


Research on the spatial effect and threshold effect of industrial structure upgrading on carbon emissions in China

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ABSTRACT

Based on panel data from 2000 to 2017 in 29 Chinese provinces, this paper analyzes the impact of industrial structure upgrading on carbon emissions by constructing a spatial panel model and a panel threshold model. The results show that (1) there is a significant spatial correlation between carbon emissions in Chinese provinces, and the carbon emissions of a province are affected by the carbon emissions of surrounding provinces; (2) in China, carbon emissions have a significant time lag feature, and current carbon emissions are largely affected by previous carbon emissions; (3) industrial structure upgrading can effectively promote carbon emission reductions in local areas, and the impact of industrial structure upgrading on carbon emissions has a significant threshold effect. With continued economic development, the promotion effect of industrial structure upgrading on carbon emission reductions will decrease slightly, but this carbon emission reduction effect is still significant. (4) In addition, there is a clear difference between the impact of energy consumption intensity and population size on carbon emissions in short and long terms. In the short term, the increase in energy consumption intensity and the expansion of population size not only increase the carbon emissions of a local area but also increase the carbon emissions of neighboring areas. In the long term, the impact of energy consumption intensity and population size on carbon emissions of neighboring areas will be weakened, but the promotion impact on carbon emissions in local areas will be strengthened.

Key words: carbon emissions, China, industrial structure upgrades, spatial effect, threshold effect

HIGHLIGHTS

- This paper studies the impact of industrial structure upgrading on carbon emissions in detail.
- This paper uses a static spatial panel model and a dynamic spatial panel model for analysis.
- This paper uses economic development as a threshold variable to determine whether the impact direction and degree of industrial structure upgrading on carbon emissions will change with economic development.

INTRODUCTION

Global warming has become one of the most serious problems in the international community, and carbon emissions resulting from human activity are known as the main cause of global warming (Mundaca & Markandya 2016). It is an indisputable fact that global warming has affected the survival and development of human society (Yang *et al.* 2015). As the world's second-largest economy, China has achieved remarkable development; however, China now consumes more energy and emits more carbon on an annual basis. To a certain extent, the rapid development of China's economy has actually come at the cost of the environment (Zhang *et al.* 2021).

At present, promoting low-carbon development has become an important task in the development of various countries. To reduce carbon emissions, various countries have formulated diverse regulatory and trading measures in their sustainability policies, such as carbon emissions trading systems, carbon allowances and trading, and carbon taxes (Ghosh *et al.* 2020). In 2020, President Xi Jinping delivered an important speech at the 75th United Nations General Assembly. In his speech, President Xi mentioned that 'China will increase its national independent contribution, adopt more powerful policies and measures, strive to reach the peak of carbon dioxide emissions by 2030, and strive to achieve carbon neutrality by 2060.'

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China is currently in a stage of rapid economic development, and the increase in demand for resources has directly led to an increase in carbon emissions. Therefore, China faces huge challenges in the reduction of carbon emissions.

Related studies have discussed and analyzed the forecasting problems, emissions patterns, and driving factors of carbon emission (Rapauch *et al.* 2007; Gregg *et al.* 2008; Du *et al.* 2015). Carbon emissions resulting from the production process are mainly determined by economic growth, technical efficiency, and industrial structure (Adom *et al.* 2012). Adjusting the industrial structure, improving energy efficiency and structure, and promoting technological progress are three major ways to improve energy conservation and ensure emissions reductions in China (Foxon 2011), among which industrial structure adjustments are considered to be particularly important (Zhang *et al.* 2019).

Scholars have conducted research on the relationship between the industrial structure and carbon emissions. Research methods mainly include the index decomposition method (Hoekstra & Jeroen 2003; Li & Wei 2015) and the input–output analysis method and the structural analysis method (Xiang & Sha 2013; Wu *et al.* 2018). With the development of econometrics, some scholars have begun to use econometric analysis to study the relationship between industrial structure upgrading and carbon emissions. Zhou *et al.* (2013) analyzed the relationship between industrial structure adjustments and carbon dioxide emissions by using provincial panel data from 1995 to 2009. Zhang & Ren (2011) discussed the relationship between industrial structure adjustment and carbon dioxide emissions in Shandong Province by using the time-series analysis method, and the results showed that adjusting the industrial structure lowered carbon dioxide emissions.

The research methods adopted previously by most scholars rarely took spatial correlation into account. According to the ‘First Law of Geography’, everything is related to everything else, but near things are more related than distant things (Tobler 1970). In China, the economic ties of various regions are becoming gradually strengthened, and economic activities are always carried out in certain temporal and spatial dimensions. These economic phenomena not only show a temporal correlation but also a spatial correlation; therefore, there may be some errors in existing research results. It is necessary to account for temporal and spatial correlations in-depth analysis and to implement relevant policies according to the research results to promote carbon emission reductions. In addition, some studies show that there is U-shaped or inverted U-shaped curve relationship between economic development and environmental pollution (Gill *et al.* 2018). In view of this, whether the impact of industrial structure upgrading on carbon emissions will change is also one of the areas that needs to be further studied.

To fill the above-mentioned research gaps, this paper takes 29 provinces in China as the research subject, selects carbon emissions as the dependent variable, and uses industrial structure upgrading as the independent variable. To improve the accuracy of estimation, some control variables including economic development, energy consumption intensity, urbanization rate, population size, international trade, foreign direct investment, and technological progress are introduced. Through the establishment of a spatial panel model and a panel threshold model, the impact of industrial structure upgrading on carbon emissions is analyzed. Compared with the existing research, the contributions of this paper mainly include the following three aspects:

1. This paper focuses on the impact of industrial structure upgrading on carbon emissions, which can enrich the research content of carbon emissions.
2. In terms of the research methods, in addition to taking the spatial correlation into account and establishing a spatial panel model for analysis, this paper also considers both spatial correlation and time lag, and constructs a dynamic spatial panel model for further analysis, which can greatly improve the accuracy of the research results.
3. In order to determine whether the impact direction and degree of industrial structure upgrading on carbon emissions change with economic development, this paper uses economic development as a threshold variable and establishes a threshold panel model, which can broaden the relevant research content.

Currently, industrial structure upgrading is understood to be an effective way for China to transform its mode of economic development. China is implementing a supply-side structural reform plan; one of the main goals is to optimize the industrial structure. In this context, carbon emission reduction and the development of low-carbon economy are key tasks of China’s sustainable development plans. Therefore, it is necessary to study the impact of industrial structure upgrading on carbon emissions and give full play to the potential for carbon emissions reduction. This research is of great significance to carbon emission reduction.

DATA AND METHODOLOGY

Data

This paper selects 29 provinces in China as its study areas. Due to the unavailability of data, Tibet, Hainan, and Taiwan are not included. We analyze panel data of those provinces from 2000 to 2017 and the main analytical purpose is to determine the impact of industrial structure upgrading on carbon emissions.

Research shows that economic development, technological progress, international trade, urbanization, population size, energy consumption, and other variables have significant impacts on carbon emissions (Özbuğday & Erbas 2015; Kang *et al.* 2016; Li *et al.* 2019). Therefore, to improve the accuracy of the estimation results, in addition to selecting the upgrading of industrial structure as an explanatory variable, this study also introduces economic development, energy consumption intensity, urbanization rate, technological progress, foreign direct investment, international trade, and population size as control variables.

Referring to descriptions of datasets in relevant research (Pekkan *et al.* 2021), all variables are explained in Table 1. The relevant data comes from the *China Statistical Yearbook*, *China Energy Statistical Yearbook*, and the *Wind* database.

On the calculation of carbon emissions, the calculation formula is as follows:

$$cp = \sum_{i=1}^8 E_i \times A_i \times C_i \quad (1)$$

cp is the carbon emissions, E_i refers to the consumption of energy i ($i = 1, 2, \dots, 8$), A_i refers to the carbon emission coefficient of the i th type of energy, and i is denoted as a type of energy, and C_i represents the standard conversion factor for the i th energy.

Referring to the related literature (Chen & Hu 2020; Miao *et al.* 2020; Zhao *et al.* 2020), the carbon emission coefficients and standard conversion coefficients of each type of energy are shown in Table 2.

The statistical description results of all variables are shown in Table 3.

Methodology

The STIRPAT model is often used to study the impact of human economic activities on the environment, and the standard form is as follows:

$$I_t = aP_t^b A_t^c T_t^d e_t \quad (2)$$

where I represents environmental impact, P represents population, A refers to affluence, and T stands for technology.

After taking natural logarithms, a convenient linear specification is gained:

$$\ln I_t = a + b(\ln P_t) + c(\ln A_t) + d(\ln T_t) + e_t \quad (3)$$

Table 1 | List of variables in the regression models

Variables	Symbol	Explanation	Unit
Carbon emission	cp	Carbon emission	Million tons
Industrial structure upgrading	cg	Ratio of the output value of tertiary industry to the output value of secondary industry	Percentage
Energy consumption intensity	ec	Ratio of total energy consumption to GDP	Thousands of tons/100 million yuan
Economic development	ag	Per capita GDP	1,000 yuan/person
Urbanization	ur	Ratio of urbanization	Percentage
Technological progress	te	Number of patent grants per year	Hundred pieces
International trade	tr	Total import and export	100 million yuan
Population size	pe	Permanent population	Million persons
Foreign direct investment	fd	Actual utilization of foreign direct investment	100 million yuan

Table 2 | Carbon emission coefficient and standard conversion coefficient of each energy

Energy	Carbon emission coefficient	Standard conversion coefficient
Coal	0.7559 (kg/kgce)	0.7143 (kgce/kg)
Coke	0.8550 (kg/kgce)	0.9714 (kgce/kg)
Crude oil	0.5857 (kg/kgce)	1.4286 (kgce/kg)
Gasoline	0.5538 (kg/kgce)	1.4714 (kgce/kg)
Kerosene	0.5714 (kg/kgce)	1.4714 (kgce/kg)
Diesel	0.5921 (kg/kgce)	1.4571 (kgce/kg)
Fuel oil	0.6185 (kg/kgce)	1.4286 (kgce/kg)
Natural gas	0.4483 (kg/kgce)	1.3300 (kgce/m ³)

Table 3 | Statistical description of all variables

Variables	Unit	Min	Max	Mean
<i>cp</i>	Million tons	3.8536	396.5577	88.2605
<i>cg</i>	Percentage	49.7053	423.6677	97.4952
<i>ec</i>	Thousands of tons/100 million yuan	2.5461	45.2403	12.7929
<i>ag</i>	1,000 yuan/person	2.7590	128.9941	31.2950
<i>ur</i>	Percentage	23.2000	91.0400	49.8308
<i>te</i>	Hundred pieces	0.7500	3,326.5200	230.3584
<i>tr</i>	100 million yuan	13.2231	68,168.8000	5,788.5200
<i>pe</i>	Million persons	5.1700	111.6900	45.2211
<i>fd</i>	100 million yuan	0.9930	2,257.3220	365.4256

where I , P , A , T are the same as in Equation (2); a is a constant term. e_t is a random error term. b , c , and d are the elasticity coefficients, that is, the percentage of change is in the environmental factor (I) when the target factors (P , A , T) change 1% under the condition that other factors are constant.

Referring to the STIRPAT model, the static spatial panel model is firstly established for analysis. Currently, the spatial econometric model mainly includes the spatial lag model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). Among them, the SDM model not only introduces the spatial lag of the explained variable but also the explanatory variables, so we first chose the SDM model as an example. The specific type of the spatial panel model will be determined by subsequent Lagrange multiplier (LM) tests. All variables are processed logarithmically to reduce heteroscedasticity.

$$\begin{aligned}
 \ln cp_{kt} = & b_0 + r_1 W \ln cp_{kt} + b \ln cg_{kt} + q_1 \ln ec_{kt} + q_2 \ln ag_{kt} + q_3 \ln ur_{kt} \\
 & + q_4 \ln te_{kt} + q_5 \ln tr_{kt} + q_6 \ln pe_{kt} + q_7 \ln fd_{kt} \\
 & + m_1 W \ln cg_{kt} + h_1 W \ln ec_{kt} + h_2 W \ln ag_{kt} + h_3 W \ln ur_{kt} \\
 & + h_4 W \ln te_{kt} + h_5 W \ln tr_{kt} + h_6 W \ln pe_{kt} + h_7 W \ln fd_{kt} + e_{kt}
 \end{aligned} \tag{4}$$

where W is the spatial weight matrix. This paper uses the geographic distance matrix for analysis; $W \ln cp$ is the spatial lag term of the dependent variable, and its main function is to estimate the degree of spatial correlation, r_1 is the coefficient of the corresponding spatial lag term; b , q_1 , q_2 , q_3 , q_4 , q_5 , q_6 , and q_7 are estimated constant regression parameters; $W \ln cg$ is the spatial lag term of the independent variable, and m_1 is the corresponding influence coefficient; $W \ln ec$, $W \ln ag$, $W \ln ur$, $W \ln te$, $W \ln tr$, $W \ln pe$, and $W \ln fd$ are the spatial lag independent variables; h_1 , h_2 , h_3 , h_4 , h_5 , h_6 , and h_7 are constant regression parameters; e_{kt} is a random error term.

According to related research (Wang *et al.* 2021), the process by which carbon emissions take place is dynamic and constantly changing; hence, we establish a dynamic spatial panel model for further research based on the static spatial panel model and take the time dependence of carbon emissions into account. Furthermore, we take the dynamic SDM as an example, and the specific form of the dynamic spatial panel model will be determined by subsequent related tests. The form of the dynamic SDM is shown in Equation (5), where $L.lncp$ represents the first-order lag item of carbon emissions, and the meanings of the other symbols are the same as those in Equation (4).

$$\begin{aligned} lncp_{kt} = & b_0 + r_2 Wlncp_{kt} + g_1 L.lncp_{kt} + g_2 L.Wlncp_{kt} + b_2 lncg_{kt} \\ & + p_1 lnc_{kt} + p_2 lnag_{kt} + p_3 lnur_{kt} + p_4 lnte_{kt} + p_5 lntr_{kt} \\ & + p_6 lnpe_{kt} + p_7 lnfd_{kt} + m_2 Wlncg_{kt} + j_1 Wlnc_{kt} \\ & + j_2 Wlnag_{kt} + j_3 Wlnur_{kt} + j_4 Wlnte_{kt} + j_5 Wlntr_{kt} \\ & + j_6 Wlnpe_{kt} + j_7 Wlnfd_{kt} + e_{kt} \end{aligned} \quad (5)$$

In addition, to examine the nonlinear correlation between industrial structure upgrading and carbon emissions, this paper also constructs the threshold panel model that was put forward by Hansen (1999) for further analysis. Using economic development (per capita GDP) as the threshold variable, this paper takes the double-threshold panel model as an example for description, as is shown in Equation (6). The number of threshold values will be determined by the threshold test results in the subsequent empirical process.

$$\begin{aligned} lncp_{kt} = & a_0 + a_1 lncg_{kt} \times I(lnag_{kt} < f_1) + a_2 lncg_{kt} \times I(f_1 \leq lnag_{kt} < f_2) \\ & + a_3 lncg_{kt} \times I(lnag_{kt} \leq f_2) + b_1 lnc_{kt} + b_2 lnur_{kt} + b_3 lnte_{kt} + b_4 lntr_{kt} \\ & + b_5 lnpe_{kt} + b_6 lnfd_{kt} + e_{kt} \end{aligned} \quad (6)$$

$I(\cdot)$ is an indicator function, f_1 and f_2 are the estimated threshold values, and $lnag$ is the threshold variable. cp , cg , ec , ag , ur , te , tr , pe , and fd are the same as in Equation (4).

RESULTS

This section mainly demonstrates and analyzes the relevant test and empirical results. To avoid spurious regression, the unit root test was firstly carried out; next, to preliminarily verify the existence of spatial correlation, the Moran's I index was measured, and its significance was also tested; finally, the estimation results of the static spatial panel model, the dynamic spatial panel model, and panel threshold model were analyzed.

Unit root test

In the panel model, spurious regression will lead to errors in the estimation results. To avoid this situation, we refer to relevant studies (Harris & Tzavalis 1999; Choi 2001; Levin *et al.* 2002; Im & Shin 2003) and adopt three commonly used unit root test methods to test the stationarity of the data.

Table 4 displays the results of the stationarity test. The first-order difference of each variable's logarithmic form has passed the significance test at the 1% level, which implies that all variables are first-order single integer variables. Therefore, we construct related models and continue with the following analysis.

Table 4 | The stationarity test of each variable

Method	D.lncp	D.lncg	D.lnc	D.lnag	D.lnur	D.lnte	D.lntr	D.lnpe	D.lnfd
IPS	-9.1103 (0.000)	-5.8782 (0.000)	-9.0555 (0.000)	-4.2957 (0.000)	-9.7658 (0.000)	-8.4326 (0.000)	-8.6966 (0.000)	-8.2721 (0.000)	-8.7362 (0.000)
Fisher -PP	-19.2402 (0.000)	-8.2751 (0.000)	-22.338 (0.000)	-6.014 (0.000)	-21.2258 (0.000)	-17.4416 (0.000)	-17.4621 (0.000)	-13.7487 (0.000)	-16.9311 (0.000)
LLC	-8.8957 (0.000)	-3.3820 (0.0004)	-7.8861 (0.000)	-2.7517 (0.003)	-26.862 (0.000)	-5.8134 (0.000)	-8.2723 (0.000)	-6.4334 (0.000)	-8.0902 (0.000)

Note: P-values are in parentheses.

Moran's *I* test

The values of Moran's *I* can be seen in Table 5. Except for several particular years, almost all of the Moran's *I* values are significantly positive, which indicate a significant positive spatial correlation between the carbon emissions of different provinces in China.

Regression results of the static spatial model

With recent developments in econometrics, the spatial econometric models mainly include SAR, SEM, and SDM. In terms of model selection, the LM test can be used to determine whether to select the SAR model or the SEM model. If the two spatial models are appropriate, the SDM should be constructed.

The test results are shown in Table 6. Whether it is the LM or Robust LM tests, the SAR passed the 1% significance level test, while the SEM did not pass the significance test, so the SAR model is adopted, and the model form is shown in Equation (7). γ_1 is the spatial autocorrelation coefficient, and b_i ($i = 1, 2 \dots 8$) is the coefficient value of each variable.

$$\begin{aligned} \ln cp_{kt} = & b_0 + \gamma_1 W \ln cp_{kt} + b_1 \ln cg_{kt} + b_2 \ln ec_{kt} + b_3 \ln ag_{kt} + b_4 \ln ur_{kt} \\ & + b_5 \ln te_{kt} + b_6 \ln tr_{kt} + b_7 \ln pe_{kt} + b_8 \ln fd_{kt} + e_{kt} \end{aligned} \quad (7)$$

Table 7 demonstrates the estimation results of the SAR model. According to the regression coefficients, the coefficient of industrial structure upgrading (*lncg*) is significantly negative, but the coefficient value is relatively small. As for other control variables, the coefficients of energy consumption intensity (*lnec*), economic development (*lnag*), urbanization (*lnur*), and population size (*lnpe*) are significantly positive, and the coefficients of technological progress (*lnte*) and foreign direct investment (*lnfd*) are significantly negative. Among these control variables, the regression coefficients of energy consumption intensity, economic development, and population size are higher than those of other control variables.

When conducting analysis using the spatial econometric model, regression coefficients can partially explain the influence of each variable, but they cannot explain the marginal effects of each variable well. Therefore, it is necessary to decompose the effect to accurately understand the spatial variation mechanism of each variable. In the spatial panel model, the total effect can be decomposed into direct and indirect effects. The direct effect refers to the average impact of the independent variable on the dependent variable in the local areas, and the indirect effect refers to the impact of the independent variable on the dependent variable in the neighboring area. The partial differential method can be used to make the correct measurement.

According to the effect decomposition in Table 7, the total effect coefficient of industrial structure upgrading is significantly negative, the upgrading of industrial structure can effectively reduce carbon emissions. Specifically, the direct effect coefficient of industrial structure upgrading is significantly negative, but its indirect effect coefficient did not pass the 10% significance level test. This implies that industrial structure upgrading can directly reduce local carbon emissions but has no significant effect on the carbon emissions of neighboring areas. Energy consumption is one of the main sources of carbon emissions. According to the results of the effect decomposition, the direct effect of energy consumption intensity is

Table 5 | The test results of Moran's *I*

Year	Moran's <i>I</i>	P-value	Year	Moran's <i>I</i>	P-value
2000	0.074	0.004	2009	0.052	0.022
2001	0.081	0.002	2010	0.053	0.020
2002	0.074	0.003	2011	0.046	0.030
2003	0.065	0.007	2012	0.035	0.063
2004	0.062	0.009	2013	0.029	0.089
2005	0.065	0.007	2014	0.028	0.094
2006	0.060	0.012	2015	0.029	0.088
2007	0.056	0.016	2016	0.026	0.111
2008	0.054	0.019	2017	0.026	0.108

Table 6 | The spatial correlation of the model test

Test method	Statistical value	P-value
LM test (spatial error)	0.168	0.682
Robust LM test (spatial error)	0.641	0.423
LM test (spatial lag)	27.198	0.000
Robust LM test (spatial lag)	27.670	0.000

Table 7 | The regression results of spatial panel model

Variables	Coefficients	Effect decomposition		
		Direct effects	Indirect effects	Total effects
<i>lncg</i>	−0.0947*** (0.001)	−0.0937*** (0.001)	0.0076 (0.117)	−0.0861*** (0.001)
<i>lnec</i>	1.1117*** (0.000)	1.1111*** (0.000)	−0.0896* (0.063)	1.0215*** (0.000)
<i>lnag</i>	1.1562*** (0.000)	1.1596*** (0.000)	−0.0942* (0.067)	1.0655*** (0.000)
<i>lnur</i>	0.2307*** (0.000)	0.2289*** (0.000)	−0.0182* (0.095)	0.2107*** (0.000)
<i>ln_{te}</i>	−0.0473*** (0.001)	−0.0484*** (0.001)	0.0040 (0.125)	−0.0444*** (0.001)
<i>ln_{tr}</i>	−0.0216 (0.175)	−0.0210 (0.185)	0.0014 (0.338)	−0.0195 (0.189)
<i>ln_{pe}</i>	0.8473*** (0.000)	0.8470*** (0.000)	−0.0698* (0.083)	0.7772*** (0.000)
<i>ln_{fd}</i>	−0.0215** (0.012)	−0.0219** (0.009)	0.0018 (0.138)	−0.0202** (0.009)

Note: ***, **, and * show the significance levels of 1, 5, and 10%, respectively, and P-values are in parentheses.

particularly high, indicating that an increase in energy consumption will directly increase local carbon emissions. Furthermore, economic development and population expansion will also greatly increase the local carbon emissions.

Similar to the effect decomposition of industrial structure upgrading, the direct effect coefficients of technological progress and foreign direct investment are significantly negative, while the indirect coefficients did not pass the significance test, indicating that technological progress and an increase in foreign direct investment will promote local carbon emissions reduction. However, in terms of specific values, compared with the energy consumption intensity, economic development level, and population size, the promotion effect of technological progress and foreign direct investment on carbon emission reduction is very limited.

Regression results of the dynamic spatial panel model

The static spatial panel model only includes the spatial lag effect of carbon emissions. However, the change in carbon emissions is actually a dynamic process of continuous accumulation, and carbon emissions are affected by some unmeasurable factors. Therefore, considering the possible time lag of carbon emissions, we use the first-order time lag of carbon emissions as an independent variable to express the comprehensive influence of other unmeasurable variables on carbon emissions. We further construct a dynamic spatial panel model for analysis. According to the above LM test results, here, the dynamic SAR rather than the dynamic SDM will be established; the specific model form is shown in Equation (8).

$$\begin{aligned}
 \ln cp_{kt} = & c_0 + \theta W \ln cp_{kt} + l_1 L \ln cp_{kt} + l_2 L \cdot W \ln cp_{kt} + d_1 \ln cg_{kt} \\
 & + d_2 \ln ec_{kt} + d_3 \ln ag_{kt} + d_4 \ln ur_{kt} + d_5 \ln te_{kt} + d_6 \ln tr_{kt} \\
 & + d_7 \ln pe_{kt} + d_8 \ln fd_{kt} + e_{kt}
 \end{aligned} \quad (8)$$

The main difference between the dynamic and the static spatial panel models is that the dynamic spatial panel model can effectively distinguish the short- and long-term effects simultaneously.

From the estimated results of the regression coefficients in Table 8, the first-order time lag coefficient of carbon emissions (*L.lncp*) is 0.7077, which passed the significance test at the 1% level, implying that carbon emissions in the early stage will have a significant impact on later carbon emissions. Furthermore, higher carbon emissions in the previous period will directly

Table 8 | Regression results and effect decomposition of the dynamic spatial panel model

Variables	Coefficients	Short-term effects			Long-term effects		
		Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
L1.lncp	0.7077*** (0.000)	–	–	–	–	–	–
lncg	–0.0157 (0.371)	–0.0140 (0.412)	–0.0080 (0.448)	–0.0220 (0.417)	–0.0474 (0.412)	–0.0039 (0.891)	–0.0513 (0.455)
lnec	0.3933*** (0.000)	0.3975*** (0.000)	0.2390*** (0.000)	0.6365*** (0.000)	1.3499*** (0.000)	0.1684 (0.722)	1.5183*** (0.001)
lnag	0.3616*** (0.000)	0.3659*** (0.000)	0.2204*** (0.001)	0.5864*** (0.000)	1.2426*** (0.000)	0.1578 (0.720)	1.4004*** (0.002)
lnur	–0.0592 (0.207)	–0.0585 (0.213)	–0.0355 (0.259)	–0.0940 (0.220)	–0.1987 (0.213)	–0.0276 (0.783)	–0.2263 (0.272)
lnre	–0.0110 (0.252)	–0.0116 (0.227)	–0.0068 (0.265)	–0.0185 (0.231)	–0.0394 (0.227)	–0.0041 (0.804)	–0.0435 (0.262)
lntr	–0.0052 (0.612)	–0.0056 (0.557)	–0.0035 (0.573)	–0.0092 (0.558)	–0.0191 (0.557)	–0.0032 (0.830)	–0.0223 (0.581)
lnpe	0.1098* (0.054)	0.1139** (0.040)	0.0684* (0.082)	0.1823** (0.045)	0.3869** (0.040)	0.0470 (0.754)	0.4339* (0.087)
lnfd	–0.0032 (0.554)	–0.0028 (0.589)	–0.0017 (0.613)	–0.0046** (0.593)	–0.0097 (0.588)	–0.0015 (0.864)	–0.0112 (0.615)

Note: ***, **, and * show the significance levels of 1, 5, and 10%, respectively, and P-values are in parentheses.

lead to an increase in carbon emissions in the current period. This also proves the effectiveness of the dynamic spatial panel model.

Regarding other control variables, in the short term, direct and indirect effect coefficients of energy consumption intensity, economic development level, and population size are all significantly positive, indicating that an increase in energy consumption intensity, economic development, and population expansion will not only increase local carbon emissions but also promote carbon emissions in neighboring areas. In the long term, the direct effect coefficients of the three variables are significantly positive, and the values are much larger than the short-term direct effect coefficients. However, their indirect effect coefficients did not pass the significance test, which shows that in the long run, the impact of energy consumption intensity, economic development level, and population size on carbon emissions of neighboring areas will be weakened, while the promotion impact on the local carbon emissions will be enhanced.

Regression results of the threshold model

Before performing the threshold model regression, the threshold effect was tested. Table 9 displays the threshold effect test results, which shows that the single- and double-threshold models passed the significant test at the 10% level. Therefore, the threshold effect indeed exists, meaning that it is appropriate to establish the threshold model for further analysis.

According to the threshold effect test results, strong evidence concludes that industrial structural upgrading has a double-threshold effect on carbon emissions when dealing with economic development as a threshold variable, so the double-

Table 9 | Threshold effect test results

Model	F-value	P-value	Critical value		
			1%	5%	10%
Single-threshold model	41.12	0.0500	57.1590	41.1126	35.1635
Double-threshold model	47.59	0.0067	43.6325	34.0890	29.5894
Triple-threshold model	30.66	0.4200	91.6662	71.2863	60.6673

threshold model should be established for analysis. The specific threshold values are presented in Table 10, and the two threshold values are 2.5854 and 3.5834.

According to relevant mathematical knowledge, when $\ln ag$ is 2.5854, $ag = e^{\ln ag} = e^{2.5854} = 13.269$ (1,000 yuan/person), that is, the per capita GDP is 13,269 RMB; similarly, when $\ln ag$ is 3.5834, the corresponding ag is 35.996 (1,000 yuan/person), that is, the per capita GDP is 35,996 RMB.

Table 11 displays the threshold regression results. It can be seen that in different stages of economic development, the impact degree of industrial structure upgrading on carbon emissions is different. According to the specific regression coefficients of industrial structural upgrading ($\ln cg$), when the per capita GDP is less than 13,269 RMB, that is $\ln ag < 2.5854$, the carbon emissions will be reduced by 0.4327% with a 1% increase in industrial structure upgrading; when the per capita GDP is between 13,269 and 35,996 RMB, that is $2.5854 < \ln ag \leq 3.5834$, the coefficient of industrial structure upgrading is -0.3819 ; when the per capita GDP is higher than 35,996 RMB, that is $\ln ag > 3.5834$, the regression coefficient of industrial structure upgrading is only -0.3433 . Therefore, the upgrading of industrial structure is indeed conducive to reducing carbon emissions, which is consistent with the estimation results of the spatial panel model. However, the carbon emission reduction effect of industrial structure upgrading will obviously be weakened by economic development.

DISCUSSION

Everything is related to everything else (Tobler 1970), especially in China, economic ties of various regions are becoming gradually strengthened, so we choose the spatial measurement method for analysis. This paper firstly established a static spatial model to determine the existence of spatial effects. Based on the static spatial panel model, we also establish the dynamic spatial model to test the time lag of carbon emissions. In addition, most scholars who examined the relationship between economic development and environmental pollution found that there was a U-shaped or inverted U-shaped non-linear relationship between the two variables (Du *et al.* 2018). Thus, to test whether the impact direction and degree of industrial structure upgrading on carbon emissions will change with economic development, this paper has constructed the threshold panel model for further analysis.

Consistent with the conclusions of most studies, the estimation results of the spatial panel model show that industrial structure upgrading can indeed promote carbon emissions reductions (Chen *et al.* 2019; Zhou & Li, 2020). However, the empirical results also show that the promotion effect is very limited in this paper. Furthermore, there are several other important

Table 10 | The values of thresholds and the confidence intervals

Model	Threshold estimators	95% Confidence intervals
Single-threshold model	2.5854	[2.5592, 2.5854]
Double-threshold model	3.5834	[3.5550, 3.5944]

Table 11 | The regression results of threshold model

Variables	Coef.	Std. Err.	t	P > t
$\ln cg (\ln ag < 2.5854)$	-0.4327	0.0449	-9.63	0.000
$\ln cg (2.5854 < \ln ag \leq 3.5834)$	-0.3819	0.0466	-8.20	0.000
$\ln cg (\ln ag > 3.5834)$	-0.3433	0.0462	-7.43	0.000
$\ln ec$	0.3457	0.0566	6.11	0.000
$\ln ur$	0.9008	0.0988	9.12	0.000
$\ln te$	0.0985	0.0236	4.18	0.000
$\ln tr$	0.1444	0.0233	6.19	0.000
$\ln pe$	0.7882	0.1376	5.73	0.000
$\ln fd$	-0.0262	0.0146	-1.79	0.074

findings. Firstly, this study discovers that the carbon emissions of the current period is greatly affected by those of the previous period; secondly, the impact of industrial structure upgrading on carbon emissions has a threshold effect – as with the development of the economy, the carbon emission reduction effect from industrial structure upgrading will be weakened; finally, regarding the impact of other variables on carbon emissions, this paper also has some new discoveries. In the short term, the increase in energy consumption intensity and population expansion not only affects local carbon emissions but also affects the carbon emissions of neighboring areas. However, in the long run, the impact of energy consumption intensity and population size on local carbon emissions will deepen, and the impact on carbon emissions in neighboring areas will gradually weaken.

The industrial structure can be simply understood as the proportion of primary, secondary, and tertiary industries in the national economic structure. Industrial structure upgrading refers to a process in which the industrial structure gradually evolves from a low- to high-level stage. The main manifestations are that the proportion of the primary and secondary industries will gradually decline, and the tertiary industry will gradually become more dominant. Eventually, the tertiary industry will be larger than the secondary industry and the secondary industry will be larger than the primary industry.

In most cases, the total energy consumption and the energy consumption structure required for the development of the three major industries are significantly different. In the primary industry, agriculture – which occupies a dominant position – does not have a high demand for energy, and its total carbon emissions are relatively low. The secondary industry includes most high-energy consumption sectors and is characterized by high pollution; the secondary industry – which is dominated by the heavy industry – has a large demand for energy consumption, thereby increasing the reliance on coal and oil, which greatly increases carbon emissions. The development of the secondary industry comes at the cost of much energy consumption (Zhang *et al.* 2018; Zhu *et al.* 2021). The tertiary industry mainly includes two major sectors: circulation and services, which are less dependent on energy and produce less carbon emission.

In this paper, the ratio of the tertiary to secondary industry output values was used to measure industrial structure upgrading. The larger the ratio, the larger the tertiary industry in the national economic structure. Most sub-industries in the tertiary industries have lower demands for energy consumption, but most industries in the secondary industry need to consume more energy. Carbon emissions are mainly attributed to fuel combustion, and the secondary industry is the main source of carbon emissions (Talukdar & Meisner 2001; Karen *et al.* 2006). With the industrial structure upgrading, the secondary industry will gradually decline, and the tertiary industry will grow larger. Therefore, the total energy consumption in society will decrease, and carbon emissions will decrease accordingly.

Except for industrial structure upgrading, technological progress is also beneficial to promoting carbon emission reductions. In all walks of life, the application of advanced technology can help improve the efficiency of energy utilization, thereby reducing the input of high-energy consumption production factors, such as coal and oil, and reduce carbon emissions. Furthermore, the increase in foreign direct investments is conducive to promoting the development of science and technology, so to a certain extent, it can also help reduce carbon emissions.

CONCLUSIONS AND POLICY RECOMMENDATIONS

Conclusions

This paper studies the influence of industrial structure upgrading on carbon emissions in China. By considering the spatial correlation among carbon emissions, the spatial panel model is selected with reference to the STIRPAT model. Here, we analyze the specific impact of industrial structure upgrading on carbon emissions. Then, the double-threshold panel model is established to investigate the threshold effect. According to the estimation results of the models, we come to the following conclusions.

Upgrading the industrial structure is helpful in reducing carbon emissions, but this carbon emission reduction effect is limited. The effect coefficients of industrial structure upgrading are relatively low. Furthermore, the specific degrees of influence differ in different stages of economic development. With economic development, the carbon emission reduction effect of industrial structure upgrading will be weakened.

Whether in the short or long term, the increase in energy consumption intensity and population expansion will directly lead to a sharp increase in carbon emissions. Moreover, according to the estimation results of the dynamic spatial panel model, in the long term, the impact of this promotion of carbon emissions will be strengthened.

Scientific and technological progress is an important step in reducing carbon emissions. The development of low-carbon technologies is beneficial in improving energy utilization, thus reducing the total amount of carbon emissions. Furthermore, with the progress of science and technology, an increased number of new products can be used in the production of high-energy consumption industries, thereby promoting carbon emission reduction.

Policy recommendations

Based on the above research results, we propose the following suggestions.

China should actively promote the process of industrial structure upgrading. In China, the upgrading of industrial structure can effectively promote carbon emission reduction. Therefore, various regions should actively promote the process of industrial structure upgrading. Preferential policies, such as taxation and subsidies, can be formulated to encourage the development of modern service and high-tech industries and other tertiary industries, including information, electronic equipment manufacturing, and other industries. Additionally, it is necessary to change the industrial structure of industrial zones and to introduce relevant laws and regulations to restrict the excessive development of high-energy consumption secondary industries, especially the excessive growth of energy- and carbon-intensive industries, such as steel, non-ferrous metals, coal, electricity, petroleum, petrochemical, chemical, building materials, and other industries. Furthermore, it is essential to improve the exit mechanisms of overcapacity industries, guide the rational layout and orderly transfer of industries, and promote the rational development of the industrial structure by optimizing the allocation of production factors and the flow of resources between industries.

The key to promote industrial structure upgrading is to improve independent innovation capabilities and strengthen technological innovation. The government should encourage the establishment of research and development centers, improve the research and development capabilities of enterprises, and promote the formation of independent intellectual property rights through the formulation of fiscal and taxation policies, national procurement policies, and the strict enforcement of intellectual property laws.

China should accelerate technological innovation, promote the recycling of industrial solid waste, and adjust energy structures. The regression results have clearly demonstrated that technological progress is an important way to reduce carbon emissions, but the energy consumption intensity will significantly increase carbon emissions. This influence will be strengthened in the long term. Therefore, government departments and enterprises should make full use of contemporary information technology, promote the deep integration of informatization and industrialization, accelerate the upgrading and transformation of traditional industries, develop low-carbon energy, and improve the efficiency of energy utilization.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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