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Impacts of energy-related CO_2 emissions in China: a spatial panel data technique

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Abstract Since carbon dioxide (CO_2) emissions cause great concern around the world, a large amount of literature focuses on the impact factors of CO_2 emissions. However, there is little specific guidance on the spatial effects of variables and regional characteristics of CO_2 emissions in China. Based on spatial panel methods, this paper used a STIRPAT (stochastic impacts by regression on population, affluence and technology) model to examine the impact of energy-related factors on CO_2 emissions in China. Then, the spillover effects of China's provincial per capita CO_2 emissions have been tested. The results indicate that there exist obvious spatial correlation and spatial agglomeration features in spatial distribution of per capita CO_2 emissions. Spatial economic model is demonstrated to offer a greater explanatory power than the traditional non-spatial panel model. Moreover, GDP per capita, energy intensity, industrial structure and urbanization have positive and significant effects on CO_2 emissions, while the coefficient of population is not significant. According to these results, this paper proposes some policy suggestions on reducing China's CO_2 emissions.

Keywords Spatial panel data model · STIRPAT model · Regional difference · China

1 Introduction

Nowadays, global warming has become the most important environmental issue, since it affects natural ecosystems and threatens human's survival (Chang and Soruco Carballo 2011). The increase in carbon dioxide (CO_2) emissions generated mostly through the

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burning of fossil fuels is considered mainly to blame for global warming. Rising sea levels, melting glaciers and other extreme weather phenomena have aroused worldwide attention. The relationship between CO_2 emissions and natural hazards is becoming a very central and critical issue, even a political issue. It is particularly important to explore the ways of CO_2 emission reduction because CO_2 emissions can lead to serious natural disasters. Combating global climate change requires multilateral international agreements, and each county has the obligation to reduce greenhouse gas emissions. This is particularly true for China which accounted for 25.4 % of the world's CO_2 emissions in 2011 and has been the largest polluter since 2006 (Yin et al. 2015). China has experienced remarkable economic growth accompanied with high demand for energy consumption. Rapid increase in CO_2 emissions in China is not only the result of energy consumption but also a unique set of inner driving factors, such as the huge population pressure, large numbers of low-efficiency high-energy-consuming industries and rapid urbanization. In 2014, China pledged to achieve the peaking of CO_2 emissions around 2030 and increase the share of non-fossil fuels in primary energy consumption to around 20 % by 2030. Hence, it is necessary to explore the driving factors of CO_2 emissions to achieve CO_2 emission reduction goal.

In addressing the impact factors of CO_2 emissions, many scholars used the STIRPAT (stochastic impacts by regression on population, affluence and technology) model to systematically explore CO_2 emissions in different countries and organizations. At the cross-country level, there are extensive studies that have focused on the determinants of CO_2 emissions among different countries by estimating panel data models. Poumanyvong and Kaneko (2010) used the STIRPAT model to investigate the influence factor of CO_2 emissions with a balanced panel dataset of 99 countries and found that there existed a positive link between population, urbanization rate, energy intensity and CO_2 emissions. Sunila Sharma Sharma (2011) investigated the determinants of CO_2 emissions for a global 66 countries and found that trade openness, GDP per capita, electric power consumption per capita and total primary energy consumption per capita had positive effects on CO_2 emissions, while urbanization had a negative impact on CO_2 emissions in high-income, middle-income and low-income countries. Shafiei and Salim (2014) used cross-country panel data to explore the determinants of CO_2 emissions in OECD countries and found evidence suggested that total population size, GDP per capita, industrialization and urbanization had positive and significant effects on CO_2 emissions. Sadorsky (2014) emphatically explored the effect of urbanization on CO_2 emissions in emerging economies and found that the estimated coefficient on the urbanization variable in most specifications was positive but statistically insignificant. Apergis and Ozturk (2015) employed panel data of 14 Asian countries to explore the relationship between GDP per capita, population density, industry shares in GDP and CO_2 emissions, and the estimates had the expected signs and were statistically significant, yielding empirical support to the presence of an EKC for the sample of 14 Asian countries.

Obviously, these studies adopted cross-country panel data and mostly assumed that the impact of determinants on CO_2 emissions is homogeneous across countries. This is a very strong assumption and one that is unlikely to hold across a large grouping of countries. As Wei (2015) pointed out that regional development emerged differences and positively related to local development path, economic structure, spatial linkages and local resource endowments. Based on unique resource and location advantages, countries always appear to be different in development mode and country policies. Hence, omitting analysis the heterogeneity of different economies easily leads to lack of strong explanatory power for the research conclusion.

In addition to cross-country analysis, there are a great number of studies concerning individual countries. Based on times series analysis, Akbostancı et al. (2009) adopted co-integration techniques to explore the CO_2 emissions in Turkey. Saboori and Sulaiman (2013) applied autoregressive distributed lag methodology to test the CO_2 emissions of Malaysia. Besides, there are CO_2 emission researches for other countries such as Brazil (Pao and Tsai 2011), United Arab Emirates (Shahbaz et al. 2014) and Tunisia (Farhani and Ozturk 2015). In the case of China, Lin and Jiang (2009) adopted STIRPAT model with data of time series to analyze the effect of population, GDP per capita, energy intensity, industrialization and urbanization level on China's environmental impact. O'Neill et al. (2012) employed the integrated population–economy–technology–science (IPETS) model to explore the effect of urbanization on energy use in China. Considering regional differences in China, Li et al. (2012) analyzed China's regional difference in determinants of energy-related CO_2 emissions and found that population, GDP per capita, industrial structure, technology level and urbanization had different impacts on CO_2 emissions in China's different emission regions. Wang et al. (2014) investigated the relationship of urbanization, energy consumption and CO_2 emissions using panel data of province level in China and found that there existed a positive bidirectional long-run relationship between the three variables; CO_2 emissions of east region are much higher than that in central and west regions. Wang and Zhao (2015) examined the impact factors including population, GDP per capita, technology, urbanization, industrialization level and foreign trade degree on energy-related CO_2 emissions in three different regions of China and found that differentiated measures for CO_2 reductions should be adopted according to local conditions of different regions in China.

Apparently, most previous studies on the determinants of CO_2 emissions in China using conventional estimation techniques with national time series data or province-level panel data and some studies had explored regional difference in CO_2 emissions. Conventional estimation techniques always assume that the research units are homogeneous, which is a very strong assumption and is unlikely to hold across a large group of provinces like China. The difference in level of development among China's provinces is similar to the heterogeneity of different countries; in other words, China's province-level data are to some extent parallel to the international multicountry data in terms of development disparity. According to the spatial econometric theory, a certain economic geography phenomenon or a certain attribute value in a regional spatial unit is related to the adjacent spatial units on the same phenomenon or attribute value, meaning that the data between cross section and time series have the corresponding spatial correlation. As for spatial econometric model, there also exist some studies mostly focusing on the environment Kuznets curve (EKC) research, such as Maddison (2006) for the EKCs (including SO_2, CO, NO_x, VOC), Wang et al. (2013) for ecological footprint, Hao and Liu (2015) for urban PM2.5 of China. However, these studies just stressed the shape of EKC and explored the relationship between economic development and pollution indicators and did not focus on the research of impacts of CO_2 emissions. Therefore, this paper will re-examine the determinants of provincial CO_2 emissions in China by a statistical STIRPAT model using spatial economic techniques. The object of this study is to test the spatial nexus of provincial CO_2 emissions in China and the driving forces of CO_2 emissions when the spatial effects are controlled. Besides, a comparative analysis of the estimated coefficients between the non-spatial panel model and spatial panel model will be conducted. It is important for China's policy-makers to understand better about the characteristics of provincial CO_2 emissions as well as the determinants for formulating appropriate policies.

The rest of the paper is organized as follows: Sect. 2 presents the model specification and the spatial panel models. Section 3 reports the empirical results and discussions. Finally, Sect. 4 concludes the paper.

2 Methodology

2.1 STIRPAT model

Ehrlich and Holdren (1971) firstly proposed the influence, population, affluence and technology (IPAT) model. Then, many scholars have paid a great deal of attention to the IPAT model to specify the determinants of environmental impact. However, there are two important limitations for IPAT model. Firstly, it does not permit hypothesis testing since the known values of some terms determine the value of the missing term. Secondly, it assumes a rigid proportionality between the variables (Sadorsky 2014). To overcome these limitations, Dietz and Rosa (1997) proposed a stochastic version of IPAT known as STIRPAT model, which is given by the following equation:

$$I_{it} = aP_{it}^{b}A_{it}^{c}T_{it}^{d}e_{it} \tag{1}$$

where a indicates the constant term, b, c and d are the exponential terms of P, A, and T, respectively. Here, i denotes province in China, t denotes the year, and e_{it} is the error term. After taking natural logarithms, Eq. (1) provides a convenient linear specification for panel estimation. Equation (1) can be written as follows:

$$\ln(I_{it}) = a + b\ln(P_{it}) + c\ln(A_{it}) + d\ln(T_{it}) + \varepsilon_{it} \tag{2}$$

Chang (2014) pointed out that China needs to optimize industrial structure to achieve CO_2 emission reduction targets. Wang and Yang (2015) stated that carbon emissions were dominated by the secondary industry in China. Besides, many scholars concluded there was a positive link between urbanization and CO_2 emissions (Wang et al. 2014; Zhang et al. 2014). As China is now in the stage of industrial adjustment and fast urbanization, in this paper, we add the industrial structure and urbanization variables to the STIRPAT model. The augmented model is:

$$\ln(I_{it}) = \alpha + \beta_1\ln(P_{it}) + \beta_2\ln(A_{it}) + \beta_3\ln(T_{it}) + \beta_4\ln(\mathrm{IS}_{it}) + \beta_5\ln(U_{it}) + \varepsilon_{it} \tag{3}$$

where I means CO_2 emissions per capita, P denotes population, A stands for real gross domestic product (GDP) per capita, T denotes technological level usually proxied by energy intensity (Lin et al. 2009; Wang and Zhao 2015). IS denotes the industrial structure. U is urbanization level. The specific descriptions of the variables used in this paper are given in Table 1.

2.2 Spatial econometric models

Following Elhorst (2012), there are mainly two kinds of spatial econometric models, named spatial lag panel model (SLM) and spatial error panel model (SEM).

Spatial lag panel model mainly explores whether there is a diffusion phenomenon (spillover effects) that economic behaviors of the adjacent regions cause to other parts of the local economic behaviors. The spatial lag panel data model can be expressed in matrix form as

Table 1 Definition of the variables used in the study over the period 1997–2012

Variables	Definition	Unit of measurement
CO_2 emissions per capita (PCO_2)	Energy-related CO_2 emissions	ton
Population (P)	Population at the end of year	10^4 units
GDP per capita (PGDP)	GDP divided by population at the end of the year	yuan in constant 1997 price
Energy intensity (EI)	Total energy use divided by GDP	tce per ten thousand yuan
Industrial structure (IS)	Proportion of the secondary industry output value over the total GDP	%
Urbanization (UR)	Percentage of the urban population in the total population	%

$$Y = \rho(I_T \otimes W_N)Y + \beta X + (t_T \otimes I_N)\mu + (I_T \otimes t_N)\delta + u \tag{4}$$

where Y is the dependent variable denoting a $(NT \times 1)$ vector. X is an $(NT \times M)$ matrix of the independent variables assuming there are m independent variables. ρ is the spatial autoregressive coefficient, which reflects the influence degree of spatial factors on the dependent variable. The term μ denotes the individual effect of spatial unit, and δ represents time effect. W_N is a $(N \times N)$ matrix of spatial weighting coefficients. In this paper, we adopt the binary contiguity matrix. That is to say, if province i and j are neighboring, then the value of matrix element is 1, otherwise it is 0. To be consistent with the other literatures, we normalize the matrix according to row standardization to interpret the spatial spillover effects as an average of all neighboring provinces. I_T and I_N denote the identity matrix, and $\otimes$ denotes the Kronecker product. u is a $(NT \times 1)$ error vector and obeys to i.i.d. $(0, \sigma^2 I)$.

While the spatial error panel model is emphasized, faced with the same external environment impact, local economic phenomenon will show similar fluctuations as adjacent areas share some common or similar features. The spatial error panel data model can be expressed as

$$\begin{aligned} Y &= \beta X + (t_T \otimes I_N)\mu + (I_T \otimes t_N)\delta + u \\ u &= \rho(I_T \otimes W_N)u + \varepsilon \end{aligned} \tag{5}$$

where u denotes the spatially autocorrelated error term and ε is a $(NT \times 1)$ error vector and obeys to i.i.d. $(0, \sigma^2 I)$. The other parameters are the same as the above mentioned. Here, ρ reflects the influence degree of spatial factors to the independent variables.

According to different assumptions, the above two kinds of spatial panel models can be divided into fixed effects and random effects models. The fixed effects models can be further divided into fixed space, fixed time, fixed space and time forms. Due to the introduction of spatially lagged dependent variable, spatial econometric models will arouse endogenous variable problem. Hence, if adopting the least squares method to estimate, the coefficient estimates are biased. Generally, the spatial panel models are estimated by maximum likelihood method (Elhorst 2012).

Besides, a third model specification enriches and develops the two kinds of model and provides with a new technical method containing spatial lag both of the dependent variable and the independent variables. It is called spatial Durbin model (SDM), which can be specified as

$$Y = \rho(I_T \otimes W_N)Y + \beta X + \gamma(I_T \otimes W_N)X + (I_T \otimes t_N)\delta + (t_T \otimes I_N)\mu + u \qquad (6)$$

where γ is a $(M \times 1)$ vector of spatial autocorrelation coefficient of independent variables and the other parameters are the same as before.

2.3 Global spatial autocorrelation

Global spatial autocorrelation can examine the overall degree of regional spatial correlation. If there is a spatial correlation of China's overall CO_2 emissions, it is generally tested by Moran's I index. The formula of global Moran's I index can be shown as follows:

$$\text{Moran' } I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \qquad (7)$$

where Y_i represents the observation of CO_2 emissions. The term ω_{ij} denotes binary space adjacent weights. If province i is adjacent to province j, the value of ω_{ij} is 1, otherwise, the value is 0. The global Moran's I index ranges from -1 to 1. The value of global Moran's I index greater than 0 indicates that environmental pollution behavior exists positive spatial autocorrelation. The stronger the value is, the greater the degree of positive autocorrelation is. Conversely, the value less than 0 means that environmental pollution behavior exists negative spatial autocorrelation. The zero value indicates that the environmental pollution behavior is not spatial autocorrelated.

3 Data

3.1 Data sources

This paper estimates the impacts of energy-related CO_2 emissions using a balanced panel dataset of 30 provinces in China over the period of 1997–2012, with a sample of 480 observations. As China has no statistical data of CO_2 emissions directly, most studies are based on the indirect calculation of primary energy consumption. In this paper, we also calculate the CO_2 emissions from the consumption of primary energy. The data on GDP, total population, urban population, the share of the second industry in GDP are from the China statistical yearbook (National Bureau of Statistics of China 1998–2013b). The data on GDP are converted into 1997 constant price (Chinese yuan). The energy data of raw coal, raw oil and natural gas are drawn from the China energy statistical yearbook (National Bureau of Statistics of China 1998–2013a). The standard coal equivalent coefficients for each energy source are also obtained from the China energy statistical yearbook (National Bureau of Statistics of China 1998–2013a).

3.2 The correlations and multicollinearity of variables

The correlation coefficients and multicollinearity test of the variables are shown in Table 2. It can be seen that most correlation coefficients are low or moderate. CO_2 emissions have strong and significant correlation with population, GDP per capita, energy intensity, industrial structure and urbanization. To test for multicollinearity, a variance inflation factor (VIF) test is used over a data range of 1.64–5.75, with a mean value of 3.14. The VIF values are all less than 10, indicating that there is no multicollinearity.

Table 2 Correlation coefficient matrix and VIF test

	VIF	$\ln PCO_2$	lnP	lnPGDP	lnEI	lnIS	lnUR
$\ln PCO_2$		1.000					
lnP	1.64	−0.2038***	1.000				
lnPGDP	5.75	0.6086***	−0.0124	1.000			
lnEI	1.83	0.3950***	−0.3029***	−0.4134***	1.000		
lnIS	1.72	0.5126***	0.3123***	0.3386***	0.137***	1.000	
lnUR	4.75	0.5795***	−0.2292***	0.8584***	0.185**	−0.2623***	1.000

* $P < 0.1$; ** $P < 0.05$; *** $P < 0.01$

4 Empirical results and discussion

4.1 Global spatial autocorrelation test

The global Moran' I index in sample period is 0.074 at a 1 % significant level, which indicates that CO_2 emissions per capita in China tend to cluster together. However, global Moran's I index only tests the overall CO_2 emissions pattern and trend. To further detect the clustering of provincial level, we conduct a Moran's I scatter plot displayed in Fig. 1. There are four quadrants in Fig. 1. The four quadrants in the scatter plot present a classification of four types of spatial autocorrelation: High–High clustering (quadrant I), Low–High clustering (quadrant II), Low–Low clustering (quadrant III) and High–Low clustering (quadrant IV).

Provinces located in the first quadrant are Shaanxi, Ningxia, Gansu, Qinghai, Xinjiang, Yunnan, Guangxi, Guizhou, Sichuan, Chongqing and Hunan. Provinces located in this quadrant area are economic less-developed western regions. It can be found that these areas are basically the largest consumption of primary energy. Provinces located in the second quadrant are Hubei, Fujian, Shandong, Inner Mongolia and Hainan. Furthermore, provinces located in the third quadrant are Zhejiang, Shanghai, Beijing, Tianjin, Hebei, Jilin,

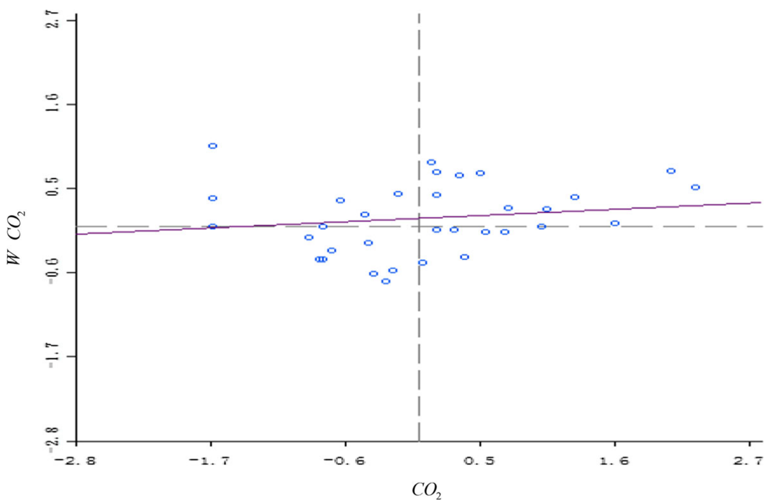

Fig. 1 Moran's scatter plot of China's provincial per capita CO_2 emissions (1997–2012)

Liaoning and Heilongjiang. These provinces or municipalities are mostly the high level of economic development areas in China. Located in the fourth quadrant provinces are Jiangsu, Anhui, Shanxi, Henan, Jiangxi and Guangdong.

Above all, it can be seen that provinces with high per capita CO_2 emissions (in quadrant I) have a tendency to cluster together (11 provinces in total) and provinces with low per capita CO_2 emissions (in quadrant III) tend to cluster together (nine provinces in total), which have accounted for 67 % of the total provinces for the sample period. Thus, spatial agglomeration of China's provincial per capita CO_2 emissions is significant, which means that the spatial autocorrelation exists in provincial per capita CO_2 emissions of China. Besides, the value of global Moran's I index also implies that China has significant spatial clustering of provincial per capita CO_2 emissions.

4.2 Empirical results of spatial panel data models

In order to determine which type of model best fits the data, following Elhorst (2012), at first the procedure begins by testing the non-spatial fixed models. Columns (1)–(4) of Table 3 list the estimation results which give the specification of: pooled OLS only, fixed effects only, time-period fixed effects only and both spatial fixed effects and time-period fixed effects, respectively. These specifications are all estimated by panel least square

Table 3 Estimation results of non-spatial panel model

Determinants	Pooled OLS	Spatial fixed effects	Time-period fixed effects	Spatial and time-period fixed effects
Intercept	−6.614922*** (−13.05720)			
lnP	−0.005104 (−0.299847)	−0.666945* (−6.429234)	−0.006920 −0.409274	−0.535796* (−4.133391)
lnPGDP	0.825791*** (23.41602)	0.779990*** (31.28437)	0.768833*** 16.247400	0.833886*** (8.884926)
lnEI	0.901877*** (35.04979)	0.373471*** (14.63344)	0.891527*** 33.217191	0.324705*** (12.39753)
lnIS	0.390970*** (5.741612)	0.236521*** (2.88392)	0.403829*** 5.945448	0.212901*** (2.60086)
lnUR	−0.001655 (−0.02757)	0.136437*** (3.481958)	0.036304 0.528904	0.255880*** (5.540635)
σ^2	0.0504	0.0118	0.049	0.0108
R^2	0.8849	0.9276	0.8376	0.6069
FE R^2		0.9731	0.8878	0.9754
Log-likelihood	38.9658	387.5093	45.1854	409.019
LM spatial lag	18.0173***	30.0160***	13.5276***	14.5993***
LM spatial error	8.6308***	9.6717***	7.667***	2.9495
Robust LM spatial lag	10.4129***	21.0259***	6.7897***	1.2404***
Robust LM spatial error	1.0265	0.6816	0.9291	7.7229***

The test statistic for the LM test is based on a Chi-squared distribution with one degree of freedom. Numbers in the parentheses represent t-stat values

* $P < 0.1$; ** $P < 0.05$; *** $P < 0.01$

method. We perform a LR test to investigate the null hypothesis that the spatial effects and time-period effects are jointly insignificant. The LR test is rejected at a 1 % significant level (707.69, 29 degrees of freedom, $P < 0.01$). Besides, the null hypothesis that the time-period fixed effects are jointly significant is also rejected (43.02, with 15 degrees of freedom, $P < 0.01$). Thus, these results justify the panel data model with two-way fixed effects including the spatial effects and time-period effects.

The non-spatial panel models may suffer from misspecification if spatial dependence exists within the data of variables. To investigate the spatial dependence, we employ Lagrange multiplier (LM) tests and their robustness to examine whether non-spatial panel data models ignore the spatial effects of data or not as shown in the bottom part of Table 3. Referring to the results of LM tests, the null hypothesis of no spatially lagged dependent variable and the null hypothesis of no spatially autocorrelated error term are strongly rejected at a 1 % significance level in the specifications of pooled OLS, spatial fixed effects only and time-period fixed effects only. The null hypothesis of no spatially autocorrelated error term cannot be rejected in the non-spatial panel model with two-way fixed effects, while the null hypothesis of no spatially lagged dependent variable can be rejected at the 1 % significance level. For these tests' robust counterparts, surprisingly, the null hypothesis of no spatially lagged dependent variable is rejected in all specifications while the null hypothesis of no spatially autocorrelated error term is only rejected in the non-spatial panel model with two-way fixed effects. Apparently, these results imply that there exists spatial correlation among the data. Hence, the OLS estimation of the STIRPAT model is not a good reflection of the real relationships among the variables. In order to obtain better parameter estimates, the spatial panel model may favor over the non-spatial panel model by the LM tests and their robustness.

To further determine which spatial econometric model is appropriate, we estimate the spatial Durbin model and then perform the Wald test and LR test. The null hypothesis (H0: $\gamma = 0$) of Wald test is to examine whether the SDM model can be simplified to the SLM model, and the null hypothesis (H0: $\gamma + \beta\rho = 0$) of LR test is to determine whether the SDM model can be simplified to SEM model. The LR and Wald test statistics are reported in Table 4. According to the results of Wald test and LR test, both of the null hypotheses are rejected at the 1 % significance level, which indicates that the SDM model is the most appropriate specification for this relationship. Hence, we utilize the maximum likelihood method to examine SDM model with spatial fixed effects, time-period fixed effects, two-way fixed effects and spatial random effects which are reported in Table 5.

We conduct a Hausman test to determine which are stronger between fixed effects and random effects, and the Hausman test presents that the random effects are rejected at a 1 %

Table 4 Diagnostic tests of spatial specification

Determinants	Spatial fixed effects	Time-period fixed effects	Spatial and time-period fixed effects	Spatial random effects and time-period fixed effects
Wald test spatial lag	45.9477***	28.7087***	38.4878***	41.254***
LR test spatial lag	45.8075***	28.9589***	36.429***	57.5782***
Wald test spatial error	59.3448***	31.6197***	53.5573***	53.8232***
LR test spatial error	58.6308***	30.828***	50.7537***	58.5523***

Both tests follow a Chi-squared distribution with K degrees of freedom

* $P < 0.1$; ** $P < 0.05$; *** $P < 0.01$

Table 5 Estimation results of spatial Durbin model

Determinants	Spatial fixed effects	Time-period fixed effects	Spatial and time-period fixed effects	Spatial random effects and time-period fixed effects
ρ	0.170430*** (2.936254)	0.172248*** (3.015608)	0.096431* (1.692498)	0.130349** (2.306529)
lnP	−0.127072 (−0.938009)	−0.027819 (−1.642991)	−0.179372 (−1.231985)	−0.139808* (−1.93525)
lnPGDP	0.979678*** (12.39517)	0.773343*** (13.02212)	0.882955*** (9.733161)	0.823412*** (10.78170)
lnEI	0.343272*** (13.36334)	0.850584*** (28.07516)	0.326610*** (12.90697)	0.327014*** (12.87595)
lnIS	0.190970** (2.307030)	0.422195*** (5.780206)	0.241382*** (2.957732)	0.316714*** (4.086962)
lnUR	0.215850*** (4.331794)	0.034434 (0.476123)	0.234831*** (4.801026)	0.213628*** (4.364268)
W*lnP	−0.574828*** (−2.776871)	0.126605*** (3.432905)	−0.654816*** (−2.920982)	−0.272778** (−2.129604)
W*lnPGDP	−0.350358*** (−3.478045)	−0.127993 (−1.219825)	−0.478309*** (−3.079777)	−0.470444*** (−3.596189)
W*lnEI	0.093809 (1.240603)	0.000618 (0.008159)	−0.024649 (−0.262663)	−0.036015 (−0.396437)
W*lnIS	0.373011** (2.175649)	0.283624* (1.896854)	0.574325*** (3.246872)	0.758876*** (4.785622)
W*lnUR	−0.093159 (−1.464716)	−0.093263 (−0.761985)	0.035401 (0.45281)	0.032277 (0.410998)
σ^2	0.0106	0.0457	0.0095	0.0103
Corr-squared	0.9376	0.8501	0.6478	0.5779
Log-likelihood	423.8973	65.9349	435.5090	338.9668

Numbers in the parentheses represent *t*-stat values

* $P < 0.1$; ** $P < 0.05$; *** $P < 0.01$

significance level (49.26, with 15 degrees of freedom, $P < 0.01$), suggesting that the fixed effects models in Table 5 are more appropriate specifications. According to the value of R^2 and the log-likelihood, listed in the bottom of Table 5, the SDM model with spatial fixed effects (SDM FE model) is chosen as the best model specification. The estimate results show that all of the spatially lagged explanatory variables are statistically significant except the population. Given our normalization of the spatial weighting matrix, the positive sign of the lagged dependent variable coefficients in SDM FE model suggests that CO_2 emissions in neighboring provinces, on average, are exerting a positive effect on local CO_2 emissions. This is consistent with the results of Moran's I index and the LM tests with their robustness for spatial autocorrelation in Table 3. As shown in Table 5, a 1 % average change of CO_2 emissions in adjacent neighborhood provinces will cause a 0.17 % change in CO_2 emissions of the home province. Since CO_2 emissions are estimated based on primary energy consumption across provinces in this paper, this coefficient implies that provinces with similar energy-related CO_2 emissions generally gather together.

A comparison of the SDM FE model in Table 5 to the corresponding non-spatial two-way fixed effect model in Table 3 reveals that all of the coefficient estimates (in absolute terms) are inconsistent. These differences arise because the non-spatial panel data model is potentially misspecified due to the presence of spatial dependence within the data (Burnett et al. 2013). Another interpretation is the feedback effects, one province can influence the CO_2 emissions of adjacent provinces and in this way the CO_2 emissions of itself can be affected in turn. The feedback effects are partially from spatially lagged dependent variable ($\rho(I_T \otimes W_N)Y$), and the other part comes from the spatially lagged independent variables ($\gamma(I_T \otimes W_N)X$). For example, the coefficient estimate of energy intensity by SDM FE model is 0.34, while the coefficient estimate by non-spatial panel data model is 0.32. Hence, the feedback effect amounts to -0.02, meaning that the elasticity of energy intensity in non-spatial panel model is underestimated. The non-spatial model results may lead policy-makers to believe that reducing energy intensity by 1 % will result in CO_2 emission reductions by 0.32 %. However, in fact, the coefficient estimate from the SDM FE model yields a larger reduction of 0.34 %. This means that China's local governments should break administrative boundaries to strengthen regional cooperation promote CO_2 reduction together. It also shows the importance for policy-maker to improve system design and institutional innovation to make the most effective way to reduce CO_2 emissions in total.

4.3 Discussion

To analyze the influence factors of CO_2 emissions, geographic spatial dependence cannot be ignored. CO_2 emissions per capita present clustering phenomenon among provinces in China. From the results of Moran's I scatter plot, China has formed two obvious CO_2 emissions' clustering zones, the western provinces (including Shaanxi, Ningxia, Gansu, Qinghai and Xinjiang) and the southwest provinces (including Yunnan, Guangxi, Guizhou, Sichuan and Chongqing) gather the core regions of high per capita CO_2 emissions; the northeast provinces (including Jilin, Liaoning and Heilongjiang) and the northern provinces (including Hebei, Beijing, Tianjin and Inner Mongolia) are the core regions of the low per capita CO_2 emissions. The spatial correlation presents an obvious apparent blocks structure in western and northern China. This spatial structure indicates that China's western provinces have more responsibility for reducing CO_2 emissions. Western provinces are economically underdeveloped with onefold economic structure. Based on the resources endowment, the pillar industry of western provinces is mostly energy-intensive industries (Meng et al. 2011). Particularly, some western provinces with heavy industry-oriented industrial structure make the CO_2 emission reduction targets quite difficult to achieve. Besides, it is even more critical that technology backwardness is the widespread phenomenon, which has caused severe environmental pollution. To address this, the key to improve the energy-saving emission reduction is corresponding pollution-reducing technology. The government should make legislative and administrative moves to foster energy conservation awareness and practices. The introduction and innovation of energy-saving technologies should also be encouraged or even forced. If the energy-saving policies are properly formulated and implemented, the goals of economic development and CO_2 emission reduction can be well balanced.

Since the diagnostic results suggest that the spatial Durbin panel data model with fixed effects provides the best fitting, we will limit our discussion to these estimates in Table 5. When it comes to CO_2 emissions in China, GDP per capita has the highest regression coefficient of 0.98, followed by urbanization level, energy intensity and industrialization level.

GDP per capita is the most important impact factor of CO_2 emissions. The growth of GDP along with large amounts of primary energy consumption directly results in large quantities of carbon dioxide emissions. The most important and primary task for China is to achieve economic and social development. China will continue to raise investment in order to maintain fast economic growth, which would increase massive fossil consumption and exhaust CO_2 emissions and inevitably result in tremendous damage to the natural environment. Hence, China needs to optimize its economic growth patterns and adjust investment structure focusing away from industries of high-energy consumptions to maintain a growth level of residents' wealth without destroying the environment (Lin et al. 2009). In this paper, the technological level is proxied by energy intensity which has a positive effect on CO_2 emissions. Energy intensity of China shows a downward trend in whole from 1997 to 2012. However, compared with developed countries, China's energy intensity is still high and has a large potential for reduction. In the 12th Five-Year National Development Plan, China has set the target of the reduction of energy intensity by 16 % and carbon dioxide emission per unit of GDP by 17 %. Zhang and Da (2013) argued that technological choices were the dominant contributor to the decline in energy intensity in China. Conforming to the viewpoint of the endogenous growth theory, the advancement of technology can reduce energy intensity and indirectly save CO_2 emissions. Besides, renewable energy can reduce environmental damage in both the short and long run (Al-mulali et al. 2015). China should optimize the energy structure by putting great weight behind the development of wind power, photovoltaic power and biomass energy and working actively to develop hydropower and nuclear power to cut carbon emissions.

Industrial structure and urbanization have a positive and significant impact on CO_2 emissions in China. The estimated coefficient on the industrial structure presents that a 1 % increase in the second industry is associated with a 0.19 % increase in CO_2 emissions, which implies that rapid development of industrialization greatly improves the energy-related CO_2 emissions. Hence, it is essential for China to take a low-carbon industrialized road. The elastic coefficient of urbanization is 0.22, which means that a 1 % increase in urban population will result in a 0.22 % increase in CO_2 emissions. However, China is now in the stage of fast industrialization and urbanization and its energy consumption is still on the rise. It is very difficult for China to reduce CO_2 emissions from these two aspects. Tian et al. (2014) pointed out that services based on providing information-intensive intangible goods are considered to generate less pollution. Theoretically speaking, optimizing and upgrading the industrial structure indicate the process of production factors such as capital, labor and technology flows from the production sectors or links of industrial chains with low value-added, poor efficiency and high consumption to those with high value-added, high efficiency and low consumption, such as the high-end producer services. The proportion of the third industry is insufficient in China, which accounted for 44.6 % share in 2012 and correspondingly restricts the urbanization process. Therefore, in the first and unprecedented urbanization, China should conduct its industrial restoring, endeavor to build an industrial system with low-carbon emissions and enter into the low-carbon services such as financial services, software industry, tourism, R&D and design, e-commerce, energy-saving service and ecological restoration, trade and logistics step by step, gradually increasing the proportion of the third industry. The adjustment of industrial structure and the corresponding spatial spillover effects will result in some effects such as the agglomeration effect, the contagion effect and the merging effect, produce a variety of economic effects and promote regional industrial cluster, leading to the emergence of urban agglomeration. This view is similar to Ma (2015), who argued that energy-saving measures such as a compact city layout and the diffusion of energy-saving technologies in the process of urbanization can lead to a decline of CO_2 emissions. Zhang and Lin (2012) also pointed out that urbanization can change the lifestyles of residents and improve the efficiency of energy consumption in a long run, therefore CO_2 emissions will eventually decrease though urbanization exerted significantly effects on CO_2 emissions at present. In the future, China's urbanization rate is projected to increase by 1.5 % annually to 73 % in 2035 (IEA 2013), which will continuously place upward pressure on CO_2 emissions. Therefore, in the process of urbanization, China needs to build a group of different functions of urban agglomeration on the basis of industry adjustment.

Overall, China is in the process of changing economic growth from the investment patterns to innovation-driven patterns, but it has traditional high-energy consumption with low-efficiency economic output abound. The government should fully recognize the importance of energy conservation and enhance the sense of responsibility to reduce energy intensity, improve the energy utilization efficiency and accelerate building an energy conserving economic development mode. To optimize and upgrade the industrial structure, technological innovation is an enduring force and source (Al-Mulali and Ozturk 2015). China should boost high-end producer services to create, extend and integrate industrial chains, and speed up the development of producer services in the process of urbanization. Besides, the construction of new urban should become the important channel and the hot spot that can cause the city development and new industry clusters.

5 Conclusions and policy recommendations

5.1 Conclusions

This paper studied the influence factors of energy-related CO_2 emissions in China with a spatial panel econometric approach over the period of 1997–2012. We provide strong evidence of spatial spillover effects of CO_2 emissions at county level in China. This situation illustrated that traditional estimation techniques can yield biased estimated parameters due to the ignorance of spatial spillover effects of variables. It is especially important when using panel datasets from across Chinese provinces to explore the elasticity of influence factors of energy-related CO_2 emissions.

Based on global Moran's *I* index statistic, we found a significant spatial autocorrelation of provincial CO_2 emissions in China. The spatial correlation presents an obvious apparent blocks structure of CO_2 emissions in China. Specifically, China's western provinces have more potential in reducing CO_2 emissions than the other provinces. This spatial structure indicates that a main way to reduce China's overall CO_2 emissions is narrowing the difference of China's regional CO_2 emissions. Policy-makers should seriously address regional differences, and the policies issued should be regionally specific. Provinces in China should take the so-called common but different responsibility to reduce the CO_2 emissions. High per capita CO_2 emissions of the provinces has more responsibility to reduce emissions.

Comparing traditional panel methods (e.g., pooled OLS, spatial effects, two-way fixed effects and random effects) with OLS, the spatial panel techniques are better estimated by maximum likelihood method. In particular, the SDM FE model is chosen as the better fit compared to SLM and SEM. The empirical results show that GDP per capita serves as the most major contributor to increasing CO_2 emissions in China, followed by urbanization level, energy intensity and industrialization level.

5.2 Policy recommendations

From the analysis results previously stated, in order to achieve the promised carbon emissions intensity target, this paper puts forward some targeted measures for Chinese government as follows.

(a) The environmental policies should consider regional characteristics and differences instead of applying the similar policy to all the regions. The spatial spillover effects indicate that economic activity in provinces has positive externalities. Interprovince cooperation on energy conservation and emissions reduction need be strengthened. The central government should make legislative and administrative moves to foster energy conservation awareness and practices. The introduction and innovation of energy-saving technologies should also be encouraged or even forced. For local governments, Western provinces such as Xinjiang, Gansu and Shaanxi with high per capita CO_2 emissions should limit the construction of heavy pollutant enterprises and strengthen cooperation with the southeast coastal provinces on related carbon-reduction technologies.

(b) The central government should abandon the high-speed growth mode and propel the combination of low-carbon urbanization and industrial restructuring. In fact, the Chinese government has claimed that annual economic growth rate is restrained to 7 % in the 12th Five-Year Plan period to adjust the industrial structure and changing the mode of economic growth to achieve economic sustainable development. Greater emphasis should be placed on the optimization of urban layout to allow for economies of scale and facilitate a low-carbon transition of energy-use patterns of urban dwellers (Ma 2015). In our views, China should vigorously promote low-carbon urbanization road and widely spread the application of green architecture technology with the topic of energy-saving and environmental protection to develop green city. Some favorable policies in taxation and special funds should be supplied for economic compensation according to introducing energy conservation and environmental protection materials. China need adjust the industrial structure, develop the low-carbon industries and restrict the market access of high-carbon industries. It can build different functions of environmental protection industry in the process of urban agglomeration such as modern service industries. The government can also create appropriate energy-saving and carbon-reduction subsidies to accelerate the development of those low-carbon industries (Zhang and Da 2015).

(c) China should reduce the use of fossil energy and increase the development of clean energy. As a coal-dominant energy mix, China's energy intensity is much higher than developed countries and has a large potential for reduction. Much attention should be paid to the potential effect of clean coal technology on CO_2 emissions change during the 13th Five-Year Plan period. China's energy transition from coal to clean energies is still in its infancy. It is necessary to decrease the share of coal in energy consumption and increase the proportion of new energies, such as solar power, wind power and hydro power to reduce the CO_2 emissions. More environmental protection policies should be promulgated in provinces such as Shanxi, Hebei, Henan and Liaoning where iron and steel enterprises or other resource-oriented industries gather as these enterprises consume large amounts of fossil fuels. It is also essential to establish a sound system to strengthen independent R&D capacity and introduce advanced foreign managerial practices for heavy pollutant enterprises for these provinces.

All in all, this paper is an attempt to investigate the influential factors of CO_2 emissions using the spatial econometric techniques in China. The purpose of this study is to arouse the attention of China's policy-makers to understand better about the spatial characteristics of provincial CO_2 emissions as well as the impacts. Inevitably, this study has some limitations. Firstly, the relationship between CO_2 emissions and economic drivers is highly complicated, and further research can explore more factors influencing the energy-related CO_2 emissions. Secondly, it seems clear that the spatial panel models may better understand the relationships between economic activity and environmental impact with a more detailed analysis with other spatial weights matrix defined on geographic and non-geographic measures of connectivity. These are a few of the potential lines for future research.

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