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Under the "Double Carbon" Target Study on the Decoupling Effect and Spatial and Temporal Characteristics of Carbon Emissions in China

—Based on Decoupling Theory and EKC Curve Theory

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Abstract

Firstly, the decoupling effect of national per capita GDP and carbon emissions was analyzed based on Tapio decoupling model. Secondly, based on the provincial panel data, the spatial Dubin model was established to conduct empirical research on the impact of regional economic development on carbon emissions, aiming to clarify the influencing factors and temporal and spatial characteristics of Carbon emissions in China, and provide theoretical basis and reference for the realization of "double carbon" target. Finally, the following conclusions were drawn: 1) The decoupling state of national per capita GDP and carbon emissions is mainly weak decoupling, and the decoupling is ideal, at the same time, the emergence of strong decoupling shows that economic development and carbon emission reduction can coexist. 2) The carbon emissions of provinces (cities, autonomous regions) have spatial autocorrelation; Per capita GDP has a significant impact on carbon emissions, and its direct and indirect effects show inverted N-shaped and N-shaped curves respectively. 3) Both FDI and R&D drive carbon emissions negatively, while urbanization and electricity consumption drive carbon emissions positively, with the spatial spillover effects of FDI and urbanization being statistically insignificant. In addition, the direct and indirect effects of industrial structure and population density are opposite. Based on the above conclusions, it is recommended that all regions should strengthen joint prevention and control in the process of carbon emission reduction, promote close cooperation in regional energy conservation and emission reduction, develop a low-carbon economy, and take multiple measures to help achieve the "double carbon" target successfully.

Keywords

Carbon Emission, Tapio Decoupling Model, EKC Curve, Spatial Dubin Model

1. Introduction

Since the reform and opening-up, China's economic development has been dependent on energy, resulting in continuous deterioration of the ecological environment. Therefore, restricting energy consumption and developing low-carbon economy are the inevitable requirements for building a beautiful China and harmonious socialist society. In addition, as the main cause of global warming, the massive emission of carbon dioxide not only exceeds the load of the ecological environment (Guo et al., 2013), but also causes practically hidden dangers to people's production, life and health (Zhang et al., 2014; Zhao & Jin, 2010). At the 75th Session of the United Nations General Assembly, General Secretary Xi Jinping proposed for the first time that China's carbon emissions should peak by 2030, and strive to achieve carbon neutrality by 2060, and that is "double carbon" target. This is a very urgent emission reduction target with considerable strength and commitment. If China wants to achieve this target within a limited time, it is imperative to correctly understand and scientifically formulate carbon emission reduction policies. In this context, it is of great significance to explore the decoupling state between economic development and carbon emissions and analyze the spatial-temporal evolution pattern of carbon emission reduction for promoting low-carbon economic development and realizing the "double carbon" target.

2. Article Structure Arrangement

The structure of this paper is as follows: The first part is the introduction, which mainly introduces the background and significance of the paper research; The second part is the structure of the article, which mainly explains the main content of each part of the article; The third part is the literature review, which mainly introduces the existing research on carbon emissions at home and abroad reviews of the literature, and points out the significance of this study. The fourth part is the decoupling effect of carbon emissions. The fifth part is the temporal and spatial characteristics of carbon emission. The sixth part is divided into the main research conclusions and countermeasures. The last part is the reference for the introduction.

3. Review of the Literature

3.1. Research on Carbon Emissions Based on Decoupling Theory

The word "decoupling" is the result of physics concept, the OECD (2002) for the first time put forward at the beginning of the industrial development, energy consumption grows along with the economic development, but in the reverse change will appear after a phase of time development, so as to realize economic growth at the same time, reduce energy consumption, this is used to describe the relationship between economic growth and energy consumption of the "decoupling" theory. The decoupling model based on this theory is not widely used because of its sensitivity to base period selection. Based on this model, Tapio established the Tapio decoupling model (Tapio, 2005) in combination with the six decoupling states proposed by Vehmas (2003). The model subdivided the decoupling states into eight kinds according to the elastic value, and the calculation did not need to select the base period, which solved the sensitivity dilemma of the base period selection of the OECD decoupling model. Therefore, this model has become the most widely used model to study the decoupling effect of carbon emissions.

For example, scholars Jiang et al. (2021), Wang et al. (2019), Pan & Zhang (2021) have studied the decoupling effect of carbon emissions from the perspectives of specific provinces, a certain region and the whole country respectively. Weng et al. (2021) analyzed the decoupling effect of China's tourism industry based on the Tapio decoupling model, and the research results showed that the decoupling index of China's tourism industry showed a significant negative correlation, with the overall state of weak decoupling and unbalanced distribution of the decoupling index, showing a phenomenon of "high in the east and low in the west".

3.2. Carbon Emission Research Based on EKC Curve Theory

Since the introduction of the inverted U-shaped environmental Kuznet curve theory (EKC curve theory) by scholars such as Panayotou (1993) and Grossman & Krueger (1995), the research on carbon emissions by using this theory mainly considers the impact of different economic activities on carbon emissions or emission intensity:

First of all, energy consumption (Shao et al., 2010), industrial structure (Yu et al., 2011), openness (Wang & Men, 2022), urban development (Chen et al., 2022), regional competition (Li et al., 2022) all have an effect on carbon emissions. Secondly, the nonlinear relationship between economic development and carbon emissions is tested. Fu & Yu (2011) analyzed the characteristics and main influencing factors of carbon dioxide emissions of various districts and cities in Jiangxi Province, and the results showed that carbon emissions showed an inverted U-shaped, N-shaped and U-shaped curve relationship with per capita GDP, industrial structure and energy intensity, respectively. Tian & Liu (2021) studied the relationship between China's economic development and carbon emissions by using nonparametric generalized additive mixed model, and the results showed that there was no inverted U-shaped relationship between the two. Yang & He (2021) conducted a linear regression study based on the data of county economic development and carbon emission in China, and the results showed that improving the level of economic development would help reduce carbon emission intensity.

3.3. Comment of Research Literature

To sum up, some studies have made macro description of the relationship between economic development and carbon emissions based on decoupling theory or micro description based on EKC curve theory, but no unified conclusion has been reached so far, and there are few explorations on the relationship between national economic development and carbon emissions by using decoupling theory and EKC curve theory comprehensively. In addition, in the existing literatures on EKC curve test of carbon emissions, ordinary panel data are mostly used while ignoring the spatial spillover effect of carbon emissions, which is a deviation in the setting of the model. Based on this, Tapio model is firstly used to analyze the decoupling effect of economic development and carbon emissions at the national level, and then the spatial Dubin model of regional carbon emissions is established based on the analysis results to empirically test the existence of EKC curve. Finally, according to the research results, countermeasures and suggestions are put forward to help achieve the goal of "double carbon" smoothly and achieve low-carbon economic development.

4. Tapio Decoupling Model Construction and Analysis of Results

4.1. Index Selection and Model Construction

1) Index selection

Based on the availability of data, this paper takes the national per capita GDP from 2000 to 2019 to represent the level of economic development, and selects seven major fossil energy consumption of coal, coke, gasoline, kerosene, diesel, fuel oil and natural gas to calculate carbon emissions. In addition, the standard coal conversion coefficient and primary energy carbon emission coefficient published in IPCC National Greenhouse Gas Inventory 2006 are used as the carbon emission accounting weights, and the correlation coefficients are shown in Table 1. The calculation formula for carbon emissions is as follows:

$$CI_t = \sum_{j=1}^{7} M_j N_j E_j \tag{1}$$

where, represents the national carbon emission in the year t, j represents the type of energy, and respectively represent the standard coal conversion coefficient, carbon emission coefficient and energy consumption of the j type of energy.

2) Tapio decoupling model construction

Table 1. Standard coal conversion coefficient and primary energy carbon emission coefficient.

Energy	Coal	Coke	Petrol	Paraffin	Diesel	Fuel oil	Natural gas
Standard coal conversion coefficient (M_j)	0.7559	0.8550	0.5538	0.5714	0.5921	0.6185	0.4483
Carbon emission coefficient (N_j)	0.7143	0.9714	1.4714	1.4714	1.4571	1.4286	1.3300

Modeling the decoupling of economic development and carbon emissions based on Tapio elasticity analysis:

$$t_{C,G} = \frac{\Delta \mathrm{CI}}{\Delta \mathrm{PGDP}} = \frac{\left(\mathrm{CI}_t - \mathrm{CI}_{t-1}\right)/\mathrm{CI}_{t-1}}{\left(\mathrm{PGDP}_t - \mathrm{PGDP}_{t-1}\right)/\mathrm{PGDP}_{t-1}} \tag{2}$$

where, $t_{C,G}$ represents the decoupling index, whose connotation is the change degree of carbon emissions with the growth of per capita GDP; ΔCI and ΔPGDP denote the growth rates of carbon emissions and GDP per capita, respectively.

4.2. Model Calculation and Result Analysis

As per capita GDP is always greater than zero, only four cases of Tapio decoupling model need to be considered (**Table 2**), among which strong decoupling is the most ideal state, that is, with continuous economic development, significant carbon emission reduction results are achieved. Based on the above model, the decoupling index of economic development and carbon emissions was calculated. The data obtained for calculation were all from the National Statistical Yearbook without missing values.

Table 2. National carbon emission decoupling index and state.

year	ΔCI	ΔPGDP	$t_{C,G}$	decoupling state
2000				
2001	0.06	0.10	0.60	Weak decoupling
2002	0.05	0.09	0.56	Weak decoupling
2003	0.18	0.12	1.50	Expansionary negative decoupling
2004	0.15	0.17	0.88	Expansive connections
2005	0.18	0.15	1.20	Expansive connections
2006	0.06	0.16	0.38	Weak decoupling
2007	0.06	0.22	0.27	Weak decoupling
2008	0.03	0.18	0.17	Weak decoupling
2009	0.15	0.09	1.67	Weak decoupling
2010	0.08	0.18	0.44	Weak decoupling
2011	0.11	0.18	0.61	Weak decoupling
2012	0.06	0.10	0.60	Weak decoupling
2013	0.03	0.09	0.33	Weak decoupling
2014	−0.01	0.08	−0.13	Strong decoupling
2015	−0.03	0.06	−0.50	Strong decoupling
2016	−0.02	0.08	−0.25	Strong decoupling
2017	0.01	0.11	0.09	Weak decoupling
2018	0.01	0.10	0.10	Weak decoupling
2019	0.02	0.07	0.29	Weak decoupling

As can be seen from Table 2, the following conclusions can be drawn: Firstly, economic development and carbon emissions have experienced four decoupling states, indicating that the relationship between economic development and carbon emissions in China is not constant, so the prediction of regional economic development and carbon emissions is non-linear. Secondly, weak decoupling indicates that China's economic development is highly dependent on energy, and the carbon emissions increase with economic development, but the carbon emissions per unit GDP decrease. Decoupling is ideal, which indicates that a series of environmental protection policies implemented in China have played a positive role in energy conservation and emission reduction. Again, the specific terms, since 2014 to enter the new normal in our country, the rapid growth from rapid growth to economic development, industrial structure optimization step by step, innovation-driven development, the tertiary industry gradually become the main body, consumer demand gap between urban and rural areas gradually narrowed, opening to the outside world further, therefore, its carbon emissions also sharply reduce, For the first time, there was a strong decoupling between per capita GDP and carbon emissions, indicating that complete decoupling of economic development and carbon emissions is not impossible. Therefore, it can be predicted that if the state of per capita GDP and carbon emissions can continue, the strong decoupling state will eventually become the "new normal" of economic development and environmental protection.

5. SDM model Construction and Empirical Test

5.1. Model Construction

1) Selection and setting of the spatial weight matrix

The "first law of geography" states that everything is related to everything else, but that things that are close to each other are more closely related, that is, the closer they are, the more they are related. In order to comprehensively analyze the relationship between economic development and carbon emissions, a spatial adjacency weight matrix is set according to the principle that the closer the relationship is, the closer the relationship is.

$$W_{ij} = \begin{cases} 0, & i \text{ is not adjacent to } j \\ 1, & i \text{ is adjacent to } j \end{cases} \tag{3}$$

2) Variable selection

a) Explained variables

The consumption of coal, coke, gasoline, kerosene, diesel, fuel oil and natural gas in all provinces (cities and districts) is selected to calculate carbon emissions. The calculation method is shown in Formula (1).

b) Core explanatory variables

GDP per capita: PGDP. Due to the large regional differences, the comparability of regional GDP is low, so per capita GDP is used as a measure index of regional economic development.

c) Control variables

Based on the results and analysis of the decoupling model above, and referring to the studies of Liu & Liu (2017), Liu et al. (2022), Xie & Xu (2019), industrial structure, foreign investment level, urbanization rate, technological innovation level, electricity consumption and population density were incorporated into the control variables. The ratio of added value of tertiary industry and secondary industry, proportion of foreign direct investment in regional GDP, proportion of permanent urban population in total resident population at the end of the year, proportion of R&D input in total GDP, electricity consumption per unit GDP and population per unit area were used as proxy variables respectively.

3) Descriptive statistical analysis

4) Model setting

Analysis based on the theory of EKC curve and the decoupling model results, need further inspection, the relationship between economic development and carbon to identify the nonlinear relationship between the two, at the same time considering the broad applicability of the model, using provincial panel data from 2000 to 2019 SDM model is established, and the model respectively, the introduction of per capita GDP, paragraphs a and square and three times.

$$\begin{aligned}\ln \mathrm{CI}_{it} &= \rho W_{ij} \ln \mathrm{CI}_{it} + \beta_1 \ln \mathrm{PGDP}_{it} + \lambda \mathrm{Controls}_{it} + \gamma_1 W_{ij} \ln \mathrm{PGDP}_{it} \\ &\quad + \theta W_{ij} \mathrm{Controls}_{it} + \mu_i + \nu_t + \varepsilon_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}\ln \mathrm{CI}_{it} &= \rho W_{ij} \ln \mathrm{CI}_{it} + \beta_1 \ln \mathrm{PGDP}_{it} + \beta_2 \ln^2 \mathrm{PGDP}_{it} + \lambda \mathrm{Controls}_{it} \\ &\quad + \gamma_1 W_{ij} \ln \mathrm{PGDP}_{it} + \gamma_2 W_{ij} \ln^2 \mathrm{PGDP}_{it} + \theta W_{ij} \mathrm{Controls}_{it} \\ &\quad + \mu_i + \nu_t + \varepsilon_{it}\end{aligned} \tag{5}$$

$$\begin{aligned}\ln \mathrm{CI}_{it} &= \rho W_{ij} \ln \mathrm{CI}_{it} + \beta_1 \ln \mathrm{PGDP}_{it} + \beta_2 \ln^2 \mathrm{PGDP}_{it} + \beta_3 \ln^3 \mathrm{PGDP}_{it} \\ &\quad + \lambda \mathrm{Controls}_{it} + \gamma_1 W_{ij} \ln \mathrm{PGDP}_{it} + \gamma_2 W_{ij} \ln^2 \mathrm{PGDP}_{it} \\ &\quad + \gamma_3 W_{ij} \ln^3 \mathrm{PGDP}_{it} + \theta W_{ij} \mathrm{Controls}_{it} + \mu_i + \nu_t + \varepsilon_{it}\end{aligned} \tag{6}$$

where i represents different provinces (cities, districts) ($i = 1, 2, \cdots, 30$), t represents the year ($t = 1, 2, \cdots, 20$), μ_i and ν_t represent spatial and temporal fixed effects respectively, ε_{it} is a random disturbance term; $\mathrm{Controls}_{it}$ represents control variables; all variables are explained in **Table 3**. W_{ij} is the (i, j) element of the spatial weight matrix; ρ is the spatial autoregressive coefficient if $\rho > 0$ indicates that carbon emissions are positively correlated. If $\rho < 0$, it indicates that carbon emissions are negatively correlated; and if $\rho = 0$, it indicates that carbon emissions are randomly distributed across regions.

5.2. Model Testing

1) Applicability test of the model

Before model fitting, it is important to test the model. Firstly, whether the data has spatial autocorrelation is investigated. Spatial autocorrelation means that the values of the regions with similar or adjacent spatial positions have high similarity. In this paper, the Moran index test and LM test are used to test the spatial adaptability of carbon emissions (**Table 4**). Moran's I, a popular index method,

Table 3. Descriptive statistics of variables.

variables	Sample size	Mean value	standard deviation	minimum value	maximum value	unit
LnCI	600	8.61	0.94	4.68	10.36	ten thousand tons
LnPGDP	600	10.00	0.84	7.92	12.01	yuan
IS	600	1.22	0.74	0.35	5.32	%
FDI	600	0.03	0.02	0.00	0.15	%
URB	600	0.52	0.15	0.23	0.90	%
R&D	600	0.01	0.01	0.00	0.07	%
ELE	600	0.13	0.09	0.03	0.55	KWH/yuan
LnPOP	600	5.43	1.27	1.97	8.28	Persons/square km.

is used for measurement, and its calculation formula is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(y_i - \bar{y}\right)\left(y_j - \bar{y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{7}$$

where, y is the carbon emission, y_i is the carbon emission of region i, and $\bar{y}$ is the average carbon emission of each region. Where, the value range of Moran index I is $[-1, 1]$: when $I > 0$, the carbon emission of each region is positively correlated; when $I < 0$, the carbon emission is negatively correlated; when $I = 0$, there is no spatial correlation of carbon emissions. Using Stata 16.0 to obtain global and local Moran indices, and the results showed that the Moran indices from 2000-2019 all passed the significance test of 1% and were greater than 0, which was consistent with the results of the global spatial autocorrelation test, indicating that carbon emissions had a strong positive correlation. In order to analyze the spatial spillover effect of carbon emissions in depth, the Moran scatter plots of carbon emissions in 2000 and 2019 were drawn respectively. The results show that under the adjacency matrix, most regions are clustered in the first or third quadrant, which further indicates that carbon emissions have strong spatial clustering characteristics and show a positive spatial correlation.

Second, to ensure the validity of the spatial econometric model, LM test was conducted (Table 4). Although the R-LM-lag of the model did not pass the test, all other tests passed the significance level test of 1%, which also showed the validity of the spatial econometric model.

Thirdly, to ensure the rationality of the spatial Durbin model, LR test and Wald test (Table 4) were conducted, and both the test results rejected the original hypothesis, that is, SDM model would not degenerate into SAR model or SEM model, justifying the use of the spatial Durbin model.

Finally, a Hausmann test was performed on the model (Table 4) and the result showed that the model should use fixed effects (Figure 1 & Figure 2).

Table 4. SDM model test.

	Variables	I	Variables	I
Spatial autocorrelation test for carbon emissions	year 2000	0.069***	year 2010	0.064***
	year 2001	0.075***	year 2011	0.065***
	year 2002	0.070***	year 2012	0.063***
	year 2003	0.066***	year 2013	0.065***
	year 2004	0.068***	year 2014	0.065***
	year 2005	0.069***	year 2015	0.063***
	year 2006	0.067***	year 2016	0.057***
	year 2007	0.066***	year 2017	0.061***
	year 2008	0.067***	year 2018	0.070***
	year 2009	0.065***	year 2019	0.066***
(3)	Moran's I	29.83***		
(3)	LM-lag	93.45***	LM-error	788.07***
(3)	R-LM-lag	1.53	R-LM-error	696.15***
(3)	LR-SDM & SAR	106.43***	LR-SDM & SEM	90.24***
(3)	Wald	25.52***	Hausman	10.99*
(4)	Moran's I	29.65***		
(4)	LM-lag	88.42***	LM-error	774.62***
(4)	R-LM-lag	1.516	R-LM-error	687.71***
(4)	LR-SDM & SAR	81.33***	LR-SDM & SEM	54.89***
(4)	Wald	15.63**	Hausman	26.45*
(5)	Moran's I	29.67***		
(5)	LM-lag	88.66***	LM-error	773.03***
(5)	R-LM-lag	1.658	R-LM-error	686.03***
(5)	LR-SDM → SAR	80.23***	LR-SD → SEM	40.19***
(5)	Wald	14.91*	Hausman	90.53***

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

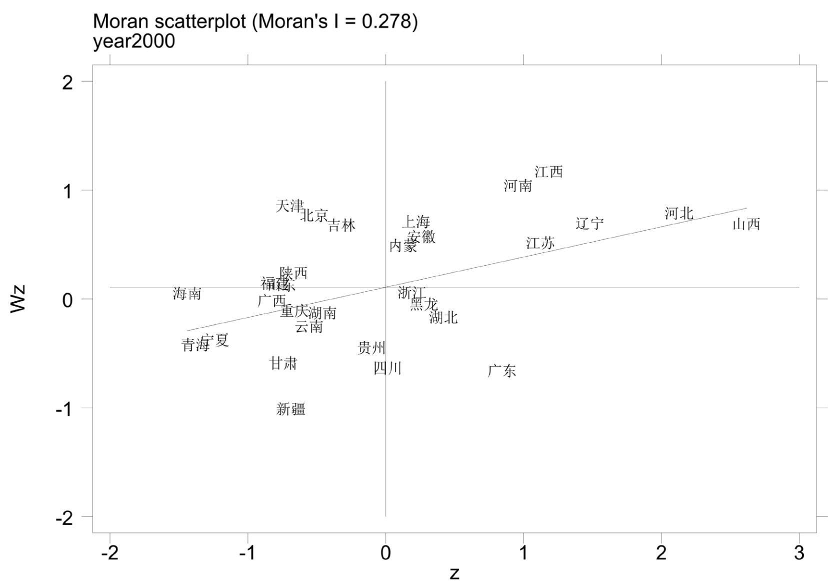

Figure 1. 2000—moran scatter plot of carbon emissions.

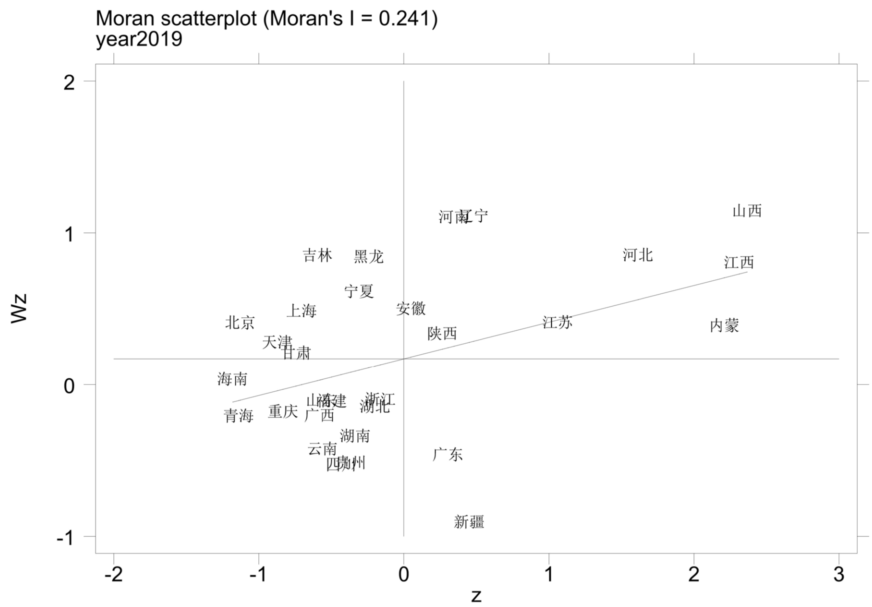

Figure 2. 2019—moran scatter plot of carbon emissions.

2) Comparison of higher order models

From **Table 5**, it can be seen that the goodness of fit, spatial autocorrelation coefficient, log-likelihood test value and significance of different variables of higher-order model are comprehensively analyzed and compared, and the fitting result of model (6) is finally confirmed to be better.

5.3. Empirical Results and Analysis

To further investigate the impact of regional economic development on carbon emissions, partial differential method proposed by LeSage & Pace (2008) was adopted to decompose the direct, indirect and total effect of model (6) (**Table 6**), and the following conclusions are drawn and analyzed:

First, in terms of core explanatory variables; the direct and indirect effect of per capita GDP on carbon emissions are not consistent, in which the direct effect shows an inverted N-shaped curve, and the indirect effect shows an N-shaped curve. This is consistent with the prediction of the decoupling model, that is, the impact of economic development on carbon emissions is nonlinear, and the heterogeneity of direct and indirect effects further verifies the spatial spillover effect of carbon emissions.

Second, from the perspective of control variables: firstly, the direct and indirect effects of FDI level and R&D investment are consistent, with their coefficients being less than zero, indicating that both FDI level and R&D input have inhibitory effects on carbon emissions in both the region and neighboring regions.

From the perspective of the level of foreign investment, foreign investment will restrain the carbon emission of the region: on the one hand, the introduction of foreign investment will bring advanced production technology and

Table 5. Spatial Durbin model regression results.

	(4)	(5)	(6)
lnRGDP	0.38*** (0.11)	2.29*** (0.54)	−16.87*** (4.18)
$lnRGDP^2$		−0.09*** (0.03)	1.86*** (0.42)
$lnRGDP^3$			−0.06*** (0.01)
IS	−0.17*** (0.04)	−0.15*** (0.04)	−0.13*** (0.04)
FDI	−1.31** (0.66)	−2.17*** (0.68)	−1.84*** (0.68)
URB	2.48*** (0.47)	2.53*** (0.47)	1.88*** (1.88)
R&D	−5.49* (3.18)	−5.77* (3.41)	−10.24*** (3.54)
ELE	2.38*** (0.37)	2.87*** (0.39)	2.60*** (0.40)
lnPOP	0.66*** (0.22)	1.27*** (0.27)	1.46*** (0.27)
$A\text{-}R^2$	0.7767	0.7841	0.7551
Log-likelihood	192.36	201.18	215.86
rho	0.24***	0.27***	0.34***

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 6. Effect decomposition of SDM model.

variables	direct effects	indirect effects	total effects
lnRGDP	−14.43*** (4.06)	35.51*** (9.68)	21.08** (9.69)
$lnRGDP^2$	1.60*** (0.41)	−3.73*** (0.99)	−2.13** (0.99)
$lnRGDP^3$	−0.06*** (0.01)	0.13*** (0.03)	0.07** (0.03)
IS	−0.12*** (0.04)	0.12* (0.11)	0.00 (0.14)
FDI	−1.96*** (0.68)	−2.05 (2.09)	−4.01* (2.40)
URB	2.00*** (0.51)	1.69 (1.44)	3.69** (1.67)
R&D	−11.86*** (3.81)	−24.57*** (8.84)	−36.43*** (10.66)
ELE	2.79*** (0.41)	3.18** (1.33)	5.98*** (1.63)
lnPOP	1.29*** (0.25)	−2.77*** (0.62)	−1.48** (0.65)

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

management concept, so that enterprises attach importance to environmental protection, so as to continuously improve the operation and awareness to promote carbon emission reduction; on the other hand, capital accumulation will attract advanced technology and high-quality labor force, and ultimately improve the green production efficiency of enterprises, thus driving the development of low-carbon economy. This also proves to some extent that the technology spillover effect brought by foreign capital is greater than the pollution paradise hypothesis. Among them, the indirect effect of foreign investment level is not significant. This may be because although the investment attraction in this region will produce positive externalities and thus drive the introduction of foreign capital in surrounding areas, the influence is yet to be strengthened.

From the perspective of technology level, the increase in R&D investment will attract talents, but also constantly eliminate old machines with high pollution and introduce new equipment with low energy consumption. These measures will eventually be translated into carbon emission reduction results through product production. The spatial spillover effect of R&D investment is also significant. On the one hand, R&D investment will encourage neighboring provinces (cities and districts) to carry out independent innovation through regional comparison; on the other hand, R&D investment will spread to neighboring regions through policies such as coordinated regional development and human factors such as talent flow. Both approaches drive carbon emission reduction in related regions to a certain extent.

Secondly, urbanization development and power consumption not only have a positive effect on local carbon emissions, but their spatial spillover effect will also increase the carbon emissions of adjacent areas.

From the perspective of urbanization, the urbanization process will bring land expansion, infrastructure expansion, building construction and other behaviors that greatly increase energy consumption, which will inevitably become the shackles of carbon emission reduction. In addition, the improvement of urbanization will greatly promote industrial development and thus increase carbon emissions. The spatial spillover effect of urbanization is not significant. This may be because the urbanization development in this region will cause imitation effect in neighboring regions, which will have a weak promotion effect on carbon emissions.

From the perspective of power consumption, the direct and indirect effects of power consumption are significant, which may be due to the fact that power consumption will increase energy consumption, which not only comes from the local area, but also generates demand for neighboring areas, thus resulting in increased carbon emissions in neighboring areas. Statistics show that so far, China's electricity production is still dominated by thermal power generation. As we all know, thermal power generation requires a large amount of fossil energy, which is also the main reason for the increase of carbon emissions from power consumption.

Finally, the direct and indirect effects of industrial structure and population density are opposite.

From the point of industrial structure, industrial structure is driving the region carbon emissions, the reason for this is that the second industry has the characteristics of high energy consumption, high pollution and high emissions, and the third industry is the main high-tech industry on because of its services, in the process of production of a product or service object costs are mainly composed of human capital, thus has the characteristics of low energy consumption, Therefore, developing the tertiary industry and optimizing the secondary industry will effectively curb carbon emissions. However, industrial restructuring will increase carbon emissions in neighboring areas, which may be due to the performance of the pollution refuge hypothesis in different regions of the same country.

From the perspective of population density, the increase of population density will promote the carbon emission in the region. On the one hand, the increase of population density will increase resource consumption and put forward a higher level of urbanization construction, thus increasing carbon emissions. On the other hand, increased population density will lead to a decrease in forest area and reduce carbon dioxide absorption. However, its spatial spillover effect significantly inhibits carbon emissions in neighboring areas. Generally speaking, the economic development of regions with large population density will be relatively better, so it will have a rainbow effect on the population in surrounding areas, and ultimately help the carbon emission reduction in surrounding areas.

5.4. Robustness Test

To ensure the reliability of research conclusions, the spatial adjacency matrix is replaced by the spatial inverse distance square weight matrix to fit Equation (6) again. As shown in Formula (8), the inverse distance squared weight matrix is the reciprocal weighting of the square distance of two regions: the farther the distance is, the smaller the weight is; The closer the distance, the greater the weight. The final regression results show that the impact of per capita GDP on

Table 7. Robustness test.

variables	direct effects	indirect effects	total effects
lnRGDP	−13.52*** (4.04)	13.98 (8.77)	0.46 (8.57)
$lnRGDP^2$	1.45*** (0.41)	−1.48* (0.89)	−0.03 (0.88)
$lnRGDP^3$	−0.05*** (0.01)	0.05* (0.03)	0.00 (0.03)
IS	−0.11*** (0.04)	−0.01 (0.09)	−0.12 (0.11)
FDI	−0.83*** (0.70)	3.38* (1.83)	2.55 (2.13)

Continued

URB	1.66*** (0.51)	0.74 (1.26)	2.39* (1.42)
R&D	−6.89371* (3.88)	−20.00** (8.56)	−26.90*** (10.31)
ELE	2.00*** (0.32)	−0.73 (1.37)	1.26 (1.47)
lnPOP	0.82*** (0.25)	−1.49** (0.64)	−0.67 (0.63)

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

carbon emissions is still significant, and it is still an inverted N-shaped curve. At the same time, although the significance level and coefficient of the impact of industrial structure, foreign investment level, urbanization rate, R&D investment, power consumption and population density on carbon emissions have undergone slight changes, the direction of the impact on carbon emissions has not changed, which proves the rationality and reliability of this study (Table 7).

$$W_{ij} = \begin{cases} 0 & (i = j) \\ 1/d_{ij}^2 & (i \neq j) \end{cases} \tag{8}$$

6. Research Conclusion and Suggestions

6.1. Research Conclusion

Firstly, the Tapio decoupling model is established to analyze the decoupling state between economic development and carbon emissions, and the relationship between the two is predicted to be nonlinear. Secondly, based on provincial panel data of China from 2000 to 2019, a spatial Dubin model was established to describe the effect curve of regional per capita GDP on carbon emissions. The research conclusions are as follows:

1) From the Tapio decoupling model, the decoupling state of national per capita GDP and carbon emissions is changeable and mainly weak, which shows that the economic development rate is higher than the growth rate of carbon emissions, and the decoupling is ideal. And strong decoupling indicates that long-term decoupling of economic development and carbon emissions can be achieved in the future.

2) The SDM regression found that there is a strong spatial autocorrelation of carbon emissions, that is, local carbon emissions will have an impact on adjacent regions. In addition, the relationship between core explanatory variable PER capita GDP and carbon emissions does not show the traditional EKC curve, and its direct and indirect effects show the inverted n-shaped curve and n-shaped curve respectively.

3) Both direct and indirect effects of FDI and R&D on carbon emissions are negatively driven. Secondly, urbanization rate and electricity consumption not

only promote local carbon emissions, but also promote the spatial spillover effect of nearby carbon emissions. Finally, the direct effect of industrial structure and population density on carbon emissions is opposite to the spillover effect, which may be due to the fact that high-polluting enterprises are pushed out to settle down in surrounding areas and areas with high level of economic development attract the population of neighboring areas.

6.2. Countermeasures and Suggestions

1) Establish a joint prevention and control mechanism for carbon emission reduction and build a modern environmental governance system. Carbon emission has a significant spatial spillover effect. Therefore, in the process of carbon emission reduction, provinces (cities, districts) must strengthen cooperation, promote the construction of regional carbon emission reduction cooperation mechanism, and build a modern joint prevention and control environmental governance system.

2) Optimize and upgrade the industrial structure to promote low-carbon economic development. All regions should take industrial structure transformation and upgrading as the focus of current work, and strengthen carbon emission constraints on high-polluting industries; at the same time, we should develop or introduce high-tech and low-energy industries to adjust the proportion of tertiary industry in regional GDP and reduce carbon emissions from the source.

3) Promote the construction of new urbanization and promote the integrated development of urban and rural areas. We will stick to the path of new-type urbanization with Chinese characteristics, promote the integrated development of urban and rural areas, encourage people to move to areas with lower population density, and ease the pressure on cities to reduce carbon emissions caused by increasing population density.

4) Intensify opening-up and actively introduce foreign direct investment. Actively expand the opening to the outside world, relax foreign investment access areas, vigorously introduce foreign direct investment, and actively guide the foreign investment flow, so that it can better promote the development of China's high-tech industry or environmental protection industry.

5) Increase R&D investment and improve the level of green technology innovation. The government should establish appropriate reward and punishment systems and fiscal subsidy systems to help enterprises carry out technological innovation, develop clean energy and technologies, and promote the "new normal" of strong decoupling between economic development and carbon emissions. Make full use of the negative drive of technology spillovers to carbon emissions, and invest more financial and material resources to strengthen the research and development of carbon emission reduction technologies.

6) Reinforce energy supply and demand constraints and promote low-carbon industrial transformation. Improve the price formation mechanism for energy resources, ensure that energy prices are basically determined by the market, and

give full play to the incentive and constraint role of the price mechanism to promote the low-carbon transformation of the energy supply structure and the optimisation of the energy consumption structure from both the supply and consumption sides.

Conflicts of Interest

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

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