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ORIGINAL PAPER

The analysis of spatial–temporal effects of relevant factors on carbon intensity in China

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Abstract

The increasing carbon emissions have been a major concern for most countries around the world. And as a result, every country is concerned about developing appropriate strategies to curtail it. As a major economy and the largest carbon emitter in the world, China has pledged to reduce the carbon intensity by 60–65% by 2030, compared with 2005 levels, and achieve carbon neutrality before 2060. Therefore, the analysis of the impact of China's carbon intensity is becoming an increasing important topic. Due to the spatial heterogeneity of carbon intensity, various spatial econometric models have been applied in this field. However, the existing literatures failed to consider the cross-products of relevant factors. This paper constructs our dynamic general nesting spatial panel model (GNS) with common factors to deal with the dilemma, and examines the direct and spatial–temporal spillover effects of industrial structure, GDP per capita, investment in anti-pollution projects as percentage of GDP and energy price on carbon intensity in China over the period 2003–2017. Our analysis shows that: (1) China's carbon intensity showed the spatial agglomeration and temporal "inertia" from 2003 to 2017. (2) From the time dimension, the long-term effect of industrial structure first increased and then gradually decreased. (3) From the spatial dimension, industrial structure and investment in anti-pollution projects as percentage of GDP accounted for the main spatial heterogeneity. Furthermore, this paper attempts to provide policy implications to help reduce carbon intensity and achieve carbon neutrality in China.

Keywords Carbon intensity · Spatial dependence · Spillover effect · Industrial structure · Spatial heterogeneity · Carbon emissions

1 Introduction

The *Production Gap Report 2020* and *Emission Gap Report 2020* released by the United Nations Environment Programme (UNEP) point out that, despite a brief dip in carbon dioxide emissions caused by the COVID-19 pandemic, the world is still heading for a temperature rise in excess of 3 °C this century—far beyond the Paris Agreement goals of limiting global warming to well below 2 °C and pursuing 1.5 °C. The increasing carbon emissions have been a major concern for most countries around the world (Shobande and Asongu 2021). And as a result, every country is concerned about developing appropriate strategies to curtail it (Chen et al. 2020; Yang et al. 2021). As a major economy and the largest carbon emitter in the world, China has pledged to reduce the carbon intensity (carbon dioxide emissions divided by gross domestic product (GDP)) by 60–65% by 2030, compared with 2005 levels, and achieve carbon neutrality before 2060 by implementing a green pandemic recovery plan.

Therefore, investigating China's carbon emissions has been attracting more attention from numerous studies. Energy consumption is the crucial impetus of the carbon emissions, and the leading factors of carbon emissions have been identified as follows: industrial structure, economic growth and investment in treatment of environmental pollution (Song et al. 2015; Xu et al. 2016; Ridzuan et al. 2020; Du and Li 2020; Xuan et al. 2020; Abbasi et al. 2021; Aluko et al. 2021; Aslam et al. 2021; Cheng et al. 2021; Hossain and Chen 2021; Shabani et al. 2021).

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Based on these factors, a large number of literatures have discussed the contributors of carbon emissions focusing on some industries or some regions in China by using the classic methods. On the one hand, there are some studies focusing on the carbon emissions of some industries in China. Teng et al. (2017) measured the carbon productivity of Chinese service industry by SBM directional distance function and GML index. Tian and Ma (2020) established the Kaya decomposition model of China's industrial carbon intensity and used LMDI method to analyse the contribution of different factors to the industrial carbon intensity. Sun et al. (2020) constructed a Stackelberg differential game model to analyse the factors that influence China's manufacturing industrial carbon emissions. Using the input–output analysis and the three-stage data envelopment analysis (DEA) model, Wang et al. (2020a) proposed an improved method for estimation of China's embodied carbon emissions efficiency in the service sector. On the other hand, some studies are focusing on carbon emissions of some regions in China. Chang et al. (2020) evaluated the impact of energy consumption structure on carbon emission performance in the Bohai Rim Economic Circle (BREC) and allocated the carbon emission quotas in 2030. Wang et al. (2020b) evaluated the spatial correlation and relevant factors of carbon emissions in Chengdu-Chongqing urban agglomeration based on SNA and QAP. Jiang et al. (2020) constructed a three-stage DEA model to evaluate and compare the transportation carbon emission efficiency of the provinces in Yangtze River Economic Belt. Huang et al. (2019) applied the life cycle assessment approach to quantify the efforts of Shenzhen's public building practices and evaluated its real 'achievement' by quantifying the carbon emissions reduction in the past decade. Taking energy intensity as the threshold variable, Wang et al. (2019) established the Threshold-STIRPAT model and determined the contributors of carbon emissions in 6 megacities.

But the above literatures have rarely taken spatial heterogeneity into consideration when analysing the relevant factors of carbon emissions. Anselin (1988) proposed spatial econometrics, which provided a basic model to contain spatial heterogeneity in classic econometric models. Pan and Zhao (2018) built a Spatial Autoregressive Model (SAR) to simulate the spatial–temporal distribution of carbon emissions in China. Cheng et al. (2018) used dynamic spatial panel models to analyse the effects of industrial structure and technical progress on carbon intensity, and explored those factors that may lead to a reduction in carbon intensity in China. Lu et al. (2019) applied Spatial Durbin Model (SDM) to analyse the direct and spillover effects of low-carbon technological innovation on carbon emissions in China. Liu and Zhang (2021) Investigated the relationship between heterogeneous industrial agglomeration, technological innovation and carbon productivity using SDM in china. Guo et al. (2021) investigated the spatial aggregation and determinants of Guangdong's energy intensity using SDM.

However, the above spatial econometric models may have some limitations: firstly, they failed to consider the cross-products of relevant factors, which may play an important role on the analysis of carbon intensity (Shi and Lee 2017). Secondly, they did not consider heterogeneity of the direct and spillover effects across space and over time (Li et al. 2019). Furthermore, they did not take into account that energy price may have a determined negative effect on energy consumption (Ren et al. 2009; Du 2019; Ashraf et al. 2020; Wang et al. 2020c; Neya et al. 2020).

In fact, Elhorst et al. (2019) proposed a dynamic general nesting spatial panel model (GNS) with common factors, which introduced cross-products and showed the direct and spillover effects of relevant factors across space and over time in their problem. In order to achieve short-term and long-term control of carbon intensity of different regions in China, this study tries to explore the spatial–temporal effects of relevant factors on carbon intensity in China. The contributions of this paper are presented as follows: (1) following the method of Elhorst et al. (2019), this paper constructs our GNS with common factors and analyses all industries of 30 provinces in China from 2003 to 2017. (2) Based on the leading factors in previous studies, this study examines the direct and spatial–temporal spillover effects of industrial structure (*IS*), GDP per capita (*PGDP*), investment in anti-pollution projects as percentage of GDP (*EI*) and energy price (*PE*) on carbon intensity. (3) This paper is a first attempt to explore the spatial–temporal effects of relevant factors on carbon intensity by introducing the cross-products in the basic models. (4) It is the inclusion of cross-products in our model that makes it possible to provide effective economic explanations and reasonable policy implications of *IS*, *PGDP*, *EI* and *PE* for the observed heterogeneity from spatial and time dimensions, respectively.

The remainder of this paper is organized as follows. Section 2 describes the research methodology, variables, data description and constructs our model. Section 3 reports and discusses the spatial aggregation of carbon intensity and the empirical results of the models. Section 4 gives the conclusions and proposes several policy implications.

2 Materials and methods

2.1 Carbon intensity estimates

According to the report of the United Nation's Intergovernmental Panel on Climate Change (IPCC), the use of fossil energy is the main source of the increase in carbon emissions. For convenient analysis, this study calculates carbon intensity from fossil energy including coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil and natural gas. Specifically, in order to obtain carbon intensity, we need firstly evaluate the carbon emissions, which can be calculated as follows:

$$C_{it} = \sum_{j=1}^{k} (E_{ijt} \times a_j \times b_j) \times \frac{44}{12} \tag{1}$$

where C_{it} represents the carbon emissions of province i in period t;E_{ijt} stands for the total consumption of energy j by province i in period t;a_j is the standard coal-equivalent coefficient of energy j, which is from *China Energy Statistical Yearbook*; b_j represents the carbon-emission coefficient of energy j, which is from *IPCC Report*. And a_j and b_j are shown in "Table 7 in Appendix".

Based on this formular, we can denote the carbon intensity as:

$$CI_{it} = \frac{C_{it}}{GDP_{it}} \tag{2}$$

where CI_{it} and GDP_{it} stand for the carbon intensity and the regional gross domestic product of province i in period t, respectively.

2.2 Testing for cross-sectional dependence

Based on the Cross-Sectional Dependence (CD) test developed in Pesaran (2015) and the α-exponent estimator developed in Bailey et al. (2016a), Bailey et al. (2016b) presented a two-step procedure to distinguish between weak and strong cross-sectional dependence. Under the null hypothesis $0 < \alpha < 1/2$, the CD-test statistic is defined as the Eq. (3), and the average correlation coefficient has the order property of Eq. (4):

$$CD = \sqrt{2T/N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{3}$$

$$\overline{\rho}_N = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \rho_{ij} = O\left(N^{2\alpha-2}\right) \tag{4}$$

where N represents the number of provinces (N = 30) and T stands for the time periods (T = 15); $\hat{\rho}_{ij}$ denotes the sample correlation coefficient between CI_{it} and CI_{jt} of two provinces i and j in period t; $\overline{\rho}_N$ is the average correlation coefficient; And $CD \overset{a}{\sim} N(0,1)$; α is a parameter that can take values on the interval (0,1) (Bailey et al. 2016b), for $0 < \alpha < 1/2$, $\overline{\rho}_N$ convergenes to zero very fast, pointing to weak dependence. The range $1/2 \leq \alpha < 3/4$ is considered to represent moderate dependence and $3/4 \leq \alpha < 1$ quite-strong cross-sectional dependence.

2.3 Testing for spatially stratified heterogeneity

The spatially stratified heterogeneity (SSH) refers to ubiquitous phenomena (those within strata are more similar than those between strata), implies potential distinct mechanisms by stratum, and enforces the applicability of statistical inferences (Wang et al. 2016). Confounding arises if a global model was applied to a SSH population, leading to statistical insignificance. The problem can be simply avoided if SSH is identified by geographical detector (GeoDetector) q-statistic then modelling in the strata, separately. The GeoDetector q-statistic is generally applied to quantitatively evaluate the SSH of an explained variable (Wang et al. 2010, 2016) and assess the determinant power of explanatory variables and their interactions without linear assumptions (Yin et al. 2019). The fundamental formula of the q-statistic is given by:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{5}$$

where q, with a value ranging from 0 to 1, is the SSH measure of an explained variable or the determinant power of a factor to the objective, and the larger the q-statistic, the more pronounced SSH of Y is; N is the number of explained variable observations, and σ^2 indicates the variance of all the observations; The explained variable is stratified into L strata, denoted by h = 1, 2,..., L, which are determined by prior knowledge, the determinant factor, or a classification algorithm; N_h is the number of observations, and σ_h^2 is the corresponding variance within stratum h.

2.4 Spatial econometric model

This paper adopts a dynamic general nesting spatial panel model (GNS) with common factors, which can be written as:

$$lnCI_{it} = \tau lnCI_{it-1} + \delta\sum_{j=1}^{N} w_{ij}lnCI_{jt} + \eta\sum_{j=1}^{N} w_{ij}lnCI_{jt-1} + \sum_{l=1}^{L}\beta_l lnx_{ilt} + \sum_{l=1}^{L}\theta_l\sum_{j=1}^{N} w_{ij}lnx_{jlt} + \frac{1}{2}\sum_{l=1}^{L}\sum_{m=1}^{L}\beta_{lm}lnx_{ilt}lnx_{imt} + \rho lnz_{it} + \sum_{r=1}^{R}\tau_{ir}f_{rt} + v_{it} \tag{6}$$

where

$$v_{it} = \lambda\sum_{j=1}^{N} w_{ij}v_{jt} + \varepsilon_{it} \tag{7}$$

where $lnCI_{it-1}$ and $\sum_{j=1}^{N} w_{ij}lnCI_{jt}$ represent, respectively, the temporal and spatial lag, and $\sum_{j=1}^{N} w_{ij}lnCI_{jt-1}$ represents spatial–temporal lag of $lnCI_{it}$; τ, δ and η are the corresponding response parameters of these variables, respectively, the serial, spatial and spatial–temporal autoregressive coefficients; w_{ij} is the element of an $N \times N$ non-negative matrix W of known constants describing the spatial arrangement of the provinces in the sample; $L = 3$,x_{i1t}, x_{i2t} and x_{i3t} represent *IS*, *PGDP, EI* of the province i in period t, respectively; And so in terms of these three explanatory variables, the number of cross-products amounts to six; β_l,θ_l and β_{lm} are the coefficients of the exogenous explanatory variables, the exogenous spatial lag explanatory variables and the cross-products of the exogenous variables, respectively; z_{it} stands for *PE*, with coefficient ρ, the first three single explanatory variables are dominated by variation in the cross-sectional domain, while *PE* is dominated by variation in the time domain; The common factors, which cover potential global cross-sectional dependence, can be subdivided into observable and non-observable factors. In our model, *PE* is an observable common factor. The hypothesis is that if *PE* in China increases (resp. decrease), the *CI* will diminish (resp. increase) in all of its provinces. In addition, the *CI* may increase or decrease due to R non-observable common factors; τ_{ir} is the i th column of τ_r, which is a vector of length N representing the factor loadings of common factor r. f_t is of order $R \times T$ such that its transpose consists of R columns of length T. The proposed model encompasses many models of empirical interest, among which the popular dynamic spatial panel model with additive spatial and time period fixed effects. Shi and Lee (2017) demonstrated that this model can be obtained by imposing the restrictions $R = 2$,$\tau_1 = (\mu_1 \ldots \mu_N)$, $\tau_2 = (1 \ldots 1)$ and $f_t = (1\xi_t)'$, where μ_i and ξ_t represent spatial and time period fixed effects, respectively; Finally, the error term v_{it} is assumed to follow a local spatial autoregressive process, where ε_{it} reflects an i.i.d disturbance term with zero mean and finite variance σ^2. The coefficients of the model specified can be estimated by the quasi-maximum likelihood (QML) estimator developed by Shi and Lee (2017).

2.5 Direct effect and spillover effect (indirect effect)

The matrix of the long-term direct and indirect effects of the expected value of the *CI* with respect to the lnx_{ilt} can be expressed as follows (Elhorst 2014; Elhorst et al. 2018):

$$\begin{pmatrix} \frac{\partial E(lnCI_{1t})}{\partial lnx_{1lt}} & \cdots & \frac{\partial E(lnCI_{1t})}{\partial lnx_{Nlt}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(lnCI_{Nt})}{\partial lnx_{1lt}} & \cdots & \frac{\partial E(lnCI_{Nt})}{\partial lnx_{Nlt}} \end{pmatrix} = ((1-\tau)I_N - (\delta+\eta)W)^{-1} \times \begin{pmatrix} \beta_l + \sum_{m=1}^{L}\beta_{lm}lnx_{1mt} & \theta_l w_{12} & \cdots & \theta_l w_{1N} \\ \theta_l w_{21} & \beta_l + \sum_{m=1}^{L}\beta_{lm}lnx_{2mt} & \cdots & \theta_l w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_l w_{N1} & \theta_l w_{N2} & \cdots & \beta_l + \sum_{m=1}^{L}\beta_{lm}lnx_{Nmt} \end{pmatrix} \tag{8}$$

where every diagonal element of this matrix represents the direct effect of one unit change in one of the factors on *CI* of the province i. Due to the inclusion of lnx_{ilt}, the diagonal elements of the second matrix on the right-hand side will vary across space and over time, so will these direct effects; Every column sum of off-diagonal elements represents the spillover effect of one unit change in one of the factors on *CI* in all provinces other than the province instigating this change. Their short-term counterparts can be obtained by setting $\tau = \eta = 0$.

2.6 Spatial weight matrix

W_1 represents a binary contiguity matrix, when the province i and province j are adjacent, $w_{ij} = 1$, otherwise $w_{ij} = 0$. Based on the inverse of the average distance (K) between the capitals of adjacent provinces, the element of W_2 takes 0 if K > 450 km or 1 otherwise. At the same time, W_1 and W_2 are standardized.

2.7 Data description

The energy consumption data, *IS* (the proportion of the output value of the secondary industry in GDP), *PGDP* and *EI* in each province and *PE* were obtained from the *Statistical Yearbooks* of each province, *China Energy Statistical Yearbook* and *China Environmental Statistical*

Yearbook. Due to the complexity of *PE*, a general method is to find a good proxy index for *PE*. This study chose the purchasing prices for raw materials, fuels and power, which has been chosen for the good proxy index for *PE* (for example Du 2019). *PGDP* and *PE* were converted into standard prices using a price index (2003 was the base year). In order to compare the regional differences of the effects of relevant factors on *CI*, this paper introduced the regional division of China (see Table 1). The distance data came from Google Maps. Following the general treatment in the studies of *CI* in China, this study did not collect data from Hong Kong, Macao, Taiwan and Tibet.

3 Results and discussion

In this section, this paper firstly gives a graphical analysis of spatial aggregation of *CI* by the software of ArcGIS. Furthermore, we show a detailed spatial econometrics analysis of *CI* based on our GNS model.

3.1 The spatial aggregation of *CI* and the three rates of change of relevant factors

ArcGIS software can depict the spatial distribution of research objects directly and vividly through a graphical display. In this paper, the degree of spatial aggregation among 30 provinces in China by dividing *CI* into four regions from low level to high level was measured by ArcGIS. For the succinctness and representative of analysis, we used the data of 2003, 2008, 2013 and 2017. The results are shown in Fig. 1. Totally, China's *CI* showed obvious spatial agglomeration. Specially, North China, Northeast China and Northwest China belonged to "high-high" agglomeration regions, while some coastal provinces in Central China and East China belonged to "low-low" agglomeration regions. In addition, China's *CI* has been declining from 2003 to 2017.

Furthermore, this paper calculated the three rates of change of relevant factors during the period 2003–2008, 2008–2013 and 2013–2017, respectively (the rate of change = ((current value)/(previous value)-1)$*$100), which are shown in Figs. 2, 3 and 4. Firstly, the *PGDP* of all provinces continued to grow during the period 2003–2017, especially the provinces in North China and East China. Secondly, during different periods, *IS* and *EI* of different provinces in China had different trends. From 2003 to 2008, except for a few provinces and cities such as Beijing and Shanghai, the *IS* of most provinces and cities was increasing. From 2008 to 2013, the *IS* of almost half of the provinces, such as Henan Province and Zhejiang Province, was decreasing, while *EI* of most provinces and cities was increasing sharply during this period. From 2013 to 2017, in the "12th Five-Year Plan"(2011–2015) and early stage of the "13th Five-Year Plan"(2016–2020), the industrial structure has been adjusted, the *IS* of all provinces were declining, while most provinces had a slight decrease in *EI*.

3.2 Empirical results of models

Cross-sectional dependence is prerequisite of using the spatial econometric analysis. In order to test the cross-sectional dependence of *CI* in China, we will apply CD-test statistic (Bailey et al. 2016b; Pesaran 2021; Elhorst et al. 2021) and global Moran's I (Zhou et al. 2019) (see "Table 8 in Appendix"). The results indicated a strong spatial dependence of *CI* in China. This result is consistent with the previous graphical analysis. Therefore, the influence of spatial effects should be taken into account in the study of *CI* in China.

Furthermore, in order to test whether there is the SSH of the huge country and confounding of a global modelling, the SSH and the degree of influence of different factors on *CI* were investigated through the GeoDetector *q*-statistic (Wang et al. 2010, 2016) of *CI* for different regions of China over the period 2003–2017 (see "Tables 9, 10 in Appendix"). The results indicated that although the cross-products detectors may reduce the validity of applying the global models (i.e. SAR models, SDM models and GNS models), the *q*-statistics imply that from the view of control functions, the primary variables such as *IS*, *PGDP* and *EI* are not affected by the spatial stratified heterogeneity, which implies the global model is a reliable spatial econometric model applied to analyze the effects of these

Table 1 Regional division of China

Region	Provinces and cities
North China	Beijing, Tianjin, Hebei, Shanxi, Shandong, Inner Mongolia
Northeast China	Liaoning, Jilin, Heilongjiang
East China	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian
Central China	Jiangxi, Henan, Hubei, Hunan, Chongqing, Sichuan
Northwest China	Shanxi, Gansu, Qinghai, Ningxia, Xinjiang
South China	Guangdong, Guangxi, Guizhou, Yunnan, Hainan

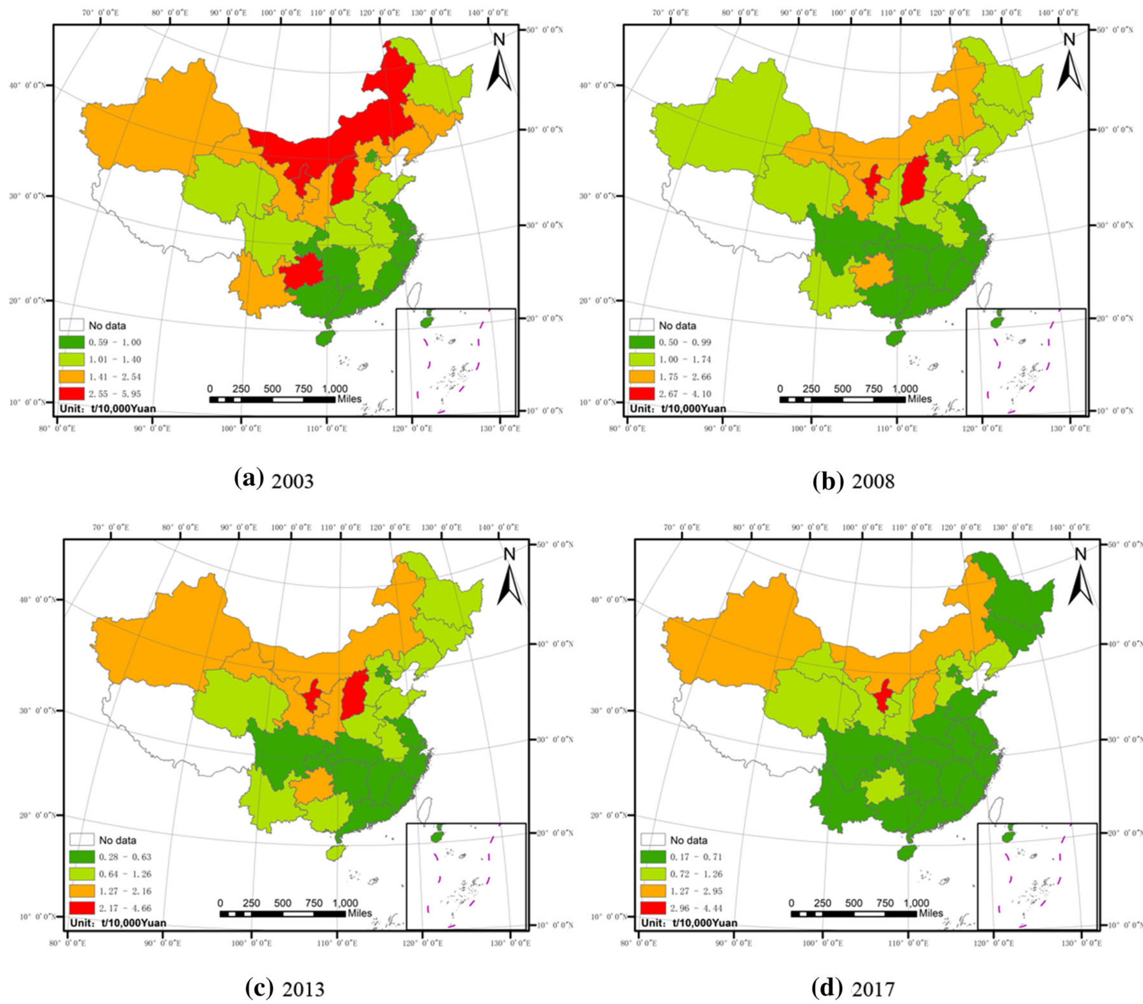

Fig. 1 China's agglomeration map of carbon intensity (t/10,000 yuan) in 2003, 2008, 2013 and 2017

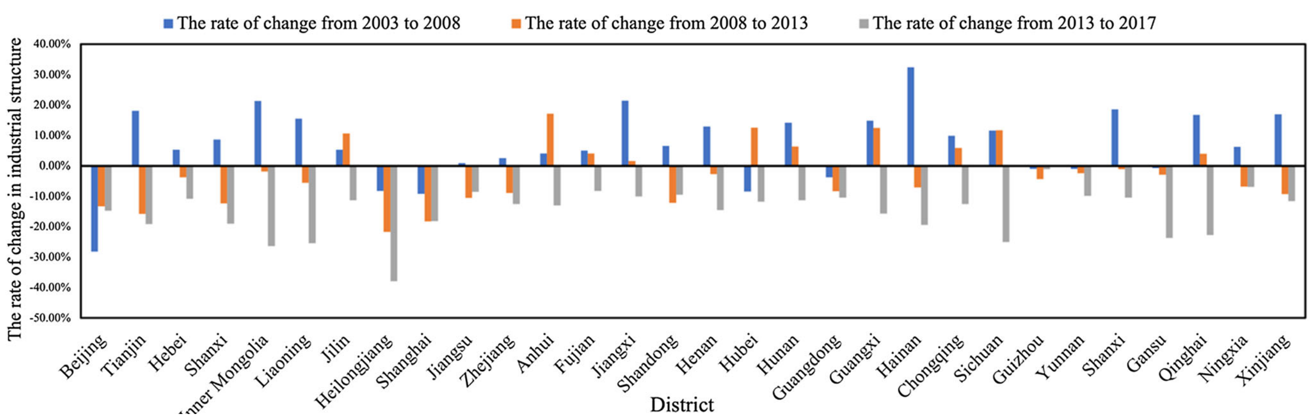

Fig. 2 The rate of change in *IS* (2003–2008, 2008–2013 and 2013–2017)

primary variables on *CI* in China. Therefore, the global models are reliable spatial econometric models applied to focus on the effects of primary variables on the dependent variable for all regions, and this paper constructs the global models for the analysis of effects of these factors on *CI* in China, respectively.[1]

[1] We thank the associate editor and the reviewers for testing the necessity of spatially stratified heterogeneity and their helpful

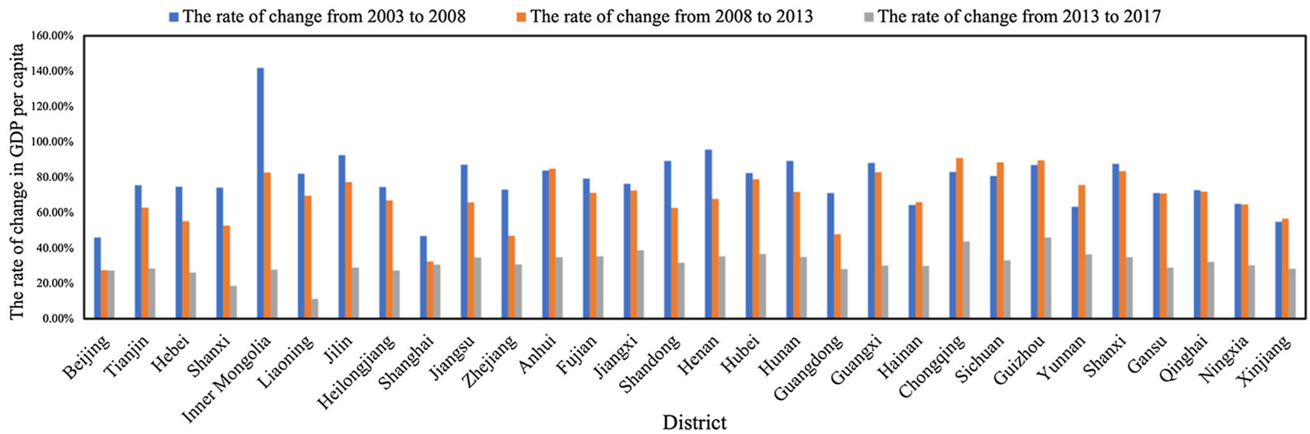

Fig. 3 The rate of change in *PGDP* (2003–2008, 2008–2013 and 2013–2017)

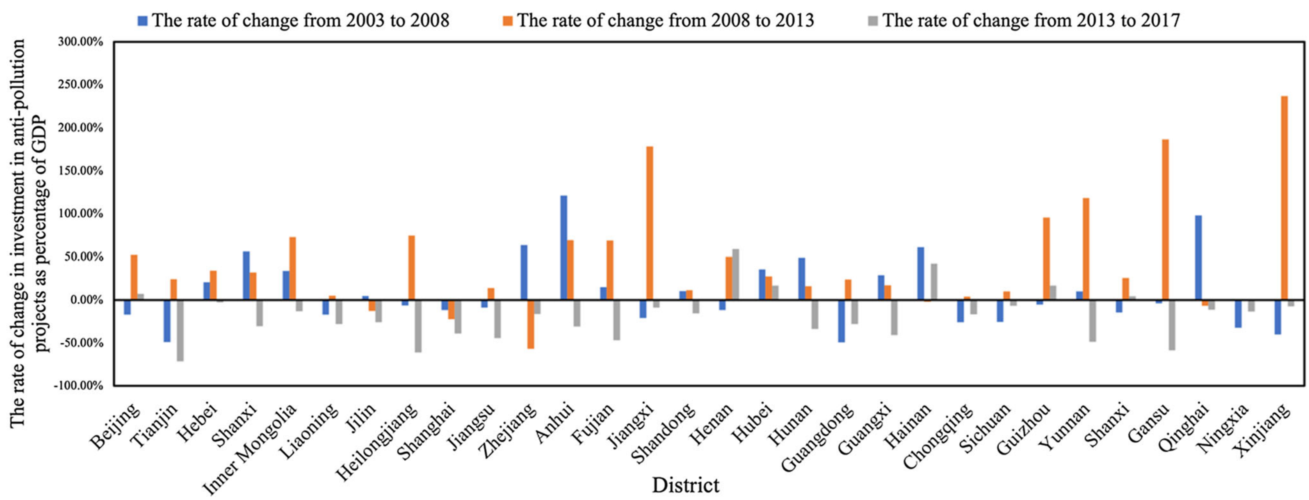

Fig. 4 The rate of change in *EI* (2003–2008, 2008–2013 and 2013–2017)

Specifying spatial weight matrix is the first step of constructing the spatial econometric model. In this paper, two spatial weight matrices, W_1 and W_2, which are introduced in Sect. 2, will be used (characteristics of two spatial weight matrices see "Table 11 in Appendix").

In terms of cross-sectional dependence above, spatial econometric models should be applied to analyze the effects of various relevant factors on *CI* in China. In this paper, based on two spatial weight matrices above, the classic SAR models (fixed effects in time and space), SDM models (fixed effects in time and space) and a kind of new model, GNS models will be applied to our analysis. Table 2 reports the estimation results of six models.

From Table 2, we can find that: firstly, the LR-test (− 2 * (460.7400–524.4776) = 127.4752) implies that the coefficients of the cross-products and spatial lags are jointly significant and that introducing the cross-products and spatial lags in the model is reasonable. Secondly, the elasticities of *PE* in three models SAR(W_1), SAR(W_2) and SDM(W_1) are all greater than 1, which are not consistent with the actual situation in China (Zhang 2008; Du 2019). Thirdly, the higher values of adjusted R-squared and log-likelihood show that the GNS is more fitting to Chinese data. Finally, the sum of absolute value of the coefficients, τ, δ and η in GNS(W_2) is greater than 1, which fails to satisfy the stability condition, and in addition, the probability of the empirical regularity (Parent and Lesage 2011, 2012) in GNS(W_2) is lower than that in GNS(W_1). Therefore, GNS (W_1) is a reliable spatial econometric model applied to the analysis of *CI* in China, and so we will focus on GNS(W_1).

The estimation results of GNS (W_1) imply that: (1) τ is greater than 0 and significant at 1% level, indicating that China's *CI* showed temporal "inertia" from 2003 to 2017, that is, for province *i*, the *CI* of the previous period was

Footnote 1 continued
comments and suggestions, which make our study more comprehensive and make the applicability of the proposed model clearer.

Table 2 The estimation results of models

Variable	SAR (W_1)	SAR (W_2)	SDM (W_1)	SDM (W_2)	GNS (W_1)	GNS (W_2)
$lnCI_{it-1}(\tau)$	0.7111*** (0.0445)	0.7934*** (0.0292)	0.5142*** (0.0406)	0.6783*** (0.0297)	0.6627*** (0.0249)	0.6489*** (0.0257)
$\sum_{j=1}^{N} w_{ij} lnCI_{jt}(\delta)$	0.0248 (0.1464)	− 0.0008 (0.1290)	0.0589 (0.1303)	0.0046 (0.1159)	− 0.0047 (0.1492)	0.0067 (0.1706)
$\sum_{j=1}^{N} w_{ij} lnCI_{jt-1}(\eta)$	− 0.1814 (0.0664)	0.0462 (0.1437)	− 0.2358*** (0.0186)	− 0.0519 (0.1419)	− 0.1298 (0.1357)	− 0.4161*** (0.1456)
lnIS	0.2417*** (0.0788)	0.1307** (0.0513)	8.7510*** (0.9696)	4.0325*** (0.6525)	1.2391** (0.5505)	0.6872 (0.51918)
lnPGDP	− 0.2973*** (0.0472)	− 0.2720*** (0.0593)	0.5156 (0.3163)	0.5353*** (0.1934)	0.5420*** (0.1811)	0.5631*** (0.1888)
lnPE	− 1.0297 (0.1414)	− 1.3484*** (0.3755)	2.8134 (2.1884)	− 0.8645*** (0.1005)	− 0.1258 (0.0791)	− 0.5702 (1.1059)
lnEI	0.3380 (0.3498)	0.1975*** (0.0274)	− 1.8079*** (0.4782)	− 0.3585** (0.1670)	− 0.4044*** (0.1432)	− 0.2898** (0.1428)
$1/2 * lnIS * lnIS$			− 2.1264*** (0.3708)	− 1.0003*** (0.1922)	− 0.3966** (0.1627)	− 0.2531 (0.1680)
$lnIS * lnPGDP$			− 0.1496 (0.1086)	− 0.1698*** (0.0449)	− 0.0204 (0.0386)	− 0.0435 (0.0404)
$1/2 * lnPGDP * lnPGDP$			− 0.0125 (0.0452)	− 0.0001 (0.0270)	− 0.0404** (0.0163)	− 0.0266* (0.0149)
$lnIS * lnEI$			− 0.0775 (0.1885)	0.0047 (0.0710)	0.0528 (0.0514)	0.0615 (0.0513)
$1/2 * lnEI * lnEI$			0.6333*** (0.1253)	0.1785*** (0.1459)	− 0.0838*** (0.0218)	− 0.0814*** (0.0194)
$lnPGDP * lnEI$			− 0.0258 (0.0051)	− 0.0293 (0.0068)	0.1102*** (0.0315)	0.0860*** (0.0309)
$W * lnIS$			0.1174 (0.1782)	0.1150 (0.0976)	− 0.0266 (0.0685)	0.2308*** (0.0857)
$W * lnPGDP$			− 0.0960** (0.0462)	− 0.0199 (0.0300)	− 0.1333*** (0.0416)	− 0.2689*** (0.0622)
$W * lnEI$			− 0.1079 (0.1376)	0.0193 (0.0575)	0.0467 (0.0566)	0.1495*** (0.0549)
$\sum_{j=1}^{N} w_{ij} v_{jt}(\lambda)$					0.1250 (0.1714)	0.2698 (0.1750)
Observations	450	450	450	450	450	450
R-squared	0.6833	0.8204	0.8066	0.8540	0.9968	0.9968
Log-likelihood	460.7400	730.4147	524.4776	771.9075	934.9276	934.4682
$\lvert\tau\rvert + \lvert\delta\rvert + \lvert\eta\rvert - 1$	− 0.0827	− 0.1596	− 0.1911	− 0.2652	− 0.2028	0.0717
Probability $\eta = -\tau * \delta$	0.2305	0.5639	0.1303	0.6398	0.0506	0.0000

(1) *, ** and *** represent significance at 10%, 5% and 1% levels, respectively. (2) The values in brackets are standard errors

significantly and positively correlated with that of the next period. This "snowball effect" illustrates that adjusting some policies such as optimizing industrial structure, regulating energy price and increasing or decreasing investment in treatment of environmental pollution, which usually had a habit persistence in China (Lu et al. 2019). In addition, δ and η are close to 0 and insignificant, which means the existence of local spillovers of *CI* and there were not global spillovers of *CI*. (2) The coefficient of *IS* is positive and significant, which implies that the higher *IS*, the larger the *CI* in China was. This might be attributed to the unreasonable *IS* of most provinces in China. This is because relative unreasonable *IS* will lead to a high level of industrial activities, which inevitably leads to a high level of *CI* (Cheng et al. 2018; Lu et al. 2019; Yang et al. 2021). In fact, about 70% of China's primary energy came from industrial energy consumption, and around 69% of that came from high energy consuming industries, such as steel,

Table 3 The short-term and long-term total effects of relevant factors on carbon intensity from 2003 to 2017

	lnIS		*lnPGDP*		*lnPE*		*lnEI*	
	ST	LT	ST	LT	ST	LT	ST	LT
2003	0.7783 (0.6295)	1.7953*** (0.6935)	0.5343*** (0.0687)	1.2222** (0.6723)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4726*** (0.1182)	− 1.0743*** (0.2854)
2004	0.7612 (0.6143)	1.7636** (0.7009)	0.5303*** (0.0645)	1.2188** (0.7083)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4688*** (0.1110)	− 1.0701*** (0.2703)
2005	0.7643 (0.5920)	1.7816** (0.7222)	0.5285*** (0.0666)	1.2232** (0.6837)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4685*** (0.1172)	− 1.0769*** (0.2857)
2006	0.8046 (0.6160)	1.8863*** (0.6771)	0.5436*** (0.0687)	1.2565** (0.6493)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4779*** (0.1176)	− 1.0957*** (0.2911)
2007	0.7799 (0.5974)	1.7912** (0.7335)	0.5311*** (0.0652)	1.2139** (0.6907)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4713*** (0.1142)	− 1.0692*** (0.2839)
2008	0.8365 (0.6059)	1.9543*** (0.6907)	0.5411*** (0.0649)	1.2454** (0.6884)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4733*** (0.1126)	− 1.0813*** (0.2807)
2009	0.7976 (0.6022)	1.8588*** (0.7032)	0.5427*** (0.0655)	1.2507** (0.6886)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4781*** (0.1125)	− 1.0923*** (0.2874)
2010	0.7930 (0.6077)	1.8509*** (0.7132)	0.5414*** (0.0662)	1.2553** (0.6683)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4768*** (0.1145)	− 1.0961*** (0.2903)
2011	0.7885 (0.6073)	1.8279** (0.7119)	0.5343*** (0.0677)	1.2286** (0.6749)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4739*** (0.1197)	− 1.0821*** (0.2901)
2012	0.8076 (0.6038)	1.8612*** (0.7168)	0.5407*** (0.0655)	1.2376** (0.7004)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4764*** (0.1123)	− 1.0836*** (0.2738)
2013	0.7839 (0.5996)	1.8088** (0.7190)	0.5406*** (0.0642)	1.2412** (0.6884)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4772*** (0.1112)	− 1.0876*** (0.2872)
2014	0.7969 (0.6248)	1.8372** (0.7161)	0.5452*** (0.0672)	1.2203** (0.6847)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4782*** (0.1179)	− 1.0915*** (0.2878)
2015	0.7804 (0.5922)	1.8144** (0.7135)	0.5305*** (0.0660)	1.2224** (0.6838)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4693*** (0.1152)	− 1.0738*** (0.2827)
2016	0.7640 (0.5899)	1.7793** (0.7209)	0.5199*** (0.0630)	1.2011** (0.6873)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4626*** (0.1100)	− 1.0603*** (0.2908)
2017	0.6999 (0.5625)	1.6345** (0.7468)	0.5083*** (0.0623)	1.1804** (0.6836)	− 0.1258 (0.0791)	− 0.3730*** (0.0783)	− 0.4596*** (0.1101)	− 1.0580*** (0.2922)

(1)** and *** represent significance at 5% and 1% levels, respectively. (2) The values in brackets are standard errors

building materials, chemical industry, coking and petroleum processing (Ren and Xia 2017). (3) The coefficient of *PGDP* is positive and significant at 1% level, however a high level of *PGDP* led to not only a high level of industrial activities but also frequent activities of daily living, such as burning gasoline when we drive, burning oil or gas for home heating and so on, which might increase *CI* in China. (4) The coefficient of *PE* is negative. On the one hand, the increasing *PE* would decrease energy consumption, which would lead to the lower *CI*. On the other hand, the rising price encouraged enterprises not only to use energy-saving products but also to improve energy efficiency, which can also decrease *CI* in China (Du 2019; Wang et al. 2020c). (5) The coefficient of *EI* is negative and significant at 1% level. Central government and local governments continued to pay more attention to the reduction of carbon emissions and pollution. In fact, China's investment in treatment of environmental pollution increased from162.77 billion yuan in 2003 to 953.895 billion yuan in 2017, accounting for around 1.5% of GDP (Du and Li 2020; Wu et al. 2021). (6) The coefficient of the cross-products between *PGDP* and *EI* is positive, suggesting that the mere pursue GDP by local governments would weaken the restrictive effect of investment in treatment of environmental pollution on *CI* (Xuan et al. 2020; Yang et al. 2021). (7) The coefficients of $W * lnIS$ and $W * lnPGDP$ are both negative, which indicates that industrial development and economic growth had a negative effect on *CI* of adjacent provinces (Lu et al. 2019; Liu and Zhang 2021).

Table 4 The short-term and long-term effects of *IS* on carbon intensity in 30 provinces

District	Direct effect		Indirect effect		Total effect	
	ST	LT	ST	LT	ST	LT
Beijing	0.3611 (0.5367)	0.7625 (0.6784)	− 0.0285 (0.1088)	0.1752* (0.1051)	0.3326* (0.2004)	0.9377 (0.7637)
Tianjin	0.7330 (0.5791)	1.6137* (0.8631)	− 0.0382 (0.1545)	0.4681*** (0.1143)	0.6948 (0.5457)	2.0818** (0.9342)
Hebei	0.7417 (0.5727)	1.6333* (0.8514)	− 0.0287 (0.1414)	0.4857*** (0.1153)	0.7130 (0.5462)	2.1190** (0.9195)
Shanxi	0.8035 (0.5732)	1.7688** (0.8570)	− 0.0394 (0.1463)	0.5162*** (0.1169)	0.7641 (0.5372)	2.2850*** (0.4867)
Shandong	0.7820 (0.5865)	1.7257** (0.8782)	− 0.0395 (0.1503)	0.5162*** (0.1208)	0.7425 (0.5521)	2.2419** (0.9382)
Inner Mongolia	0.7534 (0.5852)	1.6641* (0.8705)	− 0.0368 (0.1423)	0.4876*** (0.1212)	0.7166 (0.5530)	2.1517** (0.9295)
Liaoning	0.7184 (0.5767)	1.5921* (0.8655)	− 0.0332 (0.1418)	0.4642*** (0.1163)	0.6852 (0.5449)	2.0563** (0.9245)
Jilin	0.7371 (0.5988)	1.6239 (0.8923)	− 0.0382 (0.1357)	0.4696*** (0.1218)	0.6989 (0.5546)	2.0935** (0.9498)
Heilongjiang	0.6743 (0.5908)	1.4941* (0.8865)	− 0.0377 (0.1382)	0.4367*** (0.1198)	0.6366 (0.5451)	1.9308** (0.9353)
Shanghai	0.6069 (0.5783)	1.3411 (0.8604)	− 0.0356 (0.1338)	0.3809*** (0.1167)	0.5713 (0.5232)	1.7220* (0.8855)
Jiangsu	0.7209 (0.5879)	1.5896* (0.8774)	− 0.0269 (0.1387)	0.4669*** (0.1197)	0.6940 (0.5526)	2.0565** (0.9310)
Zhejiang	0.6966 (0.5911)	1.5353* (0.8785)	− 0.0336 (0.1422)	0.4490*** (0.1223)	0.6630 (0.5554)	1.9843** (0.9341)
Anhui	0.7073 (0.5935)	1.5630* (0.8833)	− 0.0294 (0.1416)	0.4635*** (0.1180)	0.6779 (0.5679)	2.0265** (0.9487)
Fujian	0.6878 (0.6190)	1.5249* (0.9260)	− 0.0351 (0.1480)	0.4658*** (0.1195)	0.6527 (0.5767)	1.9907** (1.0003)
Jiangxi	0.7184 (0.5998)	1.5898* (0.8990)	− 0.0305 (0.1424)	0.4812*** (0.1222)	0.6879 (0.5685)	2.0710** (0.9611)
Henan	0.7543 (0.5893)	1.6591* (0.8768)	− 0.0452 (0.1523)	0.4710*** (0.1196)	0.7091 (0.5531)	2.1301** (0.9303)
Hubei	0.6659 (0.5782)	1.4780* (0.8686)	− 0.0345 (0.1364)	0.4323*** (0.1206)	0.6314 (0.5428)	1.9103** (0.9315)
Hunan	0.5926 (0.5799)	1.3018 (0.8571)	− 0.0353 (0.1250)	0.3663*** (0.1123)	0.5573 (0.5298)	1.6681* (0.8876)
Chongqing	0.6660 (0.5647)	1.4676* (0.8381)	− 0.0365 (0.1320)	0.4430*** (0.1160)	0.6295 (0.5159)	1.9106** (0.8773)
Sichuan	0.6493 (0.6033)	1.4399 (0.9066)	− 0.0329 (0.1429)	0.4369** (0.1264)	0.6164 (0.5608)	1.8768** (0.9566)
Guangdong	0.6312 (0.6013)	1.3946 (0.8914)	− 0.0369 (0.1444)	0.3920*** (0.1184)	0.5943 (0.5588)	1.7866* (0.9422)
Guangxi	0.6343 (0.5978)	1.3972 (0.8883)	− 0.0251 (0.1381)	0.4149*** (0.1174)	0.6092 (0.5641)	1.8121* (0.9461)
Guizhou	0.6402 (0.5784)	1.4108* (0.8572)	− 0.0371 (0.1411)	0.4084*** (0.1124)	0.6031 (0.5406)	1.8192** (0.9082)
Yunnan	0.6173 (0.5847)	1.3639 (0.8657)	− 0.0348 (0.1292)	0.3871*** (0.1105)	0.5825 (0.5344)	1.7510* (0.9077)
Hainan	0.4027 (0.5486)	0.8933 (0.8148)	− 0.0237 (0.1113)	0.2432** (0.1036)	0.3790 (0.4983)	1.1365 (0.8166)
Shanxi	0.7670 (0.5924)	1.6918* (0.8854)	− 0.0393 (0.1468)	0.4882*** (0.1238)	0.7277 (0.5519)	2.1800** (0.9388)
Gansu	0.6305 (0.6157)	1.3912 (0.9104)	− 0.0404 (0.1425)	0.4058*** (0.1178)	0.5901 (0.5694)	1.7970* (0.9589)
Qinghai	0.6693 (0.6072)	1.4776 (0.9019)	− 0.0381 (0.1414)	0.4149*** (0.1201)	0.6312 (0.5578)	1.8925** (0.9319)
Ningxia	0.7041 (0.5950)	1.5394* (0.8716)	− 0.0393 (0.1391)	0.4403*** (0.1143)	0.6648 (0.5495)	1.9797** (0.9242)
Xinjiang	0.6054 (0.5818)	1.3415 (0.8732)	− 0.0320 (0.1326)	0.3912*** (0.1215)	0.5734 (0.5365)	1.7327* (0.8978)

(1) *, ** and *** represent significance at 10%, 5% and 1% levels, respectively. (2) The values in brackets are standard errors

3.3 The short-term and long-term effects of relevant factors on carbon intensity

Table 3 shows how the short-term (ST) and long-term (LT) effects of the relevant factors evolve over time, using cross-sectional averages of the variables over 30 provinces for each year (It should point out that ST effect and LT effect in Table 3 stand for total effect, which is sum of direct effect and indirect effect). Tables 4, 5 and 6 show how the short-term and long-term effects of three relevant factors vary across province, respectively, using time-average of the variables over the whole time span of the sample for each province.

3.3.1 Evolution of ST and LT of relevant factors

Table 3 shows that: (1) from 2003 to 2017, the absolute values of the coefficients of long-term effects are all larger than those of short-term effects, indicating that all relevant factors had a strong lasting impact on *CI*. (2) Specifically, the long-term effect of *IS* first increased and then gradually decreased. This result is consistent with the findings of Zhang (2015) and *China Petroleum and Chemical Industry*

Table 5 The short-term and long-term effects of *PGDP* on carbon intensity in 30 provinces

District	Direct effect		Indirect effect		Total effect	
	ST	LT	ST	LT	ST	LT
Beijing	0.5325** (0.2519)	0.8681** (0.4295)	− 0.1203*** (0.0410)	0.0692* (0.0371)	0.4122** (0.1881)	0.9372** (0.4501)
Tianjin	0.7119** (0.2992)	1.1668** (0.5024)	− 0.1229** (0.0537)	0.1117** (0.0463)	0.5890** (0.2409)	1.2785** (0.5647)
Hebei	0.7210** (0.2909)	1.1819** (0.4865)	− 0.1207** (0.0511)	0.1126** (0.0465)	0.6003** (0.2370)	1.2945** (0.5548)
Shanxi	0.7508** (0.2917)	1.2313** (0.4963)	− 0.1284** (0.0525)	0.1165** (0.0460)	0.6224*** (0.1774)	1.3478** (0.9780)
Shandong	0.7313** (0.2953)	1.1982** (0.4992)	− 0.1320** (0.0530)	0.1143** (0.0467)	0.5993** (0.2397)	1.3125** (0.5562)
Inner Mongolia	0.7236** (0.2926)	1.1892** (0.4951)	− 0.1340** (0.0536)	0.1117** (0.0475)	0.5896** (0.2393)	1.3009** (0.5589)
Liaoning	0.7182** (0.3066)	1.1816** (0.5214)	− 0.1233** (0.0540)	0.1110** (0.0473)	0.5949** (0.2482)	1.2926** (0.5808)
Jilin	0.7162** (0.2840)	1.1756** (0.4790)	− 0.1276*** (0.0480)	0.1095** (0.0462)	0.5886** (0.2295)	1.2852** (0.5422)
Heilongjiang	0.6958** (0.2964)	1.1459** (0.5020)	− 0.1294** (0.0533)	0.1095** (0.0467)	0.5664** (0.2377)	1.2554** (0.5546)
Shanghai	0.6557** (0.2790)	1.0759** (0.4720)	− 0.1187** (0.0480)	0.0992** (0.0433)	0.5370** (0.2213)	1.1750** (0.5201)
Jiangsu	0.7220** (0.2937)	1.1828** (0.4945)	− 0.1245** (0.0538)	0.1109** (0.0470)	0.5975** (0.2441)	1.2936*8 (0.5544)
Zhejiang	0.7007** (0.2969)	1.1511** (0.4954)	− 0.1187** (0.0504)	0.1125** (0.0474)	0.5820** (0.2441)	1.2636** (0.5510)
Anhui	0.7123** (0.2850)	1.1696** (0.4792)	− 0.1208** (0.0498)	0.1067** (0.0463)	0.5915** (0.2324)	1.2764** (0.5331)
Fujian	0.6845** (0.2974)	1.1258** (0.4983)	− 0.1250** (0.0527)	0.1104** (0.0439)	0.5595** (0.2369)	1.2362** (0.5542)
Jiangxi	0.6986** (0.2929)	1.1477** (0.4979)	− 0.1263** (0.0520)	0.1077** (0.0469)	0.5723** (0.2332)	1.2554** (0.5485)
Henan	0.7190** (0.3181)	1.1748** (0.5260)	− 0.1273** (0.0555)	0.1071** (0.0470)	0.5917** (0.2597)	1.2819** (0.5249)
Hubei	0.6844** (0.2919)	1.1266** (0.4937)	− 0.1217** (0.0509)	0.1059** (0.0477)	0.5627** (0.2344)	1.2325** (0.5591)
Hunan	0.6671** (0.2883)	1.0895** (0.4763)	− 0.1281*** (0.0477)	0.1006** (0.0431)	0.5390** (0.2268)	1.1901** (0.5399)
Chongqing	0.6869** (0.2875)	1.1265** (0.4852)	− 0.1253** (0.0503)	0.1094** (0.0455)	0.5616** (0.2334)	1.2360** (0.5344)
Sichuan	0.6639** (0.2919)	1.0924** (0.4959)	− 0.1257** (0.0490)	0.1046** (0.0462)	0.5382** (0.2270)	1.1970** (0.5428)
Guangdong	0.6729** (0.2945)	1.1039** (0.4967)	− 0.1322** (0.0532)	0.0994** (0.0471)	0.5407** (0.2363)	1.2033** (0.5508)
Guangxi	0.6579** (0.2749)	1.0773** (0.4605)	− 0.1163** (0.0463)	0.1010** (0.0426)	0.5416** (0.2158)	1.1783** (0.5043)
Guizhou	0.6589** (0.2826)	1.0777** (0.4685)	− 0.1319*** (0.0502)	0.0988** (0.0425)	0.5270** (0.2235)	1.1764** (0.5133)
Yunnan	0.6580** (0.2788)	1.0805** (0.4646)	− 0.1336*** (0.0497)	0.0992** (0.0401)	0.5244** (0.2209)	1.1797** (0.5240)
Hainan	0.5611** (0.2508)	0.9235** (0.4262)	− 0.1157*** (0.0412)	0.0813** (0.0386)	0.4454** (0.1862)	1.0048** (0.4549)
Shanxi	0.7313** (0.2953)	1.1993** (0.5032)	− 0.1278** (0.0512)	0.1125** (0.0489)	0.6035** (0.2365)	1.3117** (0.5614)
Gansu			− 0.1300*** (0.0477)		0.5209** (0.2314)	

Table 5 (continued)

District	Direct effect		Indirect effect		Total effect	
	ST	LT	ST	LT	ST	LT
	0.6509** (0.2980)	1.0696** (0.4987)		0.1000** (0.0449)		1.1696** (0.5433)
Qinghai	0.6747** (0.2984)	1.1093** (0.5028)	− 0.1306** (0.0520)	0.1019** (0.0452)	0.5441** (0.2365)	1.2113** (0.5505)
Ningxia	0.7159** (0.2857)	1.1693** (0.4768)	− 0.1308** (0.0518)	0.1100** (0.0453)	0.5851** (0.2296)	1.2793** (0.5349)
Xinjiang	0.6674** (0.2876)	1.0963** (0.4909)	− 0.1236*** (0.0478)	0.1025** (0.0483)	0.5438** (0.2253)	1.1988** (0.5272)

(1) *, ** and *** represent significance at 10%, 5% and 1% levels, respectively. (2) The values in brackets are standard errors

Progress Report. The report finds that, during the "12th Five-Year Plan", China's energy consumption per unit of industrial-added value continued to decline, and achieved the energy-saving targets by optimizing industrial structure and reducing the proportion of energy consuming industries. (3) Similarly, the long-term effect of *PGDP* increased initially and then continued to decline. This evolution is compatible with the fact that from 2003 to the early period of the "12th Five-Year Plan", China has been in the rapid economic development, which led to a high level of industrial activities and frequent activities of daily living and then resulted in large *CI*, however from the late period of the "12th Five-Year Plan" to the early period of the "13th Five-Year Plan", China speeded up green and low-carbon economic development, which led to slow down the trends of *CI* (Yang et al. 2021). (4) Moreover, the long-term effect of *PE* was negative and significant at 1% level, which might be attributed to the substitution effect of *PE* in China (Ren et al. 2009; Du 2019). For example, if the increase in the price of fossil fuels will encourage people to switch to renewable energy sources, such as solar and wind, which can offer the benefits of lower carbon emissions and other types of pollution. (5) Obviously, in the short and long term, the total effects of *EI* were both negative and significant, and the trends remained stable, which indicates that more and more financial resources have been committed to protection of the environment. Furthermore, according to *China's Government Work Reports*, the government expenditure on environmental protection constantly increased in the past decade. From 2003 to 2017, the Chinese government's investment in environmental protection is mainly used for nine key projects, including the capacity building of environmental supervision, the proper disposal of hazardous waste items (HHW), urban wastewater treatment, urban waste management, flue gas desulfurization (FGD), the management of important ecological function areas, the capacity building of national-level nature reserves, the nuclear safety and radiation protection, which has effectively contributed to the reduction of carbon intensity (Wu et al. 2021).

3.3.2 Spatial variation of ST and LT of relevant factors

Table 4 shows that: the short-term indirect effect of *IS* in each province on *CI* is negative and insignificant, while the long-term indirect effect is positive and significant, indicating that in the long term, the spillover effect of *IS* was evident and a rise in the proportion of heavy industry in a province would drive up the *CI* in adjacent provinces. This may be attributed to the fact that the carbon emission is a non-localized environmental challenge with significant spatial spillover characteristics, which could dissuade local governments from implementing carbon emission control (Du et al.2020; Yang et al. 2021). Table 5 shows that: the short-term indirect effect of *PGDP* is negative, while the long-term indirect effect is positive and significant, which might because that in the long term, one government's pursuit of economic growth without environmental costs has aggravated the environmental pollution, due to the adjacent provinces' pressure of competition responsibility (Lu and Yang 2019; Li and Zhang 2019). Table 6 shows that: in the short and long term, the direct and total effects of *EI* are negative, which is similar to the finding of 3.3.1 and shows that investment on environmental protection from local governments constantly decreased the *CI*.

Furthermore, based on the regional division of China, we also find that: (1) in the short and long term, the direct and total effects of *IS* and *PGDP* on *CI* in North China and Northeast China are larger than those in other regions. In fact, North China contains abundant petroleum and coal resources, for example, Shanxi has been the core territory for coal production in China, the coal resources account for 40.4% of the province's land area. According to *Announcement on the Production Capacity of the Province's Production Coal Mines* released by the Shanxi Provincial Energy Bureau points out that, by the end of

Table 6 The short-term and long-term effects of *EI* on carbon intensity in 30 provinces

District	Direct effect		Indirect effect		Total effect	
	ST	LT	ST	LT	ST	LT
Beijing	− 0.3468*** (0.0867)	− 1.0594*** (0.2740)	0.0167 (0.2577)	0.1579* (0.0951)	− 0.3301*** (0.0952)	− 0.9015*** (0.2841)
Tianjin	− 0.4200*** (0.1103)	− 1.2843*** (0.3500)	0.0255 (0.3061)	0.1987 (0.1146)	− 0.3945*** (0.1184)	− 1.0856*** (0.3588)
Hebei	− 0.4222*** (0.1058)	− 1.2914*** (0.3317)	0.0227 (0.2948)	0.1971* (0.1134)	− 0.3995*** (0.1153)	− 1.0943*** (0.3552)
Shanxi	− 0.4342*** (0.1064)	− 1.3268*** (0.3449)	0.0122 (0.2990)	0.1986* (0.1114)	− 0.4220** (0.1750)	− 1.1282*** (0.3563)
Shandong	− 0.4251*** (0.1079)	− 1.2993*** (0.3416)	0.0089 (0.3048)	0.1977* (0.1121)	− 0.4162*** (0.1226)	− 1.1016*** (0.3547)
Inner Mongolia	− 0.4255*** (0.1056)	− 1.3046*** (0.3363)	0.0104 (0.3104)	0.1978* (0.1164)	− 0.4151*** (0.1237)	− 1.1068*** (0.3578)
Liaoning	− 0.4224*** (0.1100)	− 1.2955*** (0.3573)	0.0191 (0.3046)	0.1961* (0.1140)	− 0.4033*** (0.1200)	− 1.0994*** (0.3670)
Jilin	− 0.4198*** (0.1038)	− 1.2850*** (0.3319)	0.0147 (0.2732)	0.1931* (0.1129)	− 0.4051*** (0.1156)	− 1.0919*** (0.3513)
Heilongjiang	− 0.4141*** (0.1060)	− 1.2727*** (0.3391)	0.0145 (0.3066)	0.1969* (0.1116)	− 0.3996*** (0.1199)	− 1.0758*** (0.3450)
Shanghai	− 0.3957*** (0.1012)	− 1.2123*** (0.3244)	0.0303 (0.2816)	0.1876* (0.1068)	− 0.3654*** (0.1065)	− 1.0247*** (0.3326)
Jiangsu	− 0.4234*** (0.1069)	− 1.2943*** (0.3403)	0.0187 (0.3046)	0.1960* (0.1132)	− 0.4047*** (0.1181)	− 1.0983*** (0.3536)
Zhejiang	− 0.4162*** (0.1064)	− 1.2779*** (0.3345)	0.0354 (0.2918)	0.2020* (0.1151)	− 0.3808*** (0.1145)	− 1.0760*** (0.1974)
Anhui	− 0.4176*** (0.1017)	− 1.2790*** (0.3218)	0.0225 (0.2930)	0.1897* (0.1128)	− 0.3951*** (0.1136)	− 1.0894*** (0.3447)
Fujian	− 0.4097*** (0.1052)	− 1.2578*** (0.3348)	0.0239 (0.3014)	0.1999* (0.1082)	− 0.3858*** (0.1154)	− 1.0579*** (0.3392)
Jiangxi	− 0.4124*** (0.1063)	− 1.2640*** (0.3416)	0.0121 (0.3025)	0.1915* (0.1135)	− 0.4003*** (0.1185)	− 1.0724*** (0.3481)
Henan	− 0.4224*** (0.1140)	− 1.2890*** (0.3513)	0.0183 (0.3096)	0.1923* (0.1139)	− 0.4041*** (0.1272)	− 1.0967*** (0.3295)
Hubei	− 0.4075*** (0.1032)	− 1.2511*** (0.3302)	0.0266 (0.2930)	0.1932* (0.1145)	− 0.3809*** (0.1130)	− 1.0579*** (0.3544)
Hunan	− 0.4038*** (0.1036)	− 1.2318*** (0.3205)	0.0143 (0.2832)	0.1883* (0.1050)	− 0.3895*** (0.1158)	− 1.0435*** (0.3496)
Chongqing	− 0.4102*** (0.1029)	− 1.2558*** (0.3322)	0.0225 (0.2926)	0.1968* (0.1114)	− 0.3877*** (0.1156)	− 1.0589*** (0.3356)
Sichuan	− 0.3995*** (0.1032)	− 1.2267*** (0.3332)	0.0173 (0.2883)	0.1919* (0.1098)	− 0.3822*** (0.1123)	− 1.0348*** (0.3365)
Guangdong	− 0.4025*** (0.1049)	− 1.2327*** (0.3354)	0.0078 (0.3071)	0.1845* (0.1149)	− 0.3947*** (0.1224)	− 1.0483*** (0.3518)
Guangxi	− 0.3962*** (0.0982)	− 1.2110*** (0.3086)	0.0312 (0.2734)	0.1877* (0.1021)	− 0.3650*** (0.1046)	− 1.0234*** (0.3207)
Guizhou	− 0.3988*** (0.1002)	− 1.2180*** (0.3119)	0.0117 (0.0391)	0.1861* (0.1033)	− 0.3871*** (0.1156)	− 1.0319*** (0.3243)
Yunnan	− 0.3978*** (0.0987)	− 1.2202*** (0.3119)	0.0093 (0.2810)	0.1870* (0.1024)	− 0.3885*** (0.1145)	− 1.0332*** (0.3282)
Hainan	− 0.3576*** (0.0875)	− 1.0996*** (0.2844)	0.0289 (0.2564)	0.1720* (0.0975)	− 0.3287*** (0.0929)	− 0.9276*** (0.2933)
Shanxi	− 0.4254*** (0.1062)	− 1.3004*** (0.3438)	0.0140 (0.2979)	0.1958* (0.1168)	− 0.4114*** (0.1185)	− 1.1046*** (0.3558)
Gansu						

Table 6 (continued)

District	Direct effect		Indirect effect		Total effect	
	ST	LT	ST	LT	ST	LT
	− 0.3974*** (0.1020)	− 1.2214*** (0.3276)	0.0145 (0.2827)	0.1905* (0.1086)	− 0.3829*** (0.1138)	− 1.0309*** (0.3307)
Qinghai	− 0.4051*** (0.155)	− 1.2424*** (0.3374)	0.0077 (0.2962)	0.1873* (0.1099)	− 0.3974** (0.1727)	− 1.0551*** (0.3461)
Ningxia	− 0.4204*** (0.1008)	− 1.2829*** (0.3185)	0.0142 (0.3021)	0.1960* (0.1139)	− 0.4062*** (0.1149)	− 1.0869*** (0.3381)
Xinjiang	− 0.4056*** (0.1020)	− 1.2421*** (0.3336)	0.0161 (0.2865)	0.1904* (0.1183)	− 0.3895*** (0.1118)	− 1.0517*** (0.3315)

(1) *, ** and *** represent significance at 10%, 5% and 1% levels, respectively. (2) The values in brackets are standard errors

2017, there are 613 producing coal mines in Shanxi with a production capacity of 909.8 million tons per year, and the value added of coal industry leads to more carbon emissions. Meanwhile, Northeast China is the largest old industrial base of China, the enterprises of high energy consumption and high pollution industries accounted for a large proportion in secondary industries, which were the largest source of carbon emissions (Li et al. 2016). (2) In contrast to North China and Northeast China, the short-term and long-term direct effects of *IS* in East China and some provinces and cities in Central China are relatively low, while the direct effects of *EI* are relatively large. Actually, East China and some provinces and cities in Central China took the lead in transformation of industry-oriented structure into service-oriented industrial structure, and the local governments placed a priority on investing in treatment of environmental pollution in the past decade (Li et al. 2016; Huang et al. 2019; Wang et al. 2019; Guo et al. 2021). (3) In Northwest China, the direct and total effects of *IS* and the total effects of *PGDP* are low in the short and long term, which might because that this region had slow economic development and its primary industry had a high share compared to other regions (Fan et al. 2019), such as agriculture and animal husbandry, which has long played a major role in regional gross domestic product, and its heavy industry grew slowly.

4 Conclusion and policy implications

Based on panel data from 30 provinces in China between 2003 and 2017, this paper constructs our GNS with common factors to examine the direct and spatial–temporal spillover effects of *IS*, *PGDP*, *EI* and *PE* on *CI*. Furthermore, we provide effective economic explanations for the observed heterogeneity from spatial and time dimensions, respectively. Perhaps the cross-products reduce the validity of applying the global models, while from the results of the *q*-statistic of the factors and the view of control functions, these factors are not affected by the SSH. The main findings are as follows: (1) China's carbon intensity has been declining from 2003 to 2017 and showed obvious spatial agglomeration through a graphical display. (2) The estimation results of our GNS model further verified the spatial agglomeration and temporal "inertia" of *CI* in China. (3) From the time dimension, all relevant factors had a strong lasting impact on *CI*. The long-term total effects of *IS* and *PGDP* first increased and then gradually decreased. Due to the substitution effect of *PE* in China, the long-term effect of *PE* was negative and significant. Furthermore, the short-term and long-term total effects of *EI* were both negative and significant, and the trends remained stable. (4) From the spatial dimension, there were regional differences in the short-term and long-term effects of the relevant factors on *CI*. In North China and Northeast China, the enterprises of high energy consumption accounted for a large proportion in secondary industries. In East China and some provinces and cities in Central China, the tertiary industry remained the leading sector and the local governments placed a priority on investing in treatment of environmental pollution in the past decade. Northwest China had slow economic development and its primary industry has long played a major role in regional gross domestic product.

Based on the above conclusions, this study puts forward the following policy implications: firstly, since the industrial activities and economic growth are the main factors that increase carbon intensity in China, the government should transform the mode of economic development by optimizing industrial structure, and guide and encourage individual low-carbon lifestyles, such as driving less, installing a low-flow showerhead, bringing reusable bags when shopping and so on.

Secondly, due to the spatial heterogeneity of carbon intensity, different low-carbon development strategies should be applied in different regions. North China and Northeast China should optimize secondary industry, limit industrial development with high energy consumption and high carbon emissions to some extent and encourage the utilization of clean and renewable energy. East China and Central China should continue to encourage the development of tertiary industry, further optimize the energy structure and promote the application of advanced energy technologies. Northwest China should speed up its economic development by accelerating the transformation of industrial structure and improving energy utilization efficiency.

Thirdly, China should continue to promote the market-oriented reform of energy price and gradually improve the carbon emission trading mechanism, which will encourage individuals and enterprises to use low-carbon technologies. If emitting carbon becomes more expensive, consumers and enterprises may seek technologies and products to reduce their costs. As an efficient means, the market mechanism will help promote a shift to a clean energy economy and innovation in low-carbon technologies.

Finally, since the environmental expenditure is an important factor on the path towards a low-carbon economy, all provinces and cities should increase the environmental expenditure, and ensure the efficient use of funds to protect the environment.

Table 9 Driving factor detection of *CI*

Factor	q-statistic	p-value
IS	0.4346	0.0925
PGDP	0.1572	0.8311
EI	0.3836	0.4157

Table 10 Interactive factor detection of *CI*

Interactive factor	q-statistic	Interaction
$IS \cap PGDP$	0.6714	Enhance, nonlinear
$PGDP \cap EI$	0.5310	Enhance, bivariate
$IS \cap EI$	0.5825	Enhance, bivariate

Appendix

See Tables 7, 8, 9, 10 and 11.

Table 7 The standard coal-equivalent coefficients and carbon-emission coefficients

Energy	Standard coal-equivalent coefficient (kgce/kg)	Carbon-emission coefficient (kg/kgce)
Coal	0.7143	0.7559
Coke	0.9714	0.8550
Crude oil	1.4286	0.5857
Gasoline	1.4714	0.5538
Kerosene	1.4714	0.5714
Diesel	1.4571	0.5921
Fuel oil	1.4286	0.6185
Natural gas	1.2150	0.4483

Table 8 Results of spatial correlation test

Spatial weight matrix	Average correlation coefficient	Pesaran's CD-test	α	Global Moran's I
W_1	0.7140	57.6470***	0.9896	0.4071***
W_2	0.7140	57.6470***	0.9896	0. 3483*

* and *** represent significance at 10% and 1% levels, respectively

Table 11 Characteristics of two spatial weight matrices

	W_1	W_2(K = 450)
Dimension	30*30	30*30
Number of non-zero elements	130	46
Proportion of non-zero elements (%)	14.4444	5.1111
Average number of non-zero elements per province	4.3333	1.5333
Number of provinces with the most non-zero elements	8	5
Average weight value of each non-zero element	0.1901	0.2762

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Declarations

Conflict of interest The authors declare no competing interests.

References

Abbasi KR, Kangjuan L, Magdalena R, Pervez AS (2021) Economic complexity, tourism, energy prices and environmental degradation in the top economic complexity countries: fresh panel evidence. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-021-15312-4

Aluko OA, Opoku E, Ibrahim M (2021) Investigating the environmental effect of globalization: insights from selected industrialized countries. J Environ Manage 281:111892. https://doi.org/10.1016/j.jenvman.2020.111892

Anselin L (1988) Spatial econometrics: methods and models. Springer

Ashraf N, Comyns B, Tariq S, Chaudhry HR (2020) Carbon performance of firms in developing countries: the role of financial slack, carbon prices and dense network. J Clean Prod 253:119846. https://doi.org/10.1016/j.jclepro.2019.119846

Aslam B, Hu J, Ali S, AlGarni TS, Abdullah MA (2021) Malaysia's economic growth, consumption of oil, industry and CO_2 emissions: evidence from the ARDL model. Int J Environ Sci Te. https://doi.org/10.1007/s13762-021-03279-1

Bailey N, Holly S, Pesaran MH (2016a) A two-stage approach to spatio-temporal analysis with strong and weak cross-sectional dependence. J Appl Econom 31:249–280. https://doi.org/10.1002/jae.2468

Bailey N, Kapetanios G, Pesaran MH (2016b) Exponent of cross-sectional dependence: estimation and inference. J Appl Econom 31:929–960. https://doi.org/10.1002/jae.2476

Chang L, Hao X, Song M, Wu J, Feng Y, Qiao Y, Zhang B (2020) Carbon emission performance and quota allocation in the Bohai Rim Economic Circle. J Clean Prod 258:120722. https://doi.org/10.1016/j.jclepro.2020.120722

Cheng S, Chen Y, Meng F, Chen J, Liu G, Song M (2021) Impacts of local public expenditure on CO_2 emissions in Chinese cities: a spatial cluster decomposition analysis. Resour Conserv Recy 164:105217. https://doi.org/10.1016/j.resconrec.2020.105217

Chen Y, Lu H, Li J, Xia J (2020) Effects of land use cover change on carbon emissions and ecosystem services in Chengyu urban agglomeration, China. Stoch Environ Res Risk Assess 34:1197–1215. https://doi.org/10.1007/s00477-020-01819-8

Cheng Z, Li L, Liu J (2018) Industrial structure, technical progress and carbon intensity in China's provinces. J Renew Sustain Energy Rev 81:2935–2946. https://doi.org/10.1016/j.rser.2017.06.103

Du S (2019) Research on the impact of energy price changes on energy consumption intensity-Based on the analysis of direct and regulatory effects. J Price Theory Pract 7:61–64

Du W, Li M (2020) Influence of environmental regulation on promoting the low-carbon transformation of China's foreign trade: based on the dual margin of export enterprise. J Clean Prod 244:118687. https://doi.org/10.1016/j.jclepro.2019.118687

Du W, Wang F, Li M (2020) Effects of environmental regulation on capacity utilization: evidence from energy enterprises in China. Ecol Ind. https://doi.org/10.1016/j.ecolind.2020.106217

Elhorst JP (2014) Spatial econometrics: From cross-sectional data to spatial panels. Physica-Verlag, Berlin

Elhorst JP, Gross M, Tereanu E (2018) Spillovers in space and time: where spatial econometrics and global VAR Models Meet, Working Paper Series, vol. 2134. European Central Bank, Frankfurt

Elhorst JP, Madre JL, Pirotte A (2019) Car traffic, habit persistence, cross-sectional dependence, and spatial heterogeneity: new insights using French departmental data. Transp Res Part A Policy Pract 132:614–632. https://doi.org/10.1016/j.tra.2019.11.016

Elhorst JP, Gross M, Tereanu E (2021) Cross-sectional de-pendence and spillovers in space and time: where spatial econometrics and global var models meet. J Econ Surv 35:192–226. https://doi.org/10.1111/joes.12391

Fan L, Ma L, Yu Y, Wang S, Xu Y (2019) Water-conserving mining influencing factors identification and weight determination in northwest China. Int J Coal Sci Technol 6:95–101. https://doi.org/10.1007/s40789-018-0233-2

Guo H, Tan J, Liao S, Liang Z (2021) Exploring the spatial aggregation and determinants of energy intensity in Guangdong province of China. J Clean Prod 282:124367. https://doi.org/10.1016/j.jclepro.2020.124367

Hossain MA, Chen S (2021) The decoupling study of agricultural energy-driven CO_2 emissions from agricultural sector development. Int J Environ Sci Te. https://doi.org/10.1007/s13762-021-03346-7

Huang Y, Duan H, Dong D, Song Q, Zuo J, Jiang W (2019) How to evaluate the efforts on reducing CO_2 emissions for megacities?

Public building practices in Shenzhen city. Resour Conserv Recy 149:427–434. https://doi.org/10.1016/j.resconrec.2019.06.015

Jiang Z, Jin H, Wang C, Ye S, Huang Y (2020) Measurement of traffic carbon emission and its efficiency pattern in the Yangtze River Economic Belt (1985–2016). Environ Sci 41:2972–2980

Li H, Lo K, Wang M, Zhang P, Xue L (2016) Industrial energy consumption in northeast china under the revitalization strategy: a decomposition and policy analysis. Energies 9:549. https://doi.org/10.3390/en9070549

Li J, Ma X, Yuan Q (2019) Evaluation of regional carbon emission efficiency and analysis of influencing factors. J Environ Sci 39:4293–4300

Li G, Zhang W (2019) Environmental decentralization, environmental regulation and industrial pollution control efficiency. Modern Econ Sci 41:26–38

Liu X, Zhang X (2021) Industrial agglomeration, technological innovation and carbon productivity: Evidence from China. Resour Conserv Recy 166:105330. https://doi.org/10.1016/j.resconrec.2020.105330

Lu F, Yang H (2019) Environmental decentralization, local government competition and ecological environment pollution in china. Ind Econ Res 708:113–126

Lu N, Wang W, Wang M, Zhang C, Lu H (2019) Breakthrough low carbon technology innovation and carbon emissions: direct impact and spatial spillover. China's Pop Res Environ 29:30–39

Neya T, Abunyewa AA, Neya O, Zoungrana BJB, Dimobe K, Tiendrebeogo H, Magistro J (2020) Carbon sequestration potential and marketable carbon value of smallholder agroforestry parklands across climatic zones of burkina faso: current status and way forward for REDD+ implementation. Environ Manage 65:203–211. https://doi.org/10.1007/s00267-019-01248-6

Pan J, Zhao X (2018) Simulation of spatial differences of carbon emissions in China based on spatial regression model. J Environ Sci 38:2894–2901

Parent O, Lesage JP (2011) A space-time filter for panel data models containing random effects. Compute Stat Data Anal 55:475–490. https://doi.org/10.1016/j.csda.2010.05.016

Parent O, Lesage JP (2012) Spatial dynamic panel data models with random effects. Regional Sci Urban Econ 42:727–738. https://doi.org/10.2139/ssrn.1609748

Pesaran MH (2015) Testing weak cross-sectional dependence in large panels. Econometric Rev 34:1089–1117. https://doi.org/10.1080/07474938.2014.956623

Pesaran MH (2021) General diagnostic tests for cross-sectional dependence in panels. Empirical Econ 60:13–50. https://doi.org/10.1007/s00181-020-01875-7

Ren F, Xia L (2017) Analysis of china's primary energy structure and emissions reduction targets by 2030 based on multiobjective programming. Math Probl Eng. https://doi.org/10.1155/2017/1532539

Ren T, Daniëls B, Patel MK, Blok K (2009) Petrochemicals from oil, natural gas, coal and biomass: production costs in 2030–2050. Resour Conserv Recy 53:653–663. https://doi.org/10.1016/j.resconrec.2009.04.016

Ridzuan NHAM, Marwan NF, Khalid N, Ali MH, Tseng ML (2020) Effects of agriculture, renewable energy, and economic growth on carbon dioxide emissions: evidence of the environmental Kuznets curve. Resour Conserv Recy 160:04879. https://doi.org/10.1016/j.resconrec.2020.104879

Shabani E, Hayati B, Pishbahar E, Ghorbani MA, Ghahremanzadeh M (2021) The relationship between CO_2 emission, economic growth, energy consumption, and urbanization in the ECO member countries. Int J Environ Sci Te. https://doi.org/10.1007/s13762-021-03319-w

Shi W, Lee LF (2017) Spatial dynamic panel data models with interactive fixed effects. J Econometrics 197:323–347. https://doi.org/10.1016/j.jeconom.2016.12.001

Shobande OA, Asongu SA (2021) Financial development, human capital development and climate change in East and Southern Africa. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-021-15129-1

Song M, Guo X, Wu K, Wang G (2015) Driving effect analysis of energy-consumption carbon emissions in the Yangtze River Delta region. J Clean Prod 103:620–628. https://doi.org/10.1016/j.jclepro.2014.05.095

Sun L, Cao X, Alharthi M, Zhang J, Taghizadeh-Hesary F, Mohsin M (2020) Carbon emission transfer strategies in supply chain with lag time of emission reduction technologies and low-carbon preference of consumers. J Clean Prod 264:121664. https://doi.org/10.1016/j.jclepro.2020.121664

Teng Z, Hu Z, Jiang X (2017) Research on the difference and convergence of carbon productivity change in China's service industry. J Quan Tech Econ 34:78–94

Tian H, Ma L (2020) Analysis of structural factors of carbon intensity change in China's industry. J Natural Resour 35:639–653

Wang J-F, Li X-H, Christakos G, Liao Y-L, Zhang T, Gu X, Zheng X-Y (2010) Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China. Int J Geogr Inf Sci 24:107–127. https://doi.org/10.1080/13658810802443457

Wang J-F, Zhang T-L, Fu B-J (2016) A measure of spatial stratified heterogeneity. Ecol Indic 67:250–256. https://doi.org/10.1016/j.ecolind.2016.02.052

Wang R, Hao JX, Wang C, Tang X, Yuan X (2020a) Embodied CO_2 emissions and efficiency of the service sector: evidence from China. J Clean Prod 247:119116. https://doi.org/10.1016/j.jclepro.2019.119116

Wang X, Feng Q, Song J (2020b) Evolution and influencing factors of spatial correlate ion structure of carbon emission in Chengdu-Chongqing urban agglomeration. China Environ Sci 40:4123–4134

Wang Y, Lei X, Long R, Zhao J (2020c) Green credit, financial constraint, and capital investment: evidence from China's energy-intensive enterprises. Environ Manage 66:1059–1071. https://doi.org/10.1007/s00267-020-01346-w

Wang Y, Xu Z, Zhang Y (2019) Influencing factors and combined scenario prediction of carbon emission peak in China's megacities: a study based on threshold STIRPAT model. J Environ Sci 39:4284–4292

Wu N, Wang Y, Wu J, Feng Q, Li S, Fu Z (2021) Analysis on the relationship between environmental protection investment and changes in resources and environment. J Environ Eng 11:187–193

Xuan D, Ma X, Shang Y (2020) Can China's policy of carbon emission trading promote carbon emission reduction? J Clean Prod 270:122383. https://doi.org/10.1016/j.jclepro.2020.122383

Xu SC, He ZX, Long RY, Chen H, Han HM, Zhang WW (2016) Comparative analysis of the regional contributions to carbon emissions in China. J Clean Prod 127:406–417. https://doi.org/10.1016/j.jclepro.2016.03.149

Yang Y, Yang X, Tang D (2021) Environmental regulations, Chinese-style fiscal decentralization, and carbon emissions: from the perspective of moderating effect. Stoch Environ Res Risk Assess. https://doi.org/10.1007/s00477-021-01999-x

Yin Q, Wang J, Ren Z, Li J, Guo Y (2019) Mapping the increased minimum mortality temperatures in the context of global climate change. Nat Commun 10:1–8. https://doi.org/10.1038/s41467-019-12663-y

Zhang X (2015) Petrochemical industry releases energy saving progress report. China Petro Chem Indus 296:13–13

Zhang Z (2008) Elasticity coefficient of China's energy consumption: estimation and analysis. J Quan Tech Econ 7:42–53

Zhou J, Shi X, Zhao J, Wang Y, Sun L (2019) Analysis on regional differences and influencing factors of carbon emissions from direct domestic energy consumption of Chinese residents. J Safe Environ 19:954–963