuring the industrialization level. In this paper, we adopt the ratio of industry sector value added in GDP to measure the industrialization level according to Xu and Lin [49]. 30 provinces and autonomous regions in China are divided into two parts by the average annual ratio of industrialization rate from 2004 to 2016.

Finally, from the two-dimensional structure of industrialization level and resource dependence, 30 provinces and autonomous regions in China are divided into 4 quadrants. As shown in Figure 3, Region I represents the provinces with

high industrialization levels and high resource dependence. Region II includes the provinces with high industrialization levels and low resource dependence. Region III shows the provinces with low industrialization levels and low resource dependence. Region IV represents the provinces with low industrialization levels and high resource dependence. According to the division, we test this study by subgroups.

**4.3.1. Results of Heterogeneity Analysis.** Based on the regional division above, this section further considers regional heterogeneity. And the estimated results of subgroups are shown in Table 6. The results of column (1) show the regression outcome of provinces in Region I. We can find that resource dependence and industrialization level change effects of independent variables. In these provinces, environmental regulation is significantly positive, while technological innovation is not significant. That is probably because the economic development in such provinces is highly dependent on coal and other fossil resources. The inherent path dependence will easily lead to the neglect of cultivating technology innovation ability, and then it will hinder the breakthrough in the core technology of carbon emission reduction. As a result, to combat climate change, the government will formulate the economic activities of industrial enterprises through environmental regulations rather than technological innovation. To enhance industrial carbon productivity, strengthening environmental regulation will be the dominant way in such provinces.

Column (2) indicates Region II with low resource dependence and high industrialization level, and column (3) indicates Region III with low resource dependence and low industrialization level. The results of these two columns both show the significant impact of environmental regulation at 1% level. Enhancing environmental regulation intensity can restrain the extensive carbon emission effectively. But provinces in Region II are mostly located in eastern China,

TABLE 4: Regression results of the nonspace panel model.

	(1) OLS	(2) Individual fixed effect	(3) Time fixed effect	(4) Double fixed effect	(5) Random effect
LnERI	0.625*** (7.89)	0.512*** (8.84)	0.740*** (6.82)	0.208 (1.40)	0.467*** (8.32)
LnTE	0.0725*** (3.42)	0.0795*** (5.31)	0.0515 (1.89)	0.0286 (1.13)	0.0774*** (5.13)
FDI	0.0912*** (10.42)	0.0386*** (3.62)	0.0904*** (8.54)	0.0379*** (3.66)	0.0513*** (5.13)
ECS	-0.00202 (-1.42)	-0.00937*** (-6.68)	-0.00107 (-0.71)	-0.00824*** (-5.10)	-0.00832*** (-6.05)
LnPS	0.230*** (6.64)	-0.656** (-2.69)	0.248*** (6.23)	-0.653** (-2.70)	0.198** (2.85)
_cons	-0.576 (-0.71)	8.034*** (4.57)	-1.686 (-1.60)	11.27*** (5.63)	1.534* (2.02)
Obs	390	390	390	390	390
R <sup>2</sup>	0.719	0.916	0.728	0.924	
F/Wald	196.0	113.2	58.55	90.64	786.15
BIC	234.5	-62.04	292.8	-31.50	.
Hausman test		29.32 [0.0000]			

Note: the value in the parenthesis is the *t*-statistic or *z*-statistic; \*, \*\*, and \*\*\* denote 10%, 5%, and 1% significance level, respectively.

TABLE 5: The list of resource-intensive industries.

Type	Resource-intensive industries
Mining	Oil and gas exploitation industry
	Ferrous metal mining and dressing industry
	Nonferrous metal mining and dressing industry
	Coal mining and washing industry
	Nonmetallic mining and dressing industry
Primary processing industry	Nonmetallic mineral products industry
	Petroleum processing, coking, and nuclear fuel processing
	Ferrous metal smelting and rolling processing industry
	Metal products industry
	Nonferrous metal smelting and rolling processing industry
	Electricity and heat production and supply

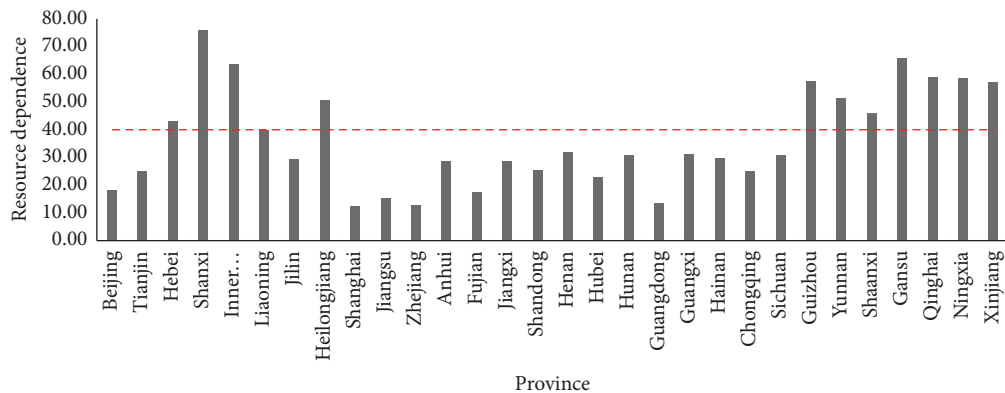


FIGURE 2: The proportion of resource-intensive industrial employees in all industrial employees.

and they are all in the late stage of industrialization. They finished the transfer of heavy industry with high emissions and their technological innovation capabilities were stronger than the central and western provinces. As a consequence, in Region II, technological innovation could offer a significant

impact. However, for the provinces in Region III, its impact is not significant. This is because the provinces with low resource dependence and low industrialization levels are all in central and western China except Beijing and Shanghai. In these provinces, the holistic capacity of innovation is

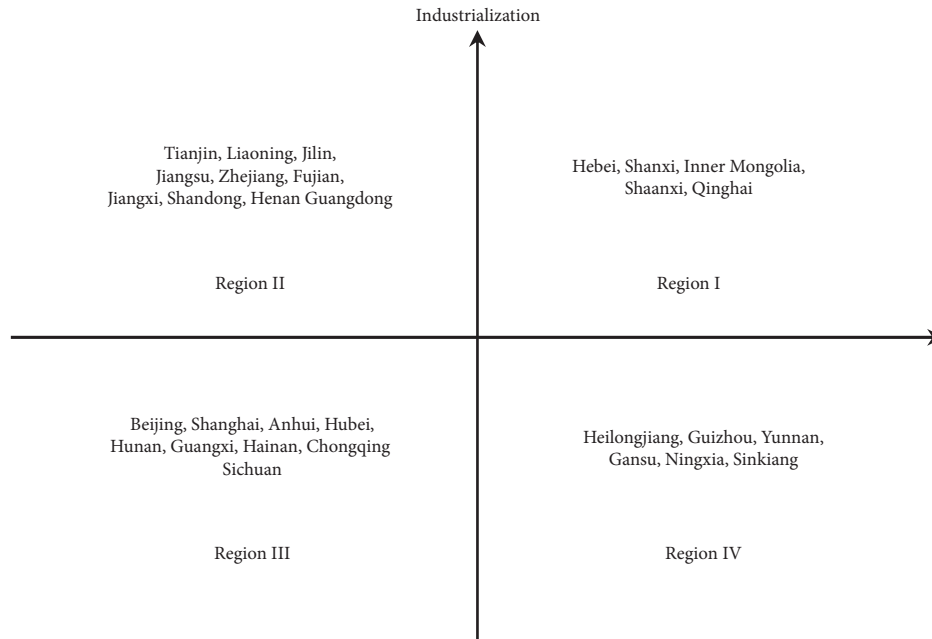


FIGURE 3: Regional division based on the two-dimensional structure.

TABLE 6: Results of heterogeneity analysis.

	(1) Model I	(2) Model II	(3) Model III	(4) Model IV
LnERI	0.752*** (7.81)	0.450*** (5.83)	0.779*** (8.56)	0.0889 (0.68)
LnTE	0.00872 (0.33)	0.122*** (5.42)	0.0242 (1.22)	0.182*** (4.48)
FDI	0.0146 (0.65)	0.0394*** (4.22)	0.0774*** (3.61)	-0.00607 (-0.09)
ECS	-0.00519* (-2.58)	-0.00368* (-2.38)	-0.0206*** (-8.87)	-0.00878* (-2.22)
LnPS	-1.406 (-1.35)	-0.105 (-0.41)	-0.635 (-1.84)	-5.467*** (-6.63)
_cons	13.30 (1.50)	3.834* (2.17)	5.846* (2.47)	51.62*** (7.59)
Obs	65	130	117	78
R2	0.950	0.893	0.928	0.892
F	116.2	68.35	102.0	55.25

Note: the value in the parenthesis is the  $t$ -statistic; \*, \*\*, and \*\*\* denote 10%, 5%, and 1% significance level, respectively.

laggard, and the productivity of green products is weak. There are few valid industrial patents so that technological innovation does not work. Comparing column (2) with column (3), it can be found that the effect of technological innovation is changed by the industrialization level. The heterogeneity is verified.

The regression results of column (4) represent the provinces in Region IV. This kind of province has superiority in natural endowment, but the level of industrialization is low. It means that primary or tertiary industry may be the dominant industry in Region IV. Pollution caused by industry is not obvious. Thus, the effect of environmental regulation is not significant anymore. As economic

development in such provinces is not strongly dependent on industry, technological innovation has shown its advantages. Besides, FDI has a positive effect in Region II and Region III (columns 2 and 3), but it is not significant in Region I and Region IV (columns 1 and 4). This means that, with high resource dependence, the way of economic development is stubborn, opening to the world and introducing foreign capital is insufficient. The influence of energy consumption structure on industrial carbon productivity is significantly negative in all provinces, indicating that China's energy consumption structure is still in a high-carbon mode.

**4.4. Endogeneity Test and Robustness Test.** The estimation results of the model may be biased due to the endogenous problems of environmental regulation and technological innovation. Thus, we use the instrumental variables to estimate. In this paper, the lagged terms of environmental regulation and technological innovation are used as instrumental variables. For environmental regulation, we introduced the first-order and second-order lagged terms of it. For technological innovation, we introduced the third-order and fourth-order lagged terms of it. Estimated results using OLS, 2SLS, and GMM are all displayed in Table 7. The result of instrument variables shows that there are no overidentification problem, underidentification problem, and weak instrumental variables. The selection of instrumental variables is reasonable. Comparing 2SLS with OLS, the coefficients of environmental regulation and technological innovation are all improved after considering endogenous variables. That is to say, the influence of environmental regulation and technological innovation was underestimated through OLS estimation. On this basis, to eliminate the heteroscedasticity of the error term, we further adopt the GMM Model to estimate. Using GMM, the coefficient of



TABLE 7: Results of endogeneity test and robustness test.

	(1) OLS	(2) 2SLS	(3) GMM		(4) OLS
LnERI	0.512*** (8.84)	0.567*** (3.64)	0.536*** (3.75)	LnERI <sub>1</sub>	0.454*** (18.54)
LnTE	0.0795*** (5.31)	0.112** (2.93)	0.112*** (3.39)	TE <sub>1</sub>	0.147** (3.15)
Control variables	Yes	Yes	Yes	Control variables	Yes
_cons	8.034*** (4.57)	-0.0789 (-0.05)	0.237 (0.16)	_cons	5.424** (3.29)
N	390	270	270	N	390
R <sup>2</sup>	0.916	0.696	0.696	R <sup>2</sup>	0.929
Sargan_p		0.1156			
Kleibergen-Paap rk LM		74.855***			
Kleibergen-Paap rk Wald F		43.770 > 9.93			

Note: the value in the parenthesis is the  $t$ -statistic; \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance level, respectively.

environmental regulation is in the middle compared with OLS and 2SLS. The coefficient of technological innovation with GMM is consistent with the estimated result of 2SLS. Environmental regulation and technological innovation still significantly enhance industrial carbon productivity.

To avoid the estimation bias caused by the selection of proxy indicators, the logarithms of the national per capita GDP (LnERI<sub>1</sub>) [42] and the R&D input intensity (TE<sub>1</sub>) are selected as substitute indicators for environmental regulation and technological innovation, respectively. TE<sub>1</sub> is the ratio of internal expenditure on R&D to the GDP of each province. It reflects the situation of technological innovation directly [50]. Estimated results are illustrated in column (4) of Table 7. We can find that there is a significantly positive impact of environmental regulation at 1%, and technological innovation is 5%. The conclusion of this paper is robust.

#### 4.5. Analysis of Spatial Spillover Effect

**4.5.1. Analysis of Spatial Autocorrelation.** This part mainly talks about the spatial autocorrelation characteristics of industrial carbon productivity. Considering the reliability of the classic method, we adopted Global Moran's I index to investigate the spatial autocorrelation. Global Moran's I index is calculated as equation (12):

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

$$S^2 = \frac{1}{n} \sum_{i=1}^n (Y_i - \bar{Y})^2, \quad (12)$$

$$\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i,$$

where  $Y_i$  and  $Y_j$  represent different space units. The subscripts  $i$  and  $j$  mean the unit number, and the total

number is  $n$ . The values of Moran's I represent a level of agglomeration, ranging from  $-1$  to  $1$ . Value  $1$  means a clustering trend, while value  $-1$  means a discrete trend in the spatial distribution [51]. Figure 4 shows the results under matrices W1, W2, and W3 from 2004 to 2016, where Global Moran's index is significantly positive in each year. We can find that there is a spatial agglomeration characteristic of industrial carbon productivity. The value of Global Moran's I in Figure 4 increased gradually, which indicated that the spatial autocorrelation of industrial carbon productivity is gradually enhancing, and the agglomeration effects are more obvious. Besides, local spatial autocorrelation in this section is verified by Local Moran scatterplot with the W1 matrix (Figure 5), and the results in 2004, 2008, 2012, and 2016 are displayed as representatives. The Local Moran's index is calculated as follows:

$$\text{Local Moran's } I_i = \frac{(Y_i - \bar{Y}) \sum_{j=1}^n W_{ij} (Y_j - \bar{Y})}{S^2}, \quad i \neq j,$$

$$S^2 = \frac{1}{n} \sum_{i=1}^n (Y_i - \bar{Y})^2,$$

$$\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i. \quad (13)$$

According to Figure 5, each year, the trend lines of industrial carbon productivity are all located in quadrants one and three, which indicate H-H agglomeration and L-L agglomeration, respectively. In 2016, only eight provinces were in the second quadrant and the fourth quadrant, which exhibits discrete trends in spatial distribution. The rest of the provinces all present the characteristics of agglomeration. Meanwhile, the provinces with H-H agglomeration characteristics increase year by year and most of them are with low resource dependence. The provinces with L-L agglomeration characteristics are

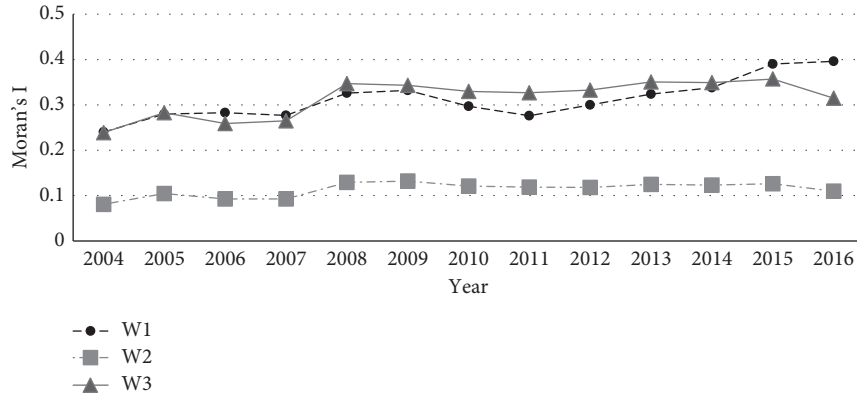


FIGURE 4: The trend of Global Moran's I index under different spatial weights.

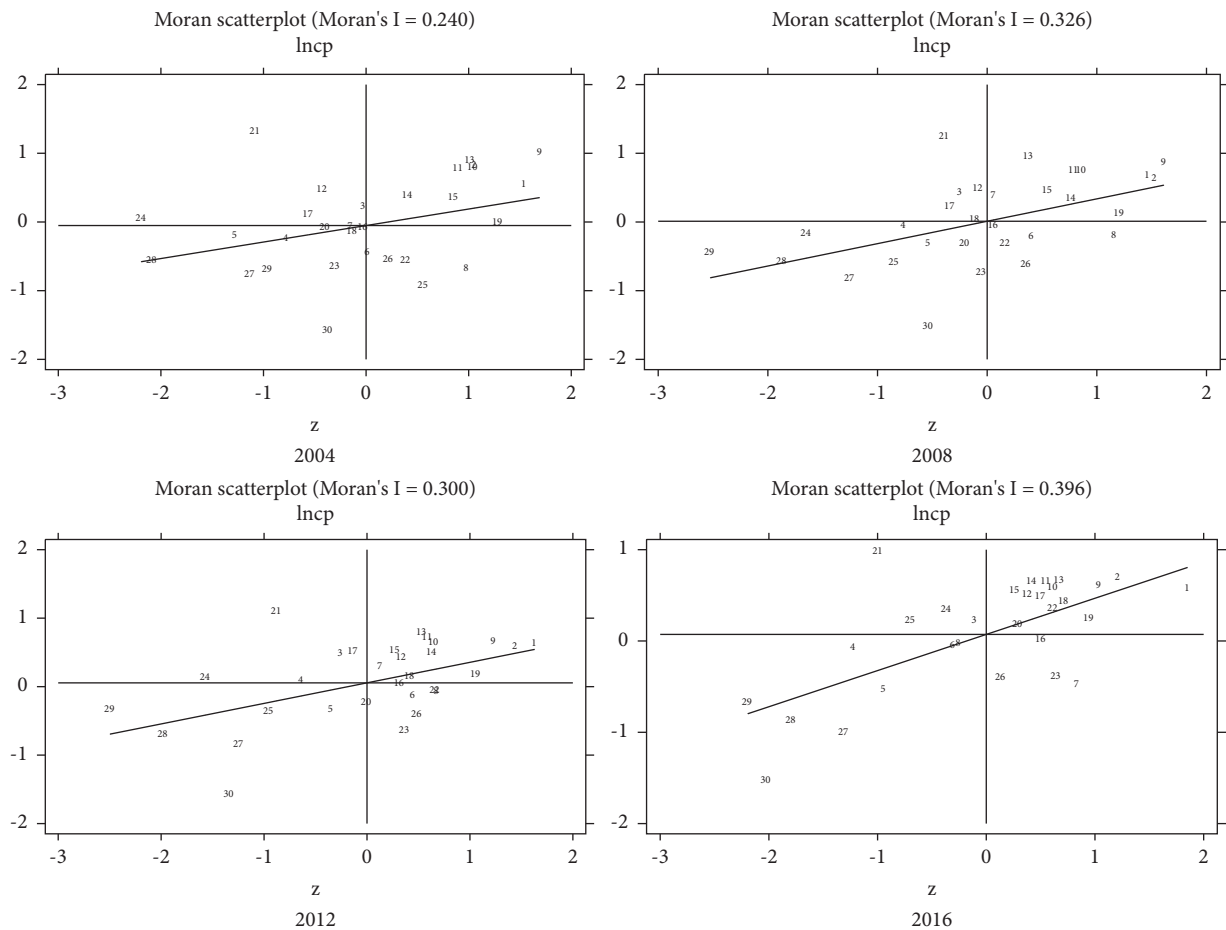


FIGURE 5: Local Moran's I index scatterplot.

mainly located in northwestern China and most of them are with high resource dependence.

4.5.2. *Spatial Durbin Model Estimation.* As mentioned in the methodology and data, we use the Durbin model to discover spatial spillover effects with three spatial weight matrices. The results are shown in Table 8. According to models (1)–(4) based on the W1 matrix, the spatial lag

coefficients ( $\rho$ ) of the dependent variable are notably positive. It indicates that industrial carbon productivity has a significantly spatial autocorrelation and shows H-H aggregation and L-L aggregation characteristics. Industrial carbon productivity in surrounding provinces will influence the local, promoting or decreasing together. For the W2 matrix and W3 matrix, model (5) and model (9) show that using spatial individual fixed effect model, the values of  $\rho$  are 0.2440 and 0.1429, respectively. They are

TABLE 8: Results of spatial panel Durbin model estimation.

	W <sub>1</sub>			W <sub>2</sub>			W <sub>3</sub>					
	(1) Individual fixed effect	(2) Time fixed effect	(3) Double fixed effect	(4) Random effect	(5) Individual fixed effect	(6) Time fixed effect	(7) Double fixed effect	(8) Random effect	(9) Individual fixed effect	(10) Time fixed effect	(11) Double fixed effect	(12) Random effect
LnERI <sub>1</sub>	0.8311*** (7.86)	0.2976*** (5.25)	0.8763*** (8.13)	0.7049*** (7.83)	0.9756*** (8.91)	0.2739*** (4.81)	1.0232*** (9.61)	0.7689*** (8.58)	0.9201*** (8.46)	0.2715*** (4.86)	0.9707*** (9.02)	0.8214*** (8.51)
TE <sub>1</sub>	0.2353*** (4.44)	0.1660*** (8.96)	0.2202*** (4.16)	0.1298*** (3.50)	0.2150*** (4.18)	0.1688*** (8.63)	0.1789*** (3.57)	0.1222*** (3.42)	0.1762*** (3.32)	0.1568*** (7.64)	0.1794*** (3.50)	0.1159*** (3.03)
FDI	0.0386*** (4.25)	0.0643*** (5.66)	0.0365*** (3.99)	0.0345*** (3.84)	0.0287*** (3.14)	0.0796*** (6.88)	0.0236*** (2.55)	0.0290*** (3.14)	0.0290*** (3.24)	0.0721*** (6.44)	0.0222*** (2.49)	0.0326*** (3.67)
ECS	-0.0040*** (-3.03)	-0.0019 (-1.36)	-0.0049*** (-3.51)	-0.0050*** (-3.83)	-0.0050*** (-3.57)	-0.0019 (-1.31)	-0.0040*** (-2.78)	-0.0053*** (-3.77)	-0.0044*** (-3.15)	-0.0022 (-1.51)	-0.0037*** (-2.65)	-0.0048*** (-3.51)
LnPS	-0.4548 (-1.55)	0.2762*** (11.70)	-0.4222 (-1.44)	0.2939*** (4.66)	-0.0381 (-0.14)	0.3089*** (13.16)	-0.1143 (-0.43)	0.3339*** (4.98)	-0.5581* (-1.80)	0.3033*** (13.77)	-0.6134** (-2.02)	0.3133*** (4.35)
-cons				-0.9187 (-0.84)				-4.6858 (-1.59)				-0.7051 (-0.61)
W * LnERI <sub>1</sub>	-0.5735*** (-5.08)	0.1119 (1.18)	-0.1899 (-0.80)	-0.4174*** (-4.17)	-0.7902*** (-4.98)	-0.7390** (-2.20)	-0.0659 (-0.11)	-0.4909*** (-3.33)	-0.6306*** (-5.11)	-0.2188* (-1.71)	0.0351 (0.14)	-0.4922*** (-4.22)
W * TE <sub>1</sub>	-0.1736** (-2.11)	-0.0200 (-0.46)	-0.0625 (-0.69)	-0.0341 (-0.52)	-0.1852 (-1.11)	0.1924 (1.54)	0.4550** (1.97)	-0.0383 (-0.29)	-0.0110 (-0.12)	0.0520 (1.23)	0.1435 (1.50)	0.0526 (0.79)
W * FDI	0.0165 (0.83)	0.0392 (1.56)	0.0082 (0.38)	0.0141 (0.76)	-0.0338 (-0.64)	0.2280*** (2.76)	-0.0998 (-1.55)	-0.0495 (-0.98)	-0.0231 (-1.05)	0.0734** (2.48)	-0.0461** (-2.02)	-0.0189 (-0.90)
W * ECS	0.0009 (0.49)	0.0114*** (3.69)	-0.0033 (-1.18)	0.0020 (1.01)	0.0051* (1.81)	0.0015 (0.12)	0.0029 (0.27)	0.0045 (1.54)	0.0035 (1.45)	0.0024 (0.61)	0.0011 (0.27)	0.0040 (1.63)
W * LnPS	1.6805*** (2.82)	-0.0025 (-0.04)	2.0712*** (3.20)	0.1158 (0.89)	2.8014*** (2.53)	0.3567** (2.07)	4.9832*** (3.11)	0.6680* (1.74)	1.4126*** (2.87)	0.0765 (1.33)	2.4207*** (4.18)	0.1882 (1.22)
rho	0.3468*** (5.18)	0.0263 (0.32)	0.2443*** (3.30)	0.3113*** (4.53)	0.2440* (1.73)	-0.2316 (-1.12)	-0.2402 (-1.19)	0.2044 (1.40)	0.1429* (1.68)	0.0787 (0.86)	0.0589 (0.67)	0.1295 (1.50)
R <sup>2</sup>	0.298	0.775	0.355	0.748	0.530	0.328	0.478	0.744	0.192	0.663	0.296	0.725

all positive at the significance level of 10%. But in models (6)–(8) and models (10)–(12), the spatial lag coefficients of industrial carbon productivity ( $\rho$ ) are not significant. Therefore, interpreting the spatial spillover effect according to the spatial individual fixed effect model is the best choice. According to the results of models (1), (5), and (9), the coefficients of environmental regulation are all positive and significant ( $W1$ : 0.8311,  $W2$ : 0.9756, and  $W3$ : 0.9201). And technological innovation is similar ( $W1$ : 0.2353,  $W2$ : 0.2150, and  $W3$ : 0.1762). It demonstrates the robustness of conclusions that strict environmental regulation and technological innovation are conducive to boosting local industrial carbon productivity. And then, we will discuss further to see the direct effects and indirect effects of each explanatory variable under  $W1$ ,  $W2$ , and  $W3$  (Table 9) [52].

Table 9 extensively shows the outcomes of direct effect, indirect effect, and total effect. And results of the spatial individual fixed effect model based on  $W1$ ,  $W2$ , and  $W3$  are displayed, respectively. The direct effects of environmental regulations under all spatial weight matrices are significantly positive at the significance level of 1% ( $W1$ : 0.8089,  $W2$ : 0.9707, and  $W3$ : 0.9110), which means that the enhancement of local environmental regulations is beneficial to local industrial carbon productivity. However, the spillover effects of environmental regulation intensity are  $-0.4136$ ,  $-0.7320$ , and  $-0.5726$ , which means that local environmental regulation has a negative relationship with industrial carbon productivity in surrounding provinces. The reason may be that strengthening local environmental regulations will lead to pollution shelter effect. Companies with heavy pollution will migrate to neighboring provinces where environmental regulation is not strict. Thus, the migration of companies with heavy pollution increases carbon emissions and reduces industrial carbon productivity in the neighboring provinces. As for technological innovation, the direct effects are all significantly positive under each spatial weight matrix ( $W1$ : 0.2254,  $W2$ : 0.2116, and  $W3$ : 0.1751), but the indirect effects of the technological innovation are not significant. It shows that the local technological innovation can increase local industrial carbon productivity but does not contribute to neighboring provinces. The reason is complex. On the one hand, technological innovation has a time lag and a dissemination effect. The dissemination effect could improve the level of technology in neighboring provinces and then push their industrial carbon productivity. But because of the existence of time lag, the impact of technological innovation in neighboring provinces does not always manifest itself promptly. On the other hand, the influence of innovation agglomeration will have both positive and bad consequences. Innovation agglomeration possibly leads to the flow of innovation elements between provinces and generates uncertain influence for the industrial carbon productivity in neighboring provinces finally. In conclusion, the spillover effect of technological innovation is neither specific.

TABLE 9: Results of the direct effects and indirect effects.

Variables	Effect	(1) $W_1$	(2) $W_2$	(3) $W_3$
LnERI <sub>1</sub>	Direct	0.8089*** (7.89)	0.9707*** (8.74)	0.9110*** (8.32)
	Indirect	-0.4136*** (-4.05)	-0.7320*** (-4.69)	-0.5726*** (-5.01)
	Total	0.3953*** (9.04)	0.23873** (2.15)	0.3384*** (7.40)
TE <sub>1</sub>	Direct	0.2254*** (4.51)	0.2116*** (4.32)	0.1751*** (3.48)
	Indirect	-0.1326 (-1.24)	-0.1688 (-0.76)	0.0179 (0.18)
	Total	0.0928 (0.82)	0.0428 (0.20)	0.19300** (2.04)
FDI	Direct	0.0423*** (4.62)	0.0291*** (3.20)	0.0293*** (3.36)
	Indirect	0.0423 (1.50)	-0.0376 (-0.52)	-0.0224 (-0.89)
	Total	0.0846*** (2.59)	-0.0086 (-0.11)	0.0070 (0.24)
ECS	Direct	-0.0041*** (-3.18)	-0.0050*** (-3.70)	-0.0043*** (-3.26)
	Indirect	-0.0004 (-0.17)	0.0054 (1.51)	0.0036 (1.36)
	Total	-0.0045 (-1.55)	0.0004 (0.12)	-0.0007 (-0.28)
LnPS	Direct	-0.3045 (-1.15)	0.0227 (0.09)	-0.5080* (-1.68)
	Indirect	2.2142*** (2.84)	3.7180** (2.43)	1.5216*** (2.80)
	Total	1.9097*** (2.65)	3.7406** (2.55)	1.0136** (2.39)

Note: the value in the parenthesis is the  $t$ -statistic; \*\*\*, \*\*, and \* indicate 1%, 5%, and 10% significance level, respectively.

## 5. Conclusion and Policy Implication

This paper examines the impact of environmental regulation and technological innovation on industrial carbon productivity using data from 30 Chinese provinces and autonomous areas from 2004 to 2016. The modified STIRPAT model and Durbin model are adopted as the main instrument for exploring spatial spillover effects. After that, we construct the two-dimensional structural heterogeneity analysis according to industrialization level and resource dependence to detect their moderating effect.

This paper reveals the following: (1) for industrial carbon productivity, environmental regulation serves as a driving force to it, similar to technological innovation. The enhancement of environmental regulation intensity can limit the carbon emission behavior of industrial enterprises so that CO<sub>2</sub> reduces and industrial carbon productivity improves. Technological innovation will also play the same role through the revolution of low-carbon technology and raising production efficiency. (2) There is an obvious heterogeneity caused by resource dependence and industrialization level. Specifically, environmental regulation has a positive effect in provinces with high resource dependence and high industrialization levels (Region I) and

provinces with low resource dependence and low industrialization levels (Region III), but technological innovation has no effect. In provinces with high resource dependence and low industrialization level (Region IV), while environmental regulation has no substantial impact on industrial carbon productivity, technological innovation does. In provinces with low resource dependence and high industrialization levels (Region II), environmental regulation and technological innovation are all significant. This implies that, to realize effective carbon reductions, diverse policies should be adopted in different regions with nonuniform industrialization levels and resource endowment. (3) Foreign direct investment is positively correlated with industrial carbon productivity. This is probably because the growth of the economy stimulated by foreign direct investment overpasses the growth of carbon emissions so that increasing foreign direct investment plays a positive role. However, the structure of energy is inversely related to industrial carbon productivity. The greater the share of coal consumption, the more adverse to the realization of carbon emission reduction targets, which is reasonable. It shows that the current energy consumption structure dominated by fossil fuels is unreasonable and needs to be adjusted urgently. (4) Industrial carbon productivity exhibits spatial autocorrelation from the perspective of spatial agglomeration. The characteristics of H-H and L-L agglomeration are obvious. Local environmental regulation and technological innovation are advantageous to local industrial carbon productivity, but the spillover effect of environmental regulation is not beneficial to neighboring provinces' industrial carbon productivity. This is because the enhancement of local environmental regulation may dislodge the polluting enterprise to the adjacent provinces and cause more CO<sub>2</sub> there. The industrial carbon productivity in adjacent provinces will decrease inevitably. Furthermore, because of the dual effects of diffusion effect and time lag, the spillover effect of technological innovation is insignificant. Technology cooperation in adjacent provinces is weak. And the linkage effect of technological innovation is not obvious so that the flow of innovation elements between different provinces is unplanned. This may exacerbate the ambiguity around technological innovation's impact on industrial productivity.

Based on the preceding conclusions, policy recommendations are made to provide advice to decision makers in order to improve industrial carbon productivity.

First, in general, the government needs to strengthen the rigor of environmental regulation and vigorously promote technological innovation. Environmental regulation policy plays a favorable role in China's emission reduction and high-quality industrial development. Technological innovation should be encouraged towards cleaner production, energy conservation, and emissions reduction, achieving green development and low-carbon transition finally.

Second, the government should make appropriate policies to promote industrial carbon productivity in different provinces respectively, taking two-dimensional structural heterogeneity of resource dependence and industrialization level into consideration. In provinces with high resource dependence and high industrialization level (Region I) and provinces with low resource dependence

and low industrialization level (Region III), environmental regulations have a greater impact on industrial carbon productivity. Environmental regulation should be regarded as the main tool to improve industrial carbon productivity in such provinces. However, in provinces with high resource dependence and low industrialization levels (Region IV), technological innovation is more effective in improving industrial carbon productivity. Hence, it needs to continuously improve technological innovation capacity and cooperation with neighboring provinces, to promote industrial carbon productivity in neighboring provinces. As for the provinces with low resource dependence and high industrialization levels (Region II), environmental regulation and technological progress both have a positive impact. Improving industrial carbon productivity in these provinces can be accomplished by tightening regulations and stimulating technological innovation.

Third, the government should pay attention to spatial linkage and regional cooperation when making industrial emission reduction policies. Environmental regulation may have a negative spillover impact, causing polluting businesses to relocate. Polluting firms want to settle in areas where environmental restrictions are slack. This may promote regional environmental polarization and enhance the difficulty of carbon reduction. Thus, the government should reinforce the collaborative governance between adjacent provinces. Additionally, the spillover effect of technological innovation is not significant. It is necessary to heighten the technical collaboration and increase the number of joint patents to realize the linkage mechanism of technological innovation among provinces. In addition, the government should focus on the flow of innovation factors, as well as the spread of technological innovation and reducing the time-lag effect of technological transformation.

This paper has some limitations which can be studied in the future. First, the conclusion of this study was inferred by provincial data. It might be more interesting to explore whether we can get the same or other meaningful outcomes using the city's data. Second, the heterogeneity caused by industrialization level and resource dependence is confirmed in this paper. But it is not clear whether they change the effects of independent variables. Future researches could pay more attention to the moderating effects of industrialization level and resource dependence, observing the difference they generate on environmental regulation and technological innovation.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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