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; Aluko et al. 2021; Aslam et al. 2021; Cheng et al. 2021; Hossain and Chen 2021; Shabani et al. 2021).
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:

\[
C_i = \sum_{j=1}^{k} (E_{ij} \times a_j \times b_j) \times \frac{44}{12}
\]  

where \( C_i \) represents the carbon emissions of province \( i \) in period \( t; E_{ij} \) 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:

\[
CI_{it} = \frac{C_i}{GDP_{it}}
\]  

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 \( \alpha \)-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):

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

\[
\bar{\rho}_N = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \hat{\rho}_{ij} = O(N^{2\alpha-2})
\]

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 \( t \); \( \bar{\rho}_N \) is the average correlation coefficient; And \( CD \sim N(0, 1) \); \( \alpha \) is a parameter that can take values on the interval (0,1) (Bailey et al. 2016b), for \( 0 < \alpha < 1/2 \), \( \bar{\rho}_N \) converges 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:

\[
q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N \sigma^2}
\]

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 \( \sigma^2 \) indicates the variance of all the observations; The explained variable is stratified into \( L \) strata, denoted by \( h = 1, 2, \ldots, L \), which are determined by prior knowledge, the determinant factor, or a classification algorithm; \( N_h \) is the number of observations, and \( \sigma_h^2 \) 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:
\[ \ln CI_t = \tau \ln CI_{t-1} + \delta \sum_{j=1}^{N} w_{ij} \ln CI_{j} + \eta \sum_{j=1}^{N} w_{ij} \ln CI_{j-1} + \frac{\sum_{j=1}^{N} \theta_j w_{ij} \ln x_{jt}}{N} + \frac{\sum_{j=1}^{N} \beta_n \ln x_{jt} \ln x_{jmt} + \rho \ln z_t}{N} + \sum_{r=1}^{N} \tau_{ir} x_r + v_{it} \] 

where

\[ v_{it} = \sum_{j=1}^{N} w_{ij} v_{jt} + e_{it} \]

where \( \ln CI_{it-1} \) and \( \sum_{j=1}^{N} w_{ij} \ln CI_{jt} \) represent, respectively, the temporal and spatial lag, and \( \sum_{j=1}^{N} w_{ij} \ln CI_{jt-1} \) represents the spatial–temporal lag of \( \ln CI_{it} \); \( \tau, \delta \) and \( \eta \) 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; \( L = 3, x_{1t}, x_{2t} \) and \( x_{3t} \) 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; \( \beta_n, \theta_l \) and \( \beta_m \) are the coefficients of the exogenous explanatory variables, the exogenous spatial lag explanatory variables and the cross-products of the exogenous variables, respectively; \( z_o \) stands for \( PE \), with coefficient \( \rho \), 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; \( \tau_{ir} \) is the \( i \)th column of \( \tau_r \), which is a vector of length \( N \) representing the factor loadings of common factor \( r \); \( f_r \) 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 \( f_r = (1, \xi_1), \) where \( \mu_1 \) and \( \xi_1 \) represent spatial and time period fixed effects, respectively; Finally, the error term \( v_{it} \) is assumed to follow a local spatial autoregressive process, where \( e_{it} \) reflects an i.i.d disturbance term with zero mean and finite variance \( \sigma^2 \). 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 \( \ln x_{it} \) can be expressed as follows (Elhorst 2014; Elhorst et al. 2018):

\[
\begin{pmatrix}
\frac{\partial E(\ln CI_1)}{\partial \ln x_{1t}} & \cdots & \frac{\partial E(\ln CI_1)}{\partial \ln x_{Nt}} \\
\vdots & \ddots & \vdots \\
\frac{\partial E(\ln CI_N)}{\partial \ln x_{1t}} & \cdots & \frac{\partial E(\ln CI_N)}{\partial \ln x_{Nt}}
\end{pmatrix}
= ((1 - \tau)I_N - (\delta + \eta)W)^{-1}
\times
\begin{pmatrix}
\beta_1 + \sum_{n=1}^{L} \beta_{mn} \ln x_{1mt} & \theta_{w12} & \cdots & \theta_{w1N} \\
\vdots & \ddots & \vdots & \vdots \\
\theta_{wN1} & \theta_{wN2} & \cdots & \beta_1 + \sum_{n=1}^{L} \beta_{mn} \ln x_{Nmt}
\end{pmatrix}
\]

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 \( \ln x_{it} \), 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

| 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 |
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
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 \((-2 \times (460.7400 - 524.4776) = 127.4752)\) 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, \( \tau, \delta \) and \( \eta \) 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) \( \tau \) 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

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Footnote 1 continued

comments and suggestions, which make our study more comprehensive and make the applicability of the proposed model clearer.
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 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 high energy consuming industries, such as steel, steel, iron and so on, which are collected in Table 2. (2) The values in brackets are standard errors.

### Table 2: The estimation results of models

| Variable | SAR (W₁) | SAR (W₂) | SDM (W₁) | SDM (W₂) | GNS (W₁) | GNS (W₂) |
|----------|----------|----------|----------|----------|----------|----------|
| lnCI_{t-1}(τ) | 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_{j}lnCI_{j-1}(δ) | 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_{j}lnCI_{j-1}(η) | -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) |

| 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 |
| | | | | | | |
| | | | | | | |

(1) *, ** and *** represent significance at 10%, 5% and 1% levels, respectively. (2) The values in brackets are standard errors.
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       | ST      | LT       |
| 2003   | 0.7783 | 1.7953***| 0.5343***| 1.2222** | −0.1258 | −0.3730***| −0.4726***| −1.0743***|
|        | (0.6295)| (0.6935) | (0.0687) | (0.6723) | (0.0791) | (0.0783) | (0.1182) | (0.2854) |
| 2004   | 0.7612 | 1.7636** | 0.5303***| 1.2188** | −0.1258 | −0.3730***| −0.4688***| −1.0701***|
|        | (0.6143)| (0.7009) | (0.0645) | (0.7083) | (0.0791) | (0.0783) | (0.1110) | (0.2703) |
| 2005   | 0.7643 | 1.7816** | 0.5285***| 1.2232** | −0.1258 | −0.3730***| −0.4685***| −1.0769***|
|        | (0.5920)| (0.7222) | (0.0666) | (0.6837) | (0.0791) | (0.0783) | (0.1172) | (0.2857) |
| 2006   | 0.8046 | 1.8863***| 0.5436***| 1.2565** | −0.1258 | −0.3730***| −0.4779***| −1.0957***|
|        | (0.6160)| (0.6771) | (0.0687) | (0.6493) | (0.0791) | (0.0783) | (0.1176) | (0.2911) |
| 2007   | 0.7799 | 1.7912** | 0.5311***| 1.2139** | −0.1258 | −0.3730***| −0.4713***| −1.0692***|
|        | (0.5974)| (0.7335) | (0.0652) | (0.6907) | (0.0791) | (0.0783) | (0.1142) | (0.2839) |
| 2008   | 0.8365 | 1.9543***| 0.5411***| 1.2454** | −0.1258 | −0.3730***| −0.4733***| −1.0813***|
|        | (0.6059)| (0.6907) | (0.0649) | (0.6884) | (0.0791) | (0.0783) | (0.1126) | (0.2807) |
| 2009   | 0.7976 | 1.8588***| 0.5427***| 1.2507** | −0.1258 | −0.3730***| −0.4781***| −1.0923***|
|        | (0.6022)| (0.7032) | (0.0655) | (0.6886) | (0.0791) | (0.0783) | (0.1125) | (0.2874) |
| 2010   | 0.7930 | 1.8509***| 0.5414***| 1.2553** | −0.1258 | −0.3730***| −0.4768***| −1.0961***|
|        | (0.6077)| (0.7132) | (0.0662) | (0.6683) | (0.0791) | (0.0783) | (0.1145) | (0.2903) |
| 2011   | 0.7885 | 1.8279** | 0.5343***| 1.2286** | −0.1258 | −0.3730***| −0.4739***| −1.0821***|
|        | (0.6073)| (0.7119) | (0.0677) | (0.6749) | (0.0791) | (0.0783) | (0.1197) | (0.2901) |
| 2012   | 0.8076 | 1.8612***| 0.5407***| 1.2376** | −0.1258 | −0.3730***| −0.4764***| −1.0836***|
|        | (0.6038)| (0.7168) | (0.0655) | (0.7004) | (0.0791) | (0.0783) | (0.1123) | (0.2738) |
| 2013   | 0.7839 | 1.8088** | 0.5406***| 1.2412** | −0.1258 | −0.3730***| −0.4772***| −1.0876***|
|        | (0.5996)| (0.7190) | (0.0642) | (0.6884) | (0.0791) | (0.0783) | (0.1112) | (0.2872) |
| 2014   | 0.7969 | 1.8372***| 0.5452***| 1.2203** | −0.1258 | −0.3730***| −0.4782***| −1.0915***|
|        | (0.6248)| (0.7161) | (0.0672) | (0.6847) | (0.0791) | (0.0783) | (0.1179) | (0.2878) |
| 2015   | 0.7804 | 1.8144** | 0.5305***| 1.2224** | −0.1258 | −0.3730***| −0.4693***| −1.0738***|
|        | (0.5922)| (0.7135) | (0.0660) | (0.6838) | (0.0791) | (0.0783) | (0.1152) | (0.2827) |
| 2016   | 0.7640 | 1.7793** | 0.5199***| 1.2011** | −0.1258 | −0.3730***| −0.4626***| −1.0603***|
|        | (0.5899)| (0.7209) | (0.0630) | (0.6873) | (0.0791) | (0.0783) | (0.1100) | (0.2908) |
| 2017   | 0.6999 | 1.6345** | 0.5083***| 1.1804** | −0.1258 | −0.3730***| −0.4596***| −1.0580***|
|        | (0.5625)| (0.7468) | (0.0623) | (0.6836) | (0.0791) | (0.0783) | (0.1101) | (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 from 162.77 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).
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 the ST effect and LT effect in Table 3 stand for the total effect, which is the 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              | Total ST     | LT           |
|                | (0.2953)      | (0.4992)        | 0.5325**     | 0.0681**     | 0.4122**(0.1881) | 0.9372**(0.4501) |
| Tianjin        | (0.2992)      | (0.5024)        | 0.7119**     | 1.1668**     | 0.5890**(0.2409) | 1.2785**(0.5647) |
| Hebei          | (0.2909)      | (0.4865)        | 0.7210**     | 1.1819**     | 0.6003**(0.2370) | 1.2945**(0.5548) |
| Shandong       | (0.2917)      | (0.4963)        | 0.7508**     | 1.2313**     | 0.6224**(0.1774) | 1.3478**(0.9780) |
| Inner Mongolia | (0.2926)      | (0.4951)        | 0.7236**     | 1.1892**     | 0.5993**(0.2397) | 1.3125**(0.5662) |
| Liaoning       | (0.3066)      | (0.5214)        | 0.7182**     | 1.1816**     | 0.5896**(0.2393) | 1.3099**(0.5589) |
| Jilin          | (0.2840)      | (0.4790)        | 0.7162**     | 1.1756**     | 0.5949**(0.2482) | 1.2926**(0.5808) |
| Heilongjiang   | (0.2964)      | (0.5020)        | 0.6958**     | 1.1459**     | 0.5886**(0.2295) | 1.2852**(0.5422) |
| Shanghai       | (0.2790)      | (0.4720)        | 0.6557**     | 1.0759**     | 0.5664**(0.2377) | 1.2554**(0.5546) |
| Jiangsu        | (0.2937)      | (0.4945)        | 0.7220**     | 1.1828**     | 0.5370**(0.2213) | 1.1750**(0.5201) |
| Zhejiang       | (0.2969)      | (0.4954)        | 0.7007**     | 1.1511**     | 0.5975**(0.2441) | 1.2936**(0.5544) |
| Anhui          | (0.2950)      | (0.4792)        | 0.7123**     | 1.1696**     | 0.5820**(0.2441) | 1.2636**(0.5510) |
| Fujian         | (0.2850)      | (0.4983)        | 0.6845**     | 1.1258**     | 0.5915**(0.2324) | 1.2764**(0.5331) |
| Jiangxi        | (0.2929)      | (0.4979)        | 0.6986**     | 1.1477**     | 0.5595**(0.2369) | 1.2362**(0.5542) |
| Henan          | (0.3181)      | (0.5260)        | 0.7190**     | 1.1748**     | 0.5723**(0.2332) | 1.2554**(0.5485) |
| Hubei          | (0.2919)      | (0.4937)        | 0.6844**     | 1.1266**     | 0.5917**(0.2597) | 1.2819**(0.5249) |
| Hunan          | (0.2883)      | (0.4763)        | 0.6671**     | 1.0895**     | 0.5627**(0.2344) | 1.2325**(0.5591) |
| Chongqing      | (0.2875)      | (0.4852)        | 0.6869**     | 1.1265**     | 0.5390**(0.2268) | 1.1901**(0.5399) |
| Sichuan        | (0.2919)      | (0.4959)        | 0.6639**     | 1.0924**     | 0.5616**(0.2334) | 1.2360**(0.5344) |
| Guangdong      | (0.2945)      | (0.4967)        | 0.6729**     | 1.1039**     | 0.5382**(0.2270) | 1.1970**(0.5428) |
| Guangxi        | (0.2749)      | (0.4605)        | 0.6579**     | 1.0773**     | 0.5407**(0.2363) | 1.2033**(0.5508) |
| Guizhou        | (0.2826)      | (0.4685)        | 0.6589**     | 1.0777**     | 0.5416**(0.2158) | 1.1783**(0.5043) |
| Yunnan         | (0.2788)      | (0.4646)        | 0.6580**     | 1.0805**     | 0.5270**(0.2235) | 1.1764**(0.5133) |
| Hainan         | (0.2508)      | (0.4262)        | 0.5611**     | 0.9235**     | 0.5244**(0.2209) | 1.1797**(0.5240) |
| Shanxi         | (0.2953)      | (0.5032)        | 0.7313**     | 1.1993**     | 0.6035**(0.2365) | 1.3117**(0.5614) |
| Gansu          |              |                 |              |              |                  | 0.5209**(0.2314) |
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 5 (continued)

| District | Direct effect | Indirect effect | Total effect |
|----------|---------------|----------------|-------------|
|          | ST            | LT             | ST          | LT          |
|          | (0.2876)      | 1.0963**       | 0.1236***   | 0.1025**    |
| Xinjiang |               |                | (0.4909)    | (0.0483)    |
| Qinghai  | 0.6747**      | 1.1093**       | -0.1306**   | 0.1019**    |
|          | (0.2984)      | (0.5028)       | (0.0520)    | (0.0452)    |
| Ningxia  | 0.7159**      | 1.1693**       | -0.1308**   | 0.1100**    |
|          | (0.2857)      | (0.4768)       | (0.0518)    | (0.0453)    |
| Xinjiang | 0.6674**      | 1.0963**       | -0.1236***  | 0.1025**    |
|          | (0.2876)      | (0.4909)       | (0.0478)    | (0.0483)    |

(1) *, ** and *** represent significance at 10%, 5% and 1% levels, respectively. (2) The values in brackets are standard errors.
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      | -0.4347*** (0.1064) | -1.3268*** (0.3449) | 0.0122 (0.2990) | 0.1986* (0.1114) | -0.4220** (0.1750) | -1.1282*** (0.3563) |
| Shandong    | -0.4527*** (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*** (0.3218) | 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 (0.3091) | 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       | -0.3875*** (0.1128) | -1.2454*** (0.3280) | 0.0189 (0.2832) | 0.1929* (0.1112) | -0.3957*** (0.1164) | -1.0895*** (0.3236) |
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.

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 | z        | 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 9** Driving factor detection of $C_I$

| 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 $C_I$

| 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  |
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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