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Spillover effects of railway and road on CO_2 emission in China: A spatiotemporal analysis

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ABSTRACT

Estimating the impact of transportation factors on environmental pressure is essential to find de-carbonization pathways for the transportation sector. Existing research mainly focused on the economic impact of transportation factors, the environmental impact is not fully involved. To identify the coupling effect of transportation factors, this study explored the spillover effects of multiple factors on CO_2 emission using the panel data of 30 administrative regions in China. A hybrid model combining expanded Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) and Spatial Durbin Model (SDM) was used to estimate spillover effects of population, economic, technological and transportation factors on CO_2 emissions. And CO_2 emission was calculated by the carbon emission from fossil fuel consumption (coal, oil and gas) and cement production according to the Intergovernmental Panel on Climate Change (IPCC) accounting method. The estimation results indicate the spatial and time-lagged effects were both obvious for CO_2 emission. In addition, transportation factors including the railway factor and the road factor were both found to have significant positive effects on CO_2 emission, 0.344% and 0.129% influence respectively. Based on research findings three main policy implications were proposed including the joint decision-making, the cross-regional de-carbonization evaluation and the integrated management. This study not only reveals important experimental problems but expands a rigorous model specification process.

1. Introduction

As one of the fundamental infrastructures, transportation network has an enormous impact on local, national and international environmental and economic system (Guimera et al., 2005; Wandelt et al., 2017). With the rapid urbanization, more and more transportation infrastructures were constructed to support passenger and freight transport. According to the statistical data from the Organization for Economic Co-operation and Development (OECD), China's passenger turnover and freight turnover volume ranked first in the world in 2015 (OECD, 2015). Huge transport capacity not only brings challenges to transportation network but impacts environmental conditions and economic activities. CO_2 emission is the main environmental negative output during the expansion of transportation network coupling economic development (Xie et al., 2017). The International Energy Agency (IEA) estimates the transportation sector consumes approximately 19% global energy directly and accounts for 23% CO_2 emission related to energy (Van der Hoeven, 2012). And it is predicted that CO_2 emission in the transportation sector will increase by approximately 50% by 2030 (IEA, 2009). In addition, it has been proved that the transport infrastructure plays an increasingly important role in the evolution of city networks (Jiao et al., 2017), the human mobility (Lee et al., 2014) and the city accessibility (Shaw et al., 2014). Therefore, exploring the socio-environmental impacts of the transportation network is essential for understanding the role of the transportation network and finding sustainable pathways for the transportation sector.

Existing researches have been paid attention to the significant contribution of transportation factors to CO_2 emission in the mitigation and sustainability research. And multiple variables related to transport activities have been selected to as transportation factors such as energy consumption of freight and passenger transport (Li et al., 2013), the length of transportation infrastructure (Wang et al.,

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2017) and the capita length (Meng and Han, 2018). In addition, existing researches have explored that different transportation modes contribute to CO_2 emissions in the long term or short term (Li et al., 2017). Compared with other transportation modes, the road network contributes to more CO_2 emissions because of the traffic emission (Li et al., 2016). And the number of vehicles is the main representative of the road factor. However, there are still some research gaps that need to be filled. Firstly, although road infrastructure contributes to more CO_2 emission from the perspective of the traffic system, the impact of the railway is important to be addressed (Meng and Han, 2018). The railway network plays an importation role in human mobility, economy and technology development because economic activities promoted by railway expansion generate emissions indirectly. In addition, some studies have focused on the environmental impact of transportation activities, especially road transportation, but the coupling effects of different modes have not been studied clearly. Therefore, according to the occupancy and significance, the road factor and railway factor were both used to account for the transportation factors in this study. Notably, airline transport was not considered in this paper because the spillover effect in this paper mainly focuses on the effect of adjacent regions and the transport proportion of airline transport is smaller relatively than that of railway or road transport.

Apart from the transportation factor, socioeconomic factors are also the main variables to estimate CO_2 emissions. It has been proved that affluence, population and technology levels are the main driving factors (Liu, et al., 2015a; Zhou and Liu, 2016). From the perspective of the coupling factors, existing studies have shown that the transportation infrastructure contributes to CO_2 emission in two perspectives: the construction and the continued production of devices release CO_2 into the atmosphere directly; the promotion to economic activities emits CO_2 indirectly (Davis et al., 2010; Wang, et al., 2011; Wang, et al., 2011). In details, the first category calculates the road traffic emission which is a bottom-up analysis (Bellasio et al., 2007). This approach is often used to analyze the vehicle emissions related to the transport sector in the city level (Dallmann et al., 2013; Sider et al., 2013). But this method restricted to the quantity and quality of collected data. The second category is usually based on index analysis to identify significances of CO_2 emission factors which is the up-bottom analysis.

In order to explore the combined impact of transportation and socioeconomic factors, many common methods were used including index decomposition analysis (IDA) (Torvanger, 1991), structural decomposition analysis (SDA) (Su and Ang, 2012) and stochastic impacts by regression on population, affluence, and technology (STIRPAT) model (Dietz and Rosa, 1994). Compared with the other two methods, the extended STIRPAT model allows for the expansion of more factors and less data limitation (Xie et al., 2017). This model has been used to explore factors' relationship driving to CO_2 emission and the role of transportation infrastructure in different magnitudes with a range of different data (Xu and Lin, 2015; Wang et al., 2017; Xie et al., 2017). Although existing research has focused on and estimated the impact of different factors on the environment, the spillover effects of factors have not been introduced to evaluate the significances of factors. It has been proved that the spillover term is a well-recognized concern for observational data related to geographical distribution (Yu et al., 2013). Three kinds of general econometric model, namely spatial lag model (SLM), spatial error model (SEM) and spatial Durbin model (SDM) are often used to analyze factors' relationships considering spatial term (Elhorst, 2014b).

The coupling among infrastructure, social, environmental and economic systems has the obvious network and spatial characteristics (Han and Liu, 2009; Wang et al., 2015a). In details, the development of a city or region mainly based on the infrastructure network and social network among regional places, economic activities and people (Camagni and Salone, 1993). In order to explore the impact factors and spatial characteristics of the transportation network, the extended STIRPAT model is combined with the SDM model. A lot of studies used time series or cross-sectional data to estimate CO_2 emission. But it has been widely recognized the panel data are better than time series or cross-sectional data on the estimation results (Kasman and Duman, 2015; Wang et al., 2015b). So in this study, the panel data over the period of 1996–2015 was used to study the spatiotemporal effect of transportation network on CO_2 emissions. The results obtained in the paper indicate the transport factors including railway factor and road factor have obviously significant direct and spillover effects on CO_2 emissions. In doing so, this study makes contributions from both experimental and theoretical perspectives. First, the finding shows spatiotemporal factors should be well-recognized for the observational data related to the geographical distribution or time series. Next, the results indicate the significant role of the transportation factor to reduce CO_2 emission to achieve sustainability. In the future, to find the specific sustainable pathway for the transportation sector, the prediction of the transportation factor's impact on the environment is necessary to support the traffic management and infrastructure expansion.

2. Mechanism analysis

Transportation demands including the transportation of people, goods and information drive to the development of the transport infrastructure, conceptualized as the circle of nodes, networks and the demand (Rodrigue et al., 2016). The fundamental and spatial characteristics of transportation networks determine its influence on CO_2 emission in multiple ways. For the direct impact, the construction of infrastructure emits CO_2 embodied in stocks of cement and other materials (Muller et al., 2013). And the expansion of road infrastructure contributes to the occupancy of vehicles and increases traffic density which promotes CO_2 emissions (Bellasio et al., 2007). From the perspective of indirect impact, transportation network increases emissions by promoting the economic, population and technological factors. First, the development of transportation infrastructure directly reduces the production cost and promote the gross domestic product (GDP). Many empirical studies have proved that transportation infrastructure promotes the economic growth by the migration of production factors (Yu et al., 2013), increased resources availability (Pradhan and Bagchi, 2013) and improved market access (Donaldson and Hornbeck, 2016). Economic growth means frequent economic activities, which inevitably leads to CO_2 emissions.

For the coupling effect with population factor, the expansion of transportation network enhances the accessibility and human mobility which impact the form of urban population (Andrienko et al., 2017; Martí-Henneberg, 2017; Tong et al., 2015). The concentration or spread of population further affects the development of urbanization and industrialization by the change in the labor accessibility. Therefore, the population scale effect always is identified as one of the coupling factors on the region's carbon emission. In addition, with the population expansion and economic growth, the transportation infrastructure enhances the spread of knowledge and technologies which is an important impact factor of innovation capacity (Lambooy, 2010). Improved technological innovation capacity is an effective way to reduce carbon emission and intensity (Xie et al., 2017). In conclusion, all of these impacts are not alone. The production and development of them are coupling and interactional which drives to both positive and negative impacts. Thus, apart from the transportation factor, the significant socio-economic factors should be considered to identify

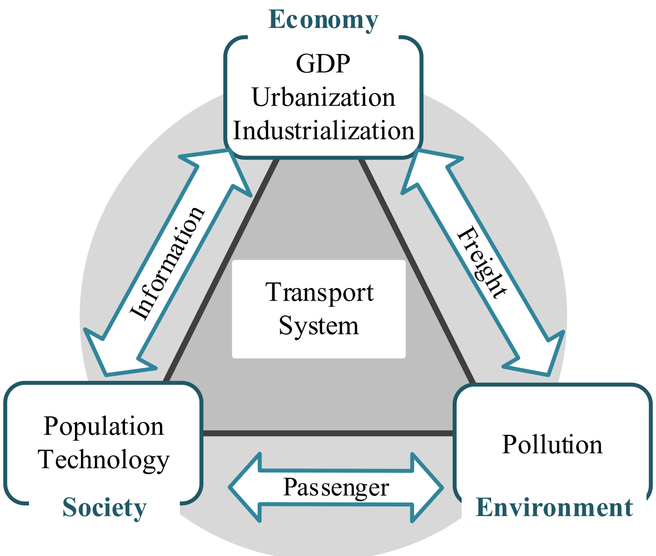

Fig. 1. Coupling impacts of transport system.

their relationships with CO_2 emissions. The interactive impact mechanism of the transport system on the environment coupling economic and social impacts is shown in Fig. 1.

In addition, the spillover effect has been widely regarded as s significant concern for the observational data related to the geographical distribution (Yu et al., 2013). As a cumulative climate impact factor, intra-regional and inter-regional carbon emissions are all necessary during the identification of the environmental driving factors (Zhang, 2017). According to the autocorrelation analysis in section 4.2, CO_2 emission shows significant spatial correlation and distribution effects during the period. Both theoretical and empirical perspectives indicate that direct and spillover-feedback effects should be considered in the empirical model. The spatial economic model involves endogenous interaction effects among the dependent variable, exogenous interaction effects among the independent variables and interaction effects among the error terms (Elhorst, 2014b). Thus, in this study, three different kinds of spatial economic models were used to analyze these endogenous effects and exogenous intersection effects.

The selection of specific transportation factors is mainly based on the spatial attributes, occupancy and importance of the different factor. As the main cross-regional carrier, the transportation infrastructure provides the material basis and motivation for the movement of populations and economic factors among different regions. Especially for the road and railway infrastructure, the former contributes to the increase in the number of vehicles which is the main source of emissions, the latter is the determining factor of the urbanization, sustainability and industrialization, particularly in China (Meng and Han, 2018). And these two transport modes account for most of the passenger and freight transportation. Notably, airline transport was not considered in this paper because the spillover effect in this paper mainly focuses on the effect of adjacent regions. Therefore, in this paper, railway and road factors were used as the main transportation driving factors the spatial spillover effects of carbon emissions.

3. Methods and data

3.1. Model specification

The IPAT model proposed by Ehrlish and Holdren explores factors driving environmental pressure which is described by I=PAT (Ehrlich and Holdren, 1971). Here, I is the environmental factor, P is the population, A is average affluence and T is the technology factor. In 1994, Dietz and Rosa updated the IPAT model to STIRPAT model which further allow for decomposing various factors (Dietz and Rosa, 1994), which is as follows:

$$I_i = \alpha P_i^{\beta_1} A_i^{\beta_2} T_i^{\beta_3} \varepsilon_i \tag{1}$$

where i represents regional unit, I_i, P_i, A_i, and T_i represent the environmental, population, economic and technological variables respectively in region i, α is a constant term, β_1, β_2 and β_3 are estimated parameters and ε is the random error. In general, the logarithmic form is used to the empirical analysis, which is as follows:

$$\mathrm{In}I_i = In\alpha + \beta_1 InP_i + \beta_2 InA_i + \beta_3 InT_i + In\varepsilon \tag{2}$$

In this form, β_1, β_2 and β_3 represent percentage changes related to environmental factor caused by 1% change in other driving factors (Stock and Watson, 2015). In this study, transportation network factors were added to extend the STIRPAT model and improve the identification of environmental driving factors. And the urbanization level and industrialized level are all main impact factors related to CO_2 emissions (Xie et al., 2017). So the STIRPAT model is decomposed as follows:

$$\begin{aligned} \mathrm{In}I_{it} &= In\alpha + \beta_1 InP_{it} + \beta_2 InA_{it} + \beta_3 InT_{it} + \beta_4 InU_{it} + \beta_5 InIN_{it} \\ &+ \beta_6 InRoVe_{it} + \beta_7 InRaND_{it} + In\varepsilon_{it} \end{aligned} \tag{3}$$

where i represent a province, t is year, α is the constant term, β_i is the parameters and ε_{it} is an error term. I_{it} is CO_2 emissions, P_{it} is population size, A_{it} is affluence, T_{it} is technology level, U_{it} is urbanization level, IN_{it} is industrialized level, $RoVe_{it}$ is the road factor and $RaND_{it}$ is the railway factor, ε_{it} is the error term. And the selection and description of factors are shown in the data section. Additionally, according to the Moran's I statistic results shown in section 3.2, the data were affected by spatial autocorrelation. So the spatial factor is necessary to be considered in the econometric model. Three kinds of general econometric model, namely spatial lag model (SLM), spatial error model (SEM) and spatial Durbin model (SDM) are often used to analyze the spatial lag term and the error term. And The SDM is the reduced form of a model with cross-sectional dependence in the errors (Mur and Angulo, 2006). The selection of the model specification depends on multiple statistics test. In the panel data, Hausman test can help to choose between fixed effects model and a random effects model (Mutl and Pfaffermayr, 2011). If the model is tested as the fixed effects model, the likelihood ratio (LR) test can be used to compares the fit of different kind of models including the spatial fixed model and the time fixed model. Additionally, Elhorst proposed the Wald test is one of the efficient criteria to determine whether the SDM can simplify the SLM and SEM models (Elhorst, 2014a). In details, the hypotheses of Wald test are: 1) H_0: $\theta = 0$, SDM model can be reduced to SLM model; H_1: $\theta \neq 0$, SDM model is preferred to SLM model; 2) H_0: $\theta + \lambda\beta = 0$, SDM model can be reduced to SEM model; H_1: $\theta + \lambda\beta \neq 0$, SDM model is preferred to SEM model. If both null hypotheses 1) and 2) are rejected, SDM is the idealistic model for the study. Table 1 shows the test results of model selection and it is clear that the SDM with spatial and time period fixed effects is more suitable for the panel data in this paper.

Based on LeSage and Pace (2010), the SDM contains a spatial lagged dependent variable and spatial lagged independent variables and it is formulated as follow (LeSage and Pace, 2010):

$$y_{it} = \rho w y_{it} + x_{it}\beta + w\bar{x}_{it}\theta + \mu_i + \lambda_t + \varepsilon_{it} \quad i = 1, \dots, N, \ t = 1, \dots, \ T \tag{4}$$

where y_{it} are dependent variables, x_{it} are independent variables, $\bar{x}_{it}$ is the independent variables which have spatial effects, ρ is the spatial autocorrelation coefficient, w is the spatial weight matrix, β and θ are regression coefficient estimates, μ_i represents the fixed spatial effect, λ_t represents the time fixed effect, ε_{it} is the error term. The spatial lagged terms related to dependent and independent variables contribute to the identification of interaction effects among these variables. For identifying the variable autocorrelation in space and time, the dynamic SDM was presented to analyze the lagged term shown as follow (Elhorst, 2014b):

$$y_{it} = \tau y_{i,t-1} + \eta w y_{i,t-1} + \rho w y_{it} + x_{it}\beta + w\bar{x}_{it}\theta + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

where $y_{i,t-1}$ is the dependent variable with time lagged term, $wy_{i,t-1}$ is the dependent variable with space and time lagged terms, τ and η are their corresponding coefficients. According to the model specification, the theoretical model based on static SDM model can be rewritten as:

$$\begin{aligned} \mathrm{In}I_{it} &= \rho\sum_{j=1}^{N} w_{ij}\mathrm{In}I_{jt} + \beta_1 InP_{it} + \beta_2 InA_{it} + \beta_3 InT_{it} + \beta_4 InU_{it} \\ &+\beta_5 InID_{it} + \beta_6 InRoVe_{it} + \beta_7 InRaND_{it} + \\ &\theta_1\sum_{j=1}^{N} w_{ij}InP_{it} + \theta_2\sum_{j=1}^{N} w_{ij}InA_{it} + \theta_3\sum_{j=1}^{N} w_{ij}InT_{it} + \\ &\theta_4\sum_{j=1}^{N} w_{ij}InU_{it} + \theta_5\sum_{j=1}^{N} w_{ij}InID_{it} + \theta_6\sum_{j=1}^{N} w_{ij}InRoVe_{it} + \\ &\theta_7\sum_{j=1}^{N} w_{ij}InRaND_{it} + In\mu_i + In\lambda_t + In\varepsilon_{it} \end{aligned} \tag{6}$$

Similarly, the theoretical model based on dynamic SDM model can be rewritten as:

$$\begin{aligned} \mathrm{In}I_{it} &= \tau InI_{i,t-1} + \eta\sum_{j=1}^{N} w_{ij}\mathrm{In}I_{j,\ t-1} + \\ &\rho\sum_{j=1}^{N} w_{ij}\mathrm{In}I_{jt} + \beta_1 InP_{it} + \beta_2 InA_{it} + \beta_3 InT_{it} + \beta_4 InU_{it} + \beta_5 InID_{it} \\ &+\beta_6 InRoVe_{it} + \beta_7 InRaND_{it} + \\ &\theta_1\sum_{j=1}^{N} w_{ij}InP_{it} + \theta_2\sum_{j=1}^{N} w_{ij}InA_{it} + \theta_3\sum_{j=1}^{N} w_{ij}InT_{it} + \\ &\theta_4\sum_{j=1}^{N} w_{ij}InU_{it} + \theta_5\sum_{j=1}^{N} w_{ij}InID_{it} + \theta_6\sum_{j=1}^{N} w_{ij}InRoVe_{it} + \\ &\theta_7\sum_{j=1}^{N} w_{ij}InRaND_{it} + In\mu_i + In\lambda_t + In\varepsilon_{it} \end{aligned} \tag{7}$$

where j represents the nearby province of I, w_{ij} is the elements of spatial weight matrix and other variables, $\beta_1, \dots, \beta_7$ and $\theta_1, \dots, \ \theta_7$ are regression coefficient of seven independent variables without spatial term and with spatial term and other parameters are defined before. In this paper the spatial weight matrix was based on first order contiguity matrix which indicates whether spatial units share a boundary or not.

Table 1
Model selection.

Test	Type	Statistics	Model specification
Hausman Test		31.985^{***}	Fixed effects
LR test	LR_spatial_lag	29.572^{**}	Spatial and time period effects
	LR_spatial_error	49.183^{***}	
Wald test	Wald_spatial_lag	29.747^{**}	SDM
	Wald_spatial_error	47.897^{***}	

**means significant at confidence level 5%, ***means significant at confidence level 1%.

3.2. Data

In this study, the panel data consists of observations of 30 administrative regions during the period of 1997–2015 in China. The data are collected from Chinese official sources, including China Statistical Yearbook and China Energy Statistical Yearbook. The data of CO_2 emission cannot be collected from existing sources. Thus, the emissions were calculated based on energy consumption and cement production data, according to emission coefficients derived from the Intergovernmental Panel on Climate Change (IPCC) (Eggleston et al., 2006).

The independent variables in this model include transportation factors, the population factor, the affluence factor and the technology factor. The measurements of these factors are as follows: region population at the end of the year represents the factor P, GDP per capita measures the factor A and energy consumption per unit of GDP accounts for the factor T. For the transportation factor, capital stock and public investment are often used to represent the development of transportation infrastructure (Xie et al., 2017). However, for showing network and spatial characteristics the transportation network density was used to describe transportation factor (Wang et al., 2017). Among the four kinds of transportation network (railway, road, airline and inland waterway), railway and road factors play significant roles in passenger and freight transport. And they all have a significant positive or the negative impact on CO_2 emission (Li et al., 2017). So railway network density (RaND) and the number of civil motor vehicles (RoVe) were used to represent the transportation factor commonly.

The dependent variable in this model is CO_2 emission. CO_2 emissions in China mainly result of fossil fuel combustion (90%) in which 68% from coal consumption, 13% from oil and 7% from gas and cement production (10%) (Liu, 2016). These three types of energy could represent the main trend of CO_2 emission (Li et al., 2015; Liu, et al., 2015b), so this paper chose coal, oil and natural gas to account for the regional environmental factor. According to the IPCC guidelines for greenhouse gas inventories, the calculation for energy-related CO_2 emission is as follows (Eggleston et al., 2006):

$$I_E = \sum_{i=1}^{3} E_i \times f_i \times \frac{44}{12} \tag{8}$$

where I_E is CO_2 emission related to energy consumption, i is the three type of energy (coal, oil and natural gas), E_i is the amount of energy consumption, f_i is the carbon emission coefficient. Similarly, CO_2 emission from cement production can be calculated using:

$$I_C = Q \times f \tag{9}$$

where I_C denotes CO_2 emission related to cement production, Q represents the quantity of cement production and f is CO_2 emission coefficient of the cement production process as shown in Table 2. And Table 3 summarizes the descriptive statistics associated with all independent and dependent variables.

4. Results and discussions

4.1. Data pre-test

Before the model estimation, it is necessary to do the data pre-test including the panel unit root test and the panel co-integration test to examine data stability to avoid the spurious regression. Panel unit root test is an effective approach to examine the data stability. This study applied four types of panel unit root tests, namely Levin-Lin-Chu (LLC)(Levin et al., 2002) which is based on common root test, Im-Pesaran-Shin (IPS) test(Im et al., 2003), Fisher-ADF test and fisher-PP test which are based on individual toot tests. The results shown in Appendix 1 indicate that most variables cannot reject the null hypothesis which means most data were not stationary at level. However, their first difference series are stationary. Thus, panel co-integration test was used to identify the co-integration relationship between dependent variable and independent variables. Pedroni test was used to assess the results shown in Appendix 2. It can be seen that the null hypothesis of no co-integration is rejected at the confidence level of 1%. This means there is a long-run integration relationship between CO_2 emission and other dependent variables during the study period.

4.2. Spatial autocorrelation analysis

Spatial autocorrelation is a well-recognized concern for observational data related to geographical distribution in general (Rousset and Ferdy, 2014). It is necessary to analyze the spatio-temporal characteristics of emissions. In this paper, CO_2 emissions of 30 provinces in China were calculated based on energy consumption and cement production from 1997 to 2015. Fig. 2 shows the regional distribution of CO_2 emissions in four selected years. It is found that emissions of many provinces remained increasing trend over time. And there are also some administrative region showed decreasing trends during the study period such as Beijing. The obvious reason for this trend is that as the capital Beijing has the bigger policy supports which also drives the imbalanced development. In contrast, Shandong province experienced the largest increase, rising from 328.34 Mt in 1997 to 1,406.18 Mt in 2015, while Qinghai province experienced the smallest increase, increasing from 16.67 to 59.46 Mt respectively. The different trends result from degrees of energy consumption and cement production in different regions.

Notably, there is a significant region-concentrated trend as shown in four maps of Fig. 2. With the continuous increase of CO_2 emissions, during the study period the higher emitter mainly located in central and Eastern regions. And it is clear that adjacent areas have obvious similar trends, for example in central and eastern coastal regions have similar higher emissions. This clustering trend became increasingly obvious from western to eastern areas. Additionally, in four administrative regions, namely Beijing, Tianjin, Shanghai, Chongqing, the emission levels are significantly lower than their neighbors. Urban roles and policy priority are possible reasons. As the municipalities, these cities play important roles in the political, economic and cultural aspects and they have higher policy priority and autonomy. These factors drive the promotion of economic and technological levels. Therefore, the environmental performances in these municipalities may be better than their neighbors. Although the map of CO_2 emission shows the spatial distribution from the perspective of geography, it is necessary to estimate the specific spatial autocorrelation of variables.

Table 2
Carbon emission coefficient (IPCC, 2006) (t C or CO_2 per t coal, oil, cement and per 1000 m^2 gas).

Energy	Coal	Oil	Gas	Cement
Carbon emission coefficient	0.713	0.828	0.521	0.106
CO_2 emission coefficient	2.614	3.036	1.910	0.389

Moran's index (Moran's I) developed by Patrick Alfred Pierce Moran was used as an indicator to assess the spatial autocorrelation of variables (Li et al., 2007). Spatial autocorrelation is characterized by a correlation in some aspects such as economy, social and technology among nearby locations in space. The calculation of Moran's I is as follow:

$$Moran\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(Y_i - \overline{Y}\right)\left(Y_j - \overline{Y}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$$

$$i = 1, \ldots, n,\ j = 1, \ldots,\ n$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2 \tag{10}$$

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

where i respects the region and j represents its adjacent region, n is the number of regions Y_i is the observation value of i region, and w_{ij} is the spatial weight matrix between i and its neighbor j, S^2 is the variance and $\overline{Y}$ is the mean of Y_i. The range of Moran's I is [-1, 1]. The results of the autocorrelation analysis shown in Fig. 3 indicate there is significant autocorrelation of CO_2 emissions during the period of 1997–2015. The statistic results including E(I), Mean, sd(I), Z-value and P-value are shown in Appendix 3. As shown in Fig. 3, the Moran's I fluctuated from 0.22 to 0.34 at the confidence of 5% or 1% during the study period which means the existence of spatial dependence. And the temporal dynamics of this index reflect the weakness or strengthens of the emission agglomeration. After 2008, the Moran's I has been declining, except for the slight increase in 2013. Therefore, it is clear that the autocorrelation became weaker gradually after 2008.

To represent the autocorrelation of different units, Fig. 4 shows the scatter distributions of Moran's I in four selected years. Four clusters have different autocorrelation meanings: HH represents high-valued points surrounded by similar points, LH represents low-valued points surrounded by high-valued points, LL means low-valued points surrounded by similar points and HL means high-valued points surrounded by low-values ones. It can be seen that most points concentrated in clusters HH and LL which is another evidence of spatial autocorrelation. This spatial autocorrelation of the variable has an important impact on model estimation. Thus, it is necessary to consider the spatial factors to econometric model in this study.

4.3. Model estimation

Before the model estimation, tests of the model selection and the model specification are necessary to ensure the described ability of the model. In this section, the results of both the non-spatial model and the spatial model are provided to test the spatial lag term and the spatial error term. SDM with different effects were estimated to test whether if it can replace the SLM and SEM. The main test methods of the model specification include the Lagrange Multiplier (LM) test and the roust LM test, the Wald test and the likelihood ratio (LR) test. Additionally, to identify the spillover effect of different factors, the direct and indirect effects estimations of SDM are provided. When the spatial autocorrelation

Table 3
Descriptive statistics of variables.

Variables	Definition	Unit	Mean	Std. Dev	Min	Max
CO_2(I)	CO_2 emission	Mt	222.09	183.03	5.31	1,406.18
Population(P)	Regional total population	10^4 persons	4,324.54	2,613.29	496	10,849
Affluence(A)	Per capita GDP	CNY	24,269.87	21,152.2	2250	107,960
Technology(T)	Energy intensity	t/10^4 CNY	1.65	1.59	0.20	14.63
Urbanization(U)	Urbanization rate	%	46.39	16.05	14.04	89.6
Industry(IN)	Industrialization rate	%	38.82	8.05	12.65	53.03
Railway(RaND)	Railway density	km/10^4 km^2	192.76	169.72	10.81	838.92
Road(RoVe)	The number of civil motor vehicles	10^4	6,064.93	4,436.14	192.80	20,818.55

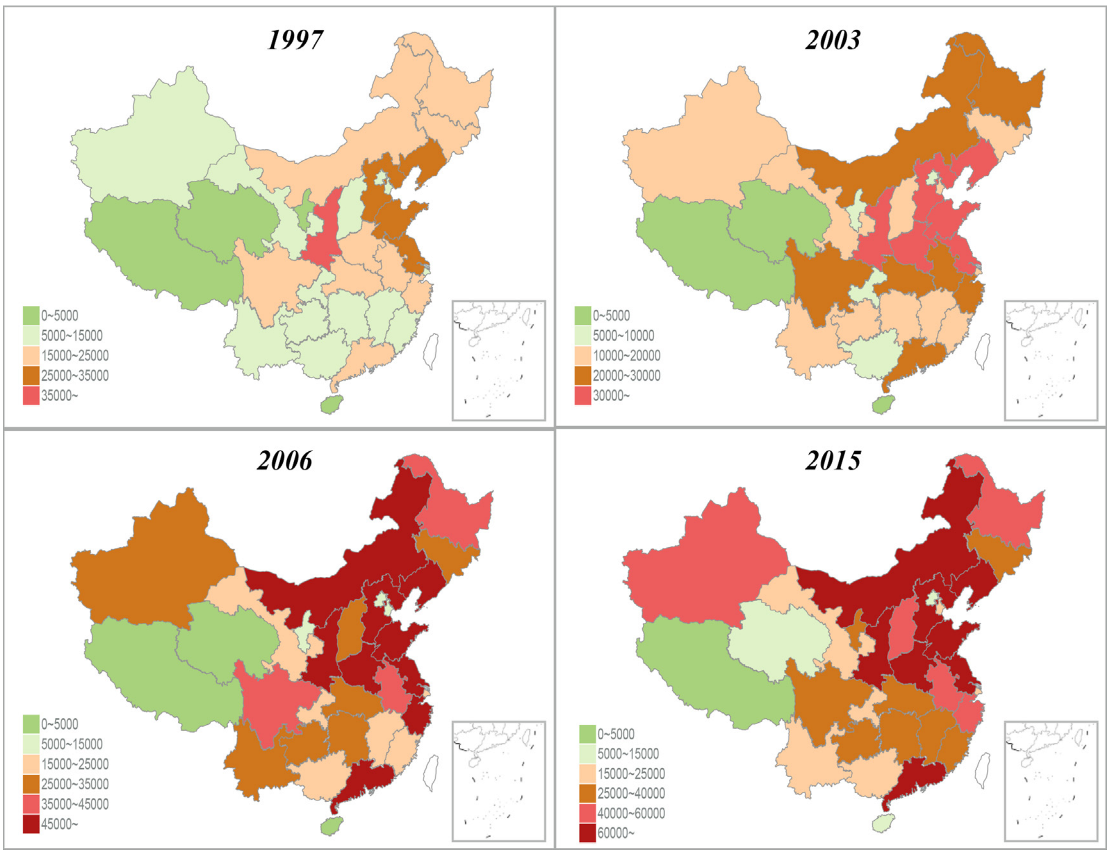

Fig. 2. Spatial distributions of CO_2 emission (10^4 t).

factor is considered in the model, the ordinary least squares regression (OLS) is no longer appropriate because of the inconsistency generated by the lagged endogenous variables (Tientao et al., 2016). The maximum likelihood estimation is the widely used method for the model with spatial autocorrelation term (LeSage and Pace, 2009). The main results of model specification and estimation are presented in Tables 4–6. In addition, since the SDM was used to estimate relationships among variables, the dependent variables also include the average of these variables from neighboring regions which was labeled by W*, such as W*lnI as shown in Table 5.

Table 4 shows estimation results when adopting the non-spatial panel data model and model specification tests. First, the Hausman test was used to differentiate between fixed effects model and the random effect model. According to the result of the Hausman test (109.39 with 15 degrees of freedom (df), $p < 0.01$), the null hypothesis (random effects model) must be rejected. Thus, the fixed effect is more suitable for the model in this study. Then, Table 4 also shows the estimation results without spatial factors and the identification of SLM or SEM by LM test (Anselin, 1988) and robust LM test (Anselin et al., 1996) based on residuals of the OLS model. According to the results of classic LM test and the robust LM test, the null hypotheses of no spatially lagged dependent variable and no spatially auto-correlated term can be rejected at 1% of 5% significance. Additionally, it is important to consider the spatial and/or time-period effects. And the likelihood ratio (LR) test provide results of spatial fixed effects (877.49, 30df, $p < 0.01$) and time-period fixed effects (64.84, 19df, $p < 0.01$) which means these two kinds of fixed effects must be considered in the model. The two results indicate the spatial error model considering spatial and time-period fixed effects is appropriate. But LeSage and Pace (2009) recommended the SDM to replace apply one of two models, the SLM or SEM (LeSage, 2008). According to all the testing results below, this study chose SDM with the spatial and time-period fixed model to estimation the significance of all effect factors.

To verify the result of the model selection further, the estimations of SLM, SEM, SDM and dynamic SDM are compared as shown in Table 5. According to the results of R^2 and σ^2, it is clear that the interpretation ability of SDM is better. In addition, Table 5 not only shows the estimation results of SDM but provides results of the

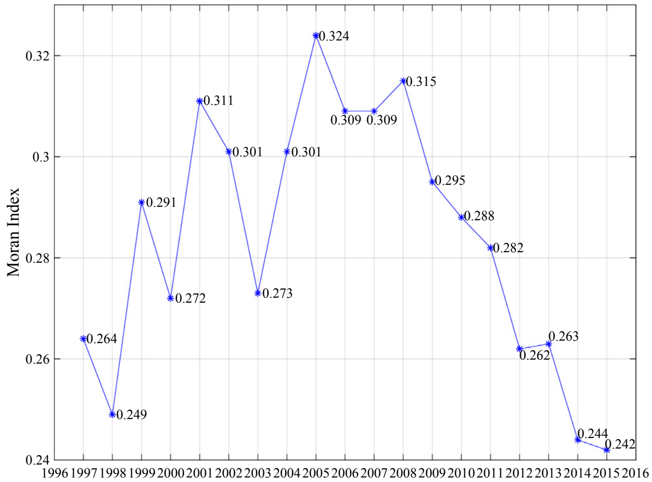

Fig. 3. Moran's I of CO_2 emissions.

Wald test and the LR test to justify the model selection further (Hayashi, 2000). In details, the results of Wald tests and LR test indicates the null hypothesizes (SDM can be simplified to SLM and SEM) can be rejected at 1% or 5% confidence level which means the SDM can replace the SLM and SEM models. Notably, the auto-regression coefficient is 0.594 and significant which means CO_2 emissions of neighboring provinces have a positive effect on one province. This is consistent with the results of Moran's index. Moreover, if the model contains both spatial and time-period fixed effects, parameters need to be bias-corrected (Lee and Yu, 2010). Thus, the compared results without bias correction and with bias correction are shown in column 4 and 5. It is clear that there is little difference for dependent variables and σ^2 among the two models but the lagged dependent and independent variables show more sensitive in the bias-corrected model. In general, bias correction is the default option in panel data estimation and many studies have shown the importance of bias correction for models (Bun and Carree, 2005; Hahn and Moon, 2006). Additionally, to increase the accuracy of model estimation, the results of dynamic SDM were shown in column 6 of Table 5. The goal of dynamic estimation is identifying the serial dependence between the observations on each spatial unit. Therefore, the dependent variable lnI(-1) lagged in time and the dependent variable W*lnI(-1) lagged in both space and time were added. It is clear that all testing results prove the selection of model specification.

According to the results of the five models in Table 5, multiple interesting findings are as follows:

(1) It is clear that the results of R^2 are significant in three models, SLM, SEM and SDM (estimates are 0.984, 0.974 and 0.984 respectively). The spatial auto-regression terms, the spatial

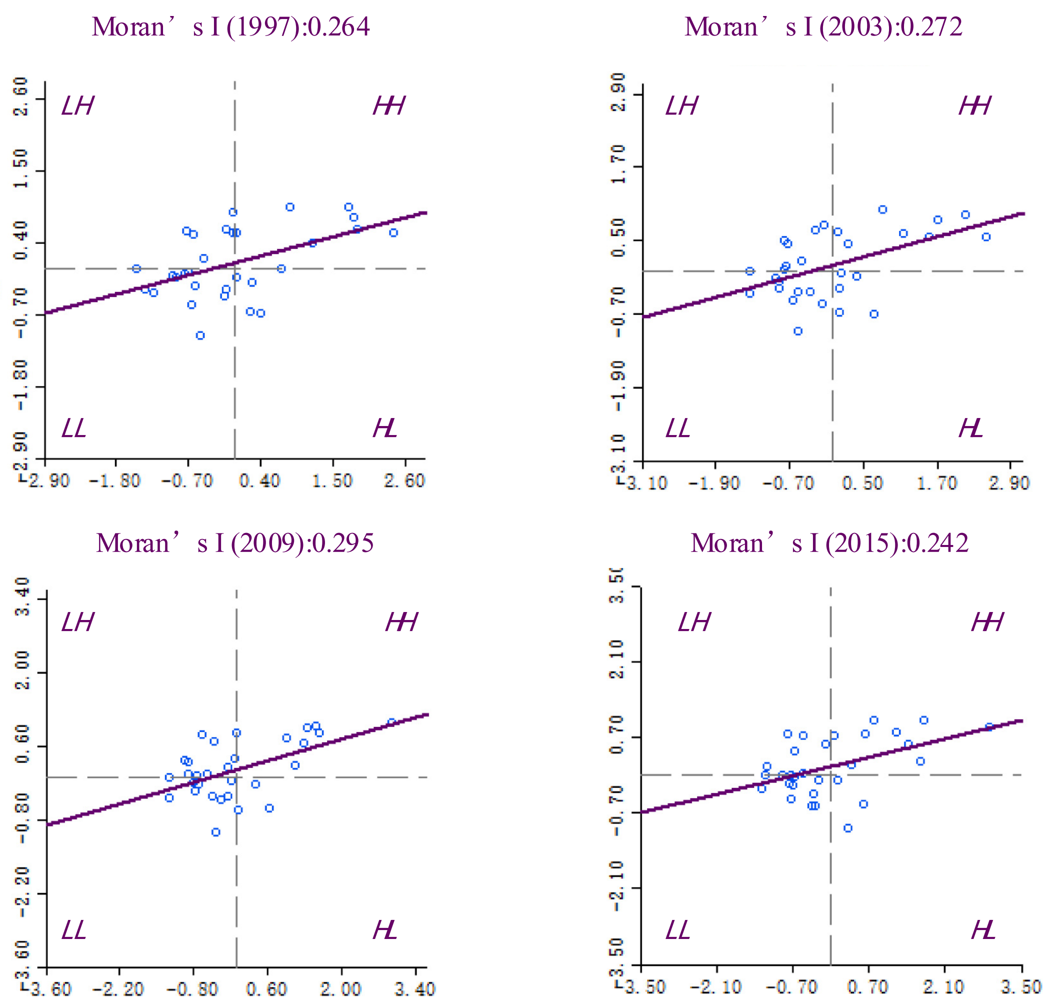

Fig. 4. The scatter distributions of Moran's Indexes (points mean provinces).

Table 4
Estimation results without spatial interaction effects.

Variables/Model	Pooled OLS	Spatial fixed effects	Time-period fixed model	Spatial and time-period fixed effects
lnP	0.432*** (8.218)	0.302** (2.558)	0.495*** (8.797)	0.218* (1.658)
lnA	0.282*** (4.131)	0.534*** (8.887)	0.140** (1.904)	0.472*** (5.548)
lnT	0.497*** (13.509)	0.101*** (4.490)	0.514*** (13.796)	0.073*** (3.293)
lnRaND	0.064*** (3.261)	0.403*** (8.633)	0.091*** (4.516)	0.454*** (9.832)
lnRoVe	0.412*** (8.550)	−0.093** (−1.694)	0.345*** (6.497)	0.094 (1.437)
lnU	−0.168*** (−2.290)	0.210*** (3.986)	0.033 (0.390)	0.152*** (2.643)
lnIN	0.985 (13.901)	0.631*** (8.323)	0.976*** (13.913)	0.452*** (5.831)
Intercept	−1.293** (−1.762)			
σ^2	0.104	0.024	0.099	0.021
R^2	0.875	0.900	0.844	0.898
LogL	−160.052	261.431	−144.893	293.853
LM spatial lag	153.349***	235.619***	116.591***	211.096***
LM spatial error	281.481***	249.659***	261.904***	209.870***
Robust LM spatial lag	4.475**	17.561***	0.899	11.070***
Robust LM spatial error	132.607***	31.601***	146.212***	9.844***

Note: t-values are placed in parentheses under the coefficient values; *means significant at confidence level 10%, **means significant at confidence level 5%, ***means significant at confidence level 1%.

Table 5
Estimation results of SDM with spatial and time-fixed effects.

Variables/Model	SLM	SEM	SDM	SDM with bias-correction	Dynamic SDM
lnP	0.444***(4.128)	0.431***(3.225)	0.623***(3.721)	0.621***(3.618)	0.160** (2.095)
lnA	0.494***(7.107)	0.532***(6.435)	0.618***(6.961)	0.618***(6.797)	0.172***(3.639)
lnT	0.074***(4.089)	0.083***(3.548)	0.087***(3.300)	0.086***(3.197)	0.023*(1.739)
lnRaND	0.334***(8.764)	0.391***(8.747)	0.343***(6.563)	0.344***(6.440)	0.057***(2.982)
lnRoVe	0.092*(1.710)	0.135**(2.056)	0.131**(1.779)	0.129**(1.713)	0.049*(0.831)
lnU	0.092**(1.958)	0.142***(2.696)	0.134**(2.387)	0.135**(2.348)	0.042*(1.725)
lnIN	0.359***(5.654)	0.321***(4.427)	0.232***(2.970)	0.229***(2.854)	0.021(0.897)
lnI(-1)			–	–	0.861***(25.958)
W*lnI(-1)			–	–	−0.191***(-2.818)
W*lnI/λ	0.586***(16.10)	0.638***(17.206)	0.544***(12.731)	0.594***(12.677)	0.445***(6.900)
W*lnP			−0.464(-1.443)	−0.476(-1.446)	−0.089(-0.744)
W*lnA			−0.453***(-2.694)	−0.473***(-2.749)	−0.333***(-2.750)
W*lnT			−0.010(-0.253)	−0.015(-0.372)	−0.043 (−1.463)
W*lnRaND			−0.018(-0.156)	−0.050(-0.407)	−0.163**(-1.892)
W*lnRoVe			−0.093(-0.659)	−0.101(-0.697)	0.134 (1.597)
W*lnU			−0.070(-0.550)	−0.077(-0.585)	−0.188***(-2.436)
W*lnIN			0.397**(2.312)	0.363**(2.067)	0.051***(1.107)
σ^2	0.014	0.013	0.013	0.013	0.004
R^2	0.984	0.974	0.984	0.985	0.995
Corrected R^2	0.389	0.389	0.415	0.412	0.851
LogL	333.344	328.77	340.464	340.429	682.061
Wald_spatial_lag			14.523**	14.485**	16.778**
LR_spatial_lag			14.217**	14.154**	89.015***
Wald_spatial_error			22.912***	20.049***	38.162***
LR_spatial_error			23.359***	23.303***	60.794***

Note: t-values in parentheses; *means significant at confidence level 10%, **means significant at confidence level 5%, ***means significant at confidence level.

lagged term (W*ln(I)) and spatial error term (λ) are significant too (coefficients are 0.586 and 0.638) which indicate the existing of spatial effects.

(2) By comparing the results of three model, it is clear that the R^2 (0.984), corrected R^2 (0.414), log-Likelihood (340.46) of SDM are higher than other two models which mean the explanatory ability of SDM is stronger. This result is consistent with the model tests before. Notably, the spatial dependent and independent variables added in the SDM model lead to huge changes to driving factors of CO_2 emission.

(3) In the static SDM, seven dependent variables have positive and significant impacts on CO_2 emission which means population increase, economic development, technology improvement, transportation network expansion, urbanization and industrialization promote CO_2 emission. Among all impact factors, the biggest drivers are the population factor (P) and the economic factor (A) and their coefficients are 0.621 and 0.618. This means the 1% increase in population or GDP drives to 0.621% or 0.618% increase in CO_2 emission.

(4) Apart from the population and economic factors, the transportation factors have the more obvious impact on CO_2 emission (coefficients of railway factor and road factor are 0.344 and 0.129 respectively) which means transportation factor has become the significant driver contributing to the emission. Notably, the effect of railway factor is much more significant than that of road factor which drives to the rethinking of the effect mechanism of railway network.

(5) According to the results of spillover impact, the W*lnA and W*lnIN variables have significant impacts (the coefficients are −0.473 and 0.363) which means the economic development and industrialization have negative and positive impacts on the emission of neighboring regions. Although not all spillover effects of variables are significant, the autocorrelations of the dependent variable and some independent

Table 6
Direct and Indirect effects estimates.

Variables	Effects	Spatial and time fixed effects	Spatial and time fixed effects bia-corrected	Random spatial and fixed-time period effects
lnP	Direct	0.604***(4.030)	0.592***(3.822)	0.676***(7.267)
	Indirect	−0.272(-0.438)	−0.229(-0.379)	−0.654**(-2.116)
	Total	0.331(0.703)	0.362(0.608)	0.022(0.075)
lnA	Direct	0.597***(7.102)	0.601***(7.061)	0.496***(6.040)
	Indirect	−0.244(-0.806)	−0.248(-0.748)	−0.628**(-2.584)
	Total	0.353(1.181)	0.352(1.019)	−0.131(-0.553)
lnT	Direct	0.093***(3.993)	0.094***(3.689)	0.098***(4.165)
	Indirect	0.069(1.193)	0.076(1.024)	0.076***(1.200)
	Total	0.163**(2.686)	0.170**(2.309)	0.175***((2.809)
lnRa	Direct	0.371***(8.161)	0.375***(7.933)	0.336***(7.643)
	Indirect	0.340(1.679)	0.351(1.477)	0.019(0.114)
	Total	0.711***(3.502)	0.727***(3.077)	0.356**(2.173)
lnRo	Direct	0.130**(1.814)	0.124**(1.818)	0.166**(2.666)
	Indirect	−0.041(-0.132)	−0.036(-0.137)	0.072(0.331)
	Total	0.089(0.354)	0.088(0.330)	0.239(1.089)
lnU	Direct	0.133**(2.500)	0.133**(2.350)	0.123**(2.323)
	Indirect	−0.010(0.022)	−0.005(-0.019)	−0.122(-0.549)
	Total	0.123(0.537)	0.128(0.440)	0.001(0.005)
lnIN	Direct	0.323***(4.810)	0.331***(4.636)	0.398***(5.578)
	Indirect	0.054***(3.407)	0.142***(3.319)	0.189***(4.277)
	Total	0.377***(4.358)	0.473***(4.156)	0.587***(5.760)

Note: t-values in parentheses; *means significant at confidence level 10%, **means significant at confidence level 5%, ***means significant at confidence level 1%.

variables have important impacts on the estimation of coefficients.

(6) Compared with the static SDM, results of the dynamic model show that the coefficients of all variables without the space term are smaller. However, the dependent variable lnI(-1) lagged in time and the dependent variable W*lnI(-1) lagged in both space and time indicate significant impacts on CO_2 emission. The coefficients of them are 0.861 and −0.191. This means the existing of the time autocorrelation for the dependent variable, CO_2 emission.

Additionally, to investigate the accurate direct and spillover effects of different factors, the two-side effects are shown in Table 6. The direct impacts of all variables are positive and significant which is consistent with the results in Table 6. It is notable that the direct effects are different from the coefficient estimates because of the feedback effects from neighboring items. For example, the direct effect of variable P is 0.592 and the coefficient estimate is 0.218, which means the non-spatial model is underestimated by 37.4%. It is clear that some estimations of lagged variables are not significant which is limited to the data (Elhorst, 2014b). Only the coefficient IN is positive and significant (the coefficient is 0.142) which means the 1% improvement of industrialization of a region not only rise 33.1% CO_2 emission of his own but bring 14.2% increase of neighboring region. Additionally, it is clear that the direct estimates are different from the results of coefficient estimates in Table 6. For example, the direct impact of P is 0.592 and its coefficient estimate is 0.621, thus its feedback effect is −0.019 of the direct effect. This two-sided estimation identifying the direct and indirect impact provide more accurate spillover impact results which are consistent with the results in Table 5.

The empirical findings are partly in line with previous studies (Meng and Han, 2018; Xie et al., 2017), for example, the population, economic, technological factors are the most important contributors to CO_2 emission. Meanwhile, urbanization and industrialization levels also have significant abilities to explain this emission. The economic growth, population mobility and technological development generally put pressures on the environment. It is necessary to estimate the significances of impact factors to support the decision-making for economic sectors. In this study, the model decomposes to transportation factors to estimate the role of transportation infrastructure. And the results indicate the road factor represented by the number of cars is the main contributor because of the traffic emission. It is notable that the ignored railway network is also an important factor driving environmental pressure. Although existing studies show railway expansions leads to long-term decreases in CO_2 emission(Li et al., 2017), the integrated impact between railway infrastructure and other factors, population factor, economic factor or technological factor should not be ignored. According to the estimation of SDM, the railway network has a positive and significant impact on the carbon emission which is higher than traffic emission. In China, although the rapid expansion of railway network facilities the transportation mode selection and people mobility, negative impacts such as emission should not be neglected.

4.4. Robustness test

To test the consistency of our results, the CEADs public data is used as the explanatory variable for the spatial model regression. This database subdivides three main types of fossil fuel into 17 types from the perspective of the socioeconomic sectors (Shan et al., 2018). And it follows the Intergovernmental Panel on Climate Change (IPCC) emissions accounting method with a territorial administrative scope, which is the same as the measurement method in the original study. The specific results of this robustness test are illustrated in Appendix 4. Before the regression, some model tests also are used to model specification. The LR test results including the spatial fixed effect (435.91, $p < 0.01$) and time fixed effect (52.00, $p < 0.01$) indicate the spatial panel model should be expanded the one with spatial and time fixed effect. According to the LM test results, although the LM test for spatial lag and spatial error are all significant at the 1% significance, the robust LM test for spatial error is not significant. Therefore, the spatial lag model was used to estimate the endogenous interaction effects among the dependent variables in different regions. According to the model estimation results shown in Appendix 4, the independent variables are all positive and significant apart from the urbanization variable. And the degrees of significance for all variables are consistent with the original results. Notably, the transportation factors and the lagged variable are all significant, which also verify the original hypothesizes.

In addition, multiple endogenous problems have been considered in this paper. Most empirical studies are based on nonexperimental data and basically faced endogenous problems (Lee and Yu, 2016). Sources of these problems mainly include the omitted variable, missing value bias, measurement error and reverse causality between variables. Compared with traditional econometric models, the spatial econometric model has unique endogenous sources and treatments. This study mainly controls endogeneity problems from two aspects, the variable selection and the model estimation. For the first aspect, the extended STIRPAT theoretical model was applied to identify the driving factors and a large number of existing empirical studies have proven the validity of this theoretical model. For the model estimation, the spatial Durbin model (SDM) was used to account for endogenous interaction effects among the dependent variable and exogenous interaction effects among the independent variables (Elhorst, 2014b). And the fixed effect model was used to control the endogenous problem caused by unobserved factors that do not change over time (Sun et al., 2016). Thus, the maximum likelihood (ML) method was used to the parameter estimation to match the non-strict exogenous explanatory variables. In addition, the dynamic spatial panel model has been identified one of the effective tools to explain the endogenous problem (Yu et al., 2012) and the dynamic SDM results consistent with the model without time-lagged variable.

Although the spatial panel model in this paper explains and controls the endogenous problems from several aspects, instrumental variables (IV) regression under the strict exogenous variables is an effective way to test the robustness and efficiency of model estimation. Therefore, in this part, IV (2SLS) method was used to the regression with possibly endogenous variables. As shown in Appendix 5, the first-order lag railway factor and road factor are introduced into the model as the instrumental variable respectively to test the consistency. We can see that the instrumental variables are highly related to the endogenous variables according to the results of LM and Wald F statistics. The independent variables are all positive and significant similar to the original SDM estimation. In particular, two transportation factors significantly and positively influence the dependent variable in these models, showing our original results to be robust.

5. Conclusions and policy implications

As one of the largest contributors to CO_2 emissions, the transportation sector has the responsibility to find a way to achieve traffic reduction and sustainable transportation. The effect identification of the transportation factor on CO_2 emission is a significant pathway to understand the role of the transportation network. Some studies have given evidence on the impact of the transportation factor on the emission particular in the developing countries. However, spatial and time-lagged impacts of different factors have not been fully considered. In order to estimate the significances of population, economic, technological and transportation factor accurately, this study identified the model specification rigorously based on multiple testing indexes, such as Hausman, LR and Wald tests. This study estimated the coefficients of four models, SLM, SEM, SDM and dynamic SDM, based on the panel data of 30 administrative regions in China. By comparing the models' results, the direct and spillover effect of transport factor on CO_2 emissions are proved. The direct and spillover effects of the transportation network has been considered in many countries in different research levels, the city, region and country. In this study, apart from direct emissions from the road and railway factors, the indirect impact was represented by the economic and technical factors and the spillover effect by adjacent regions. And the spillover effects have been identified and proved for the dependent variable and some independent variables. Notably, not only the traditional traffic emission was identified as the main emitter, but the railway network was proved the positive relationship with CO_2 emission.

Based on the findings of this study, some policy implications are presented as follows:

(1) The significant existence of spatial auto-correlation for CO_2 emission implies that the decision-making unit of emission reduction should expand from intra-regions to inter-regions. From the perspective of the theory, when evaluating the levels of CO_2 emission the cross-regional impact should not be ignored. In addition, the existence of spatial auto-correlation for emission indicates the serial lagged impact should also be considered when evaluating the level of regions or their neighboring regions. Apart from the reduction evaluation, the joint decision-making must be an efficient way to achieve the whole reduction goal accompanying the sub-goal achievement for each region.

(2) Apart from the population and economic factors, transportation factors have positive and significant spillover effects on CO_2 emissions based on the results of all models. In particular, the railway network has more obvious impacts than the road factor (the number of vehicles) which has been ignored. The impact mechanism of the railway network is the integrated impacts with other population, economic and technological factors which have been proved in some studies (Li et al., 2017). Thus, the sustainable evaluation or policy plans of transportation sector should not only focus on the road traffic but the expansion of the railway network. In other words, the environmental impact of railway construction should be importation decision factor during the fast track of Chinese railway expansion. Because the goal of the expansion is achieving the maximum of all economic, environmental and social profits which means sustainability.

(3) As for indirect factors, especially the technology factor, there are many improved potentials for the transport sector. Low-carbon and efficient transportation technologies are the main de-carbonization pathways. From the perspective of the transportation network, optimizing mobility structure could reduce the mobility cost and optimize the path selection for freight and passenger transportation. And now the inter-mobility mode for freight transportation and mobility as a service (MasS) for passenger transportation are the hot topics. In addition, new energy vehicles including hybrid electric, battery electric and fuel cell electric vehicles are also a significant de-carbonization pathway.

This paper reveals the important experimental problems based on solid theory and multiple test methods to select variables and model specification. From the perspective of the methodology, the results show that the spatial and time-lagged factors have significant impacts on the estimation. Thus, the spatiotemporal factors should be well-recognized for the observational data related to the geographical distribution or regional analysis. Additionally, the results obtained from this study indicate that transportation factors play an increasingly important role in the reduction of CO_2 emission. In particular, the significant impact of railway network ignored before has to be considered as one of the driving factors to the environmental pressure. This means the expansion plan of the transportation network should integrate both economic and environmental evaluation indexes. The significance identifications of population, economic, technological and transportation factors are the first step to find a way to reduce CO_2 emissions to achieve sustainable goals. In the future, the prediction of the transportation factor's impact on the environment is necessary to support the traffic management and infrastructure expansion. For the transport sector, finding a sustainable development way is an urgent task.

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Appendixes

Appendix 4. Robustness test results with new data

Model Variables	Coefficient	t-stat	z-probability
lnP	0.631	2.464	0.003
lnA	0.661	3.984	0.000
lnT	0.072	1.645	0.09
lnRaND	0.425	4.713	0.000
lnRoVe	0.083	0.650	0.005
lnU	0.174	1.544	0.122
lnIN	0.189	1.250	0.011
W*lnI/λ	0.524	11.954	0.000
LM spatial lag	159.177		0.000
LM spatial error	145.781		0.000
Robust LM spatial lag	14.945		0.000
Robust LM spatial error	1.549		0.213
σ^2	0.080		
R^2	0.929		
Corrected R^2	0.160		
LogL	−147.900		

Appendix1. Results of panel unit root tests

	Series	LLC test (common root)			IPS (individual root)			ADF-fisher (individual root)			PP-fisher (individual root)		
		N	I	I &T	N	I	I &T	N	I	I &T	N	I	I &T
Levels	lnI	13.4	−2.7***	4.6	–	3.2	2.4	3.2	29.6	48.0	1.4	17.4	26.4
	lnP	12.1	−13.5***	−3.9***	–	−2.8***	−0.5	12.8	173.1***	81.0**	6.4	171.0***	58.3
	lnA	22.5	−9.2***	3.0	–	−0.4	0.9	2.9	80.1**	45.2	0.0	30.1	33.7
	lnT	−1.8**	5.8	−0.2	–	10.6	3.4	85.1**	8.4	32.4	93.9***	8.7	31.1
	lnRaND	11.5	6.4	−3.5***	–	10.3	−1.1*	1.3	5.7	85.9**	1.0	7.4	103.4***
	lnRoND	10.9	−4.1***	0.9	–	1.6	2.3	1.1	45.5	27.9	0.8	32.2	33.9
	lnU	13.1	−6.8***	−35.8***	–	−3.0***	−8.8***	4.8	118.7***	77.9*	2.7	255.3***	56.0
	lnID	2.2	−1.5*	0.5	–	1.7	2.0	48.8	44.4	44.9	52.0	26.2	19.7
First difference	lnI	−8.5***	−6.9***	−8.3***	–	−7.0***	−4.4***	160.2***	154.3***	112.0***	189.7***	156.6***	114.0***
	lnP	−5.8***	−11.9***	−13.5***	–	−10.8***	−9.2***	234.9***	227.3***	189.5***	243.6***	251.6***	236.7***
	lnA	−4.2***	−4.7***	0.8	–	−3.4***	6.2	65.1	89.3***	29.5	62.1	85.5**	45.1
	lnT	−11.5***	−18.4***	−16.0***	–	−14.6***	−12.4***	264.8***	295.6***	245.1***	314.9***	365.9***	364.6***
	lnRaND	−20.4***	−20.9***	−20.5***	–	−17.1***	−16.2***	424.3***	352.0***	307.3***	427.6***	822.6***	467.1***
	lnRoND	−17.7***	−20.4***	−17.7***	–	−15.0***	−12.5***	361.8***	302.2***	236.1***	368.8***	307.7***	277.5***
	lnU	−11.8***	−15.3***	−34.4***	–	−12.7***	−20.6***	272.4***	268.7***	277.4***	280.4***	273.1***	317.0***
	lnID	−14.3***	−10.9	−9.0***	–	−9.0***	−5.9***	285.2***	199.5***	138.9***	293.7***	193.5***	151.4***

*means significant at confidence level 10%, **means significant at confidence level 5%, ***means significant at confidence level 1%.

Appendix 2. Pedroni test for co-integration relationship

	Statistic	p-value
Modified Phillips-Perron t	8.5803	0.0000
Phillips-Perron t	−7.3193	0.0000
Augmented Dickey-Fuller t	−6.7382	0.0000

H0: No co-integration. Ha: All panels are co-integrated.

Appendix 3. Moran's Indexes of CO_2 emissions

Variables	I	E(I)	Mean	sd(I)	Z-value	P-value
CO_2_1997	0.264	−0.035	−0.0311	0.1165	2.5305	0.004
CO_2_1998	0.249	−0.035	−0.0317	0.115	2.440	0.009
CO_2_1999	0.291	−0.035	−0.0315	0.115	2.7934	0.007
CO_2_2000	0.272	−0.035	−0.0388	0.1148	2.7029	0.009
CO_2_2001	0.311	−0.035	−0.0327	0.1141	3.0111	0.003
CO_2_2002	0.301	−0.035	−0.0324	0.1138	2.9279	0.004
CO_2_2003	0.273	−0.035	−0.0415	0.1125	2.7988	0.004
CO_2_2004	0.301	−0.035	−0.0408	0.1124	3.0419	0.003
CO_2_2005	0.324	−0.035	−0.0413	0.1107	3.301	0.001
CO_2_2006	0.309	−0.035	−0.0345	0.1100	3.185	0.001
CO_2_2007	0.309	−0.035	−0.0417	0.1106	3.1697	0.001
CO_2_2008	0.315	−0.035	−0.0418	0.1094	3.2626	0.001
CO_2_2009	0.295	−0.035	−0.0364	0.1138	2.9107	0.001
CO_2_2010	0.288	−0.035	−0.0342	0.1156	2.7881	0.003
CO_2_2011	0.282	−0.035	−0.379	0.1133	2.8196	0.004
CO_2_2012	0.262	−0.035	−0.0323	0.1129	2.6062	0.007
CO_2_2013	0.263	−0.035	−0.0367	0.1114	2.6927	0.006
CO_2_2014	0.244	−0.035	−0.0340	0.1167	2.383	0.007
CO_2_2015	0.242	−0.035	−0.0335	0.1147	2.4025	0.008

Appendix 5. Robustness test results with IV regression

Variables	Coefficient	t-stat	z-probability	Coefficient	t-stat	z-probability
lnP	0.197	1.52	0.129	0.247	1.93	0.054
lnA	0.604	9.04	0.000	0.687	9.63	0.000
lnT	0.084	3.63	0.000	0.087	3.75	0.000
lnRaND	0.582	7.06	0.000	0.442	8.78	0.000
lnRoVe	0.205	3.06	0.002	0.245	3.69	0.000
lnU	0.267	4.25	0.000	0.277	4.48	0.000
lnIN	0.549	6.70	0.000	0.501	6.05	0.000
LM statistic	185.965***			402.403***		
Wald F statistic	288.673			1,881.168		
Instrumental variable	First-order lag lnRaND			First-order lag lnRoVe		

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