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Carbon emission effect of urbanization at regional level: empirical evidence from China

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Abstract
Historically, global urbanization has been an essential ingredient for national economic growth and beneficial social transformation. However, with the global urban population currently generating two-thirds of all carbon emissions, global policymakers are urging mayors and regional leaders to make difficult decisions to reduce the negative impacts of urbanization on the environment. The authors begin their examination of the implications of local and regional factors by applying the Dynamic Spatial Durbin Panel Data Model to empirically examine aspects of developing low-carbon strategies for the rapidly expanding size and number of the world's urban areas. The results indicate that the contribution of urbanization to carbon emissions can be positively affected when regional policy makers collaborate to focus on spillover effects to simultaneously manage the scope, diversity, and complexity of economic and environmental issues from the perspective of creating a balance between rapid urbanization and relevant regional factors. Regional leaders can make a difference by creating both short-term goals and long-term strategies for maintaining low-carbon urbanization, nurturing regional coordination, monitoring and managing eco-friendly regional spillover effects, supporting low-carbon technology innovations, and maintaining optimal city size.

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Keywords Carbon emission effect; urbanization; local and regional focus; STIRPAT; Dynamic Spatial Durbin Panel Data Model

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1 Introduction

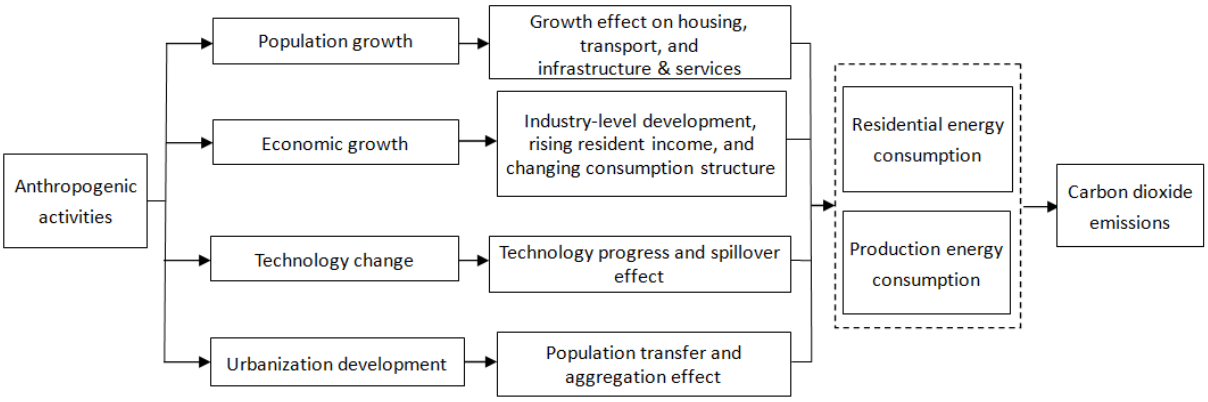
The world's nations focused on both the contributions of and responsibilities inherent to urbanization in achieving global carbon emissions levels in the COP21 Paris Pledge for Action in the Paris City Hall Declaration (2015). Urban populations generate two-thirds of global greenhouse gas emissions. Fifty-five percent of the global population resides in urban areas, a percentage that is expected to increase to 66 percent by 2050 (United Nations, Department of Economic and Social Affairs, Population Division, 2014). According to the Paris City Hall Declaration (2015), advancing solutions to climate change is a shared responsibility, especially for those in urban areas. The undersigned mayors, governors, premiers, and other local government leaders committed collectively to deliver up to 3.7 gigatons of urban greenhouse gas emission reductions annually by 2030. Achieving this impressive goal requires that these leaders assume important new responsibilities for generations they have led. Especially they should focus on the problems of excessive carbon emission, and unplanned, unregulated expansion of carbon-focused development. They are currently being asked, and will most likely be required, to dramatically change their practices. Our research helps develop a new blueprint formulated via a bottom-up, rather than top-down, perspective—with a national focus—that reflects regional differences and synergy effects and fully embodies provincial administrative diversity and interregional collaboration.

Urban leaders need new tools and knowledge to develop, utilize, and improve this new blueprint. They will be responsible for meeting low-carbon goals, yet there exists little scientific and/or research basis for designing, integrating, operating, and managing the required multichannel and interdisciplinary low-carbon enabling functions. Complicating their responsibilities is that a low-carbon blueprint must be developed in parallel with managing growing urbanization. People worldwide look to cities to improve their quality of life. A snapshot of urbanization reveals migration from rural areas to cities or towns, a phenomenon associated with numerous metrics: household size, changing industrial structure, new housing and public facilities, city size distribution, etc. Basically, urbanization creates upward pressure on energy consumption and carbon emissions. Our research focuses on one element of urbanization: its effect on carbon emissions from a conceptual framework containing four main elements (Figure 1).

The inclusion of urbanization in the global environmental carbon emission mandates has generated intense debate, particularly regarding aspects of emerging nations' economic development versus urbanization's impact on carbon emissions relative to the correlation of regional contributions (Zhang and Lin, 2012; Sharma, 2011; Hossain, 2011; Kasman and Duman, 2015). Besides, the effect of urbanization on carbon emissions is continuous and accumulative, presupposing a dynamic relationship between the two—a relationship that has not been the focus of previous studies.

From the above, it is very meaningful to make clear the effect of urbanization on carbon emission from regional or continuous perspective. So this paper extends the STIRPAT model and, with the application of the Dynamic Spatial Durbin Panel Model, uses China as a case study to empirically investigate the effect of urbanization on carbon emissions. In addition, we

Figure 1: Conceptual framework of factors influencing carbon emissions



included a new variable—city size distribution—representing the aggregation effect caused by urbanization (Figure 1). This is the first time this variable has been added in developing low-carbon urbanization in regional coordination along with city size control.

There are several reasons why we should set and utilize such models of panel data and spatial effects. Firstly, our research empirically investigates the dynamic relationship between urbanization and carbon emissions. Our panel data model has several advantages over cross-sectional and time-series data models, including improved degrees of freedom and efficiency, resulting in more effective and reliable estimation of parameters. Secondly, in our models, urbanization is inclusive of both urban and regional areas. Carbon emissions generated in regional areas are not fully independent, as actions in adjacent areas can influence overall carbon emissions. Within urbanization the population migration and industrial transfer bring transboundary pollution; the spillovers of provincial government environmental regulation produce free-riding effect. Thus the correlation between provincial carbon emissions is strengthened. More specifically, as one external factor in our economic development, carbon emission not only spreads across regions with the change of natural climate condition, but also along with the development of infrastructure and communications technology stemming from urbanization (Liu et al., 2010; Zhouet al., 2015; Han and Xie, 2017), it is much likely to spatially diffuse by the way of factor flow and industrial transfer. Besides, the regional growth competition also indirectly leads to spatial correlation of carbon emissions. For example, in order to gain growth advantage one region may attract enterprise investment, promote factor aggregation and industrial transfer by lowering environmental or energy use intensity standards. This probably induces the similar behavior of local governments in the other regions. In contrast, their efforts to reduce carbon emission by strengthening environmental regulation and optimizing industrial structure can result in the free-riding behavior of neighborhood environment governance. And some researchers have proved that there is one kind of spatial spillover effect from urbanization level, economic aggregate, energy intensity, industrial structure and other factors (Yu et al., 2014). Therefore spatial correlation should be taken into account or else the estimation of model parameter is biased. And our research investigates the spatial correlation among these areas using the spatial econometric model. Actually the model is very common and widely put into use in this field (Liu et al., 2014).

We use China as a case study for several reasons: (1) nearly 90% of the increase in worldwide urban population is concentrated in Asian and African nations, with China being the largest developing country among them; (2) China's total CO_2 emissions at the end of 2014 was approximately 9 billion tons—29% of global CO_2 emissions; (3) the International Energy Agency (IEA) perceives China's reduction in coal use in 2014 to be the main reason for the reduction of global carbon emissions. Therefore, the effect of Chinese urbanization on carbon emissions is both dramatic and representative of a growing emerging country. Using China as a case study provides opportunities for generating conclusions that have implications for formulating and implementing low-carbon urbanization strategies in countries throughout the world.

2 Brief literature review

Many researchers have investigated the relationship between urbanization and carbon emissions in recent years; however, as shown in Table 1, these studies have a national or international focus—only two studies have a regional focus without a dynamic focus (Liu et al., 2014; He et al., 2017). In addition, these studies can be differentiated based on their distinct methodological perspectives. The majority employ varieties of the STIRPAT model, varieties of Environment Kuznets Curve, or a combination of the two. Those using a Logarithmic Mean Divisia Index (LMDI) (Feng et al., 2013; Xu et al., 2014; He et al., 2005), input-output analysis (Liang et al., 2007), or Granger Causality Test (Farhani and Ozturk, 2015) are also exhibited in a few articles. Furthermore, most related research builds on empirical models with similar variables related to population, GDP, technology, and urbanization. This research may also include additional variables such as trade openness, industrial structure, energy consumption structure, and household size. Besides, the results regarding the urbanization effect on carbon emissions are not entirely consistent (see Table 1).

Our research makes several important contributions to previous studies:

(1) In considering the spatial correlation of carbon emissions among provinces, this study is specifically focused on analyzing the effect of urbanization on carbon emissions rather than on conducting an extensive analysis of all influencing factors (which is more common in the research), thus imbuing our research with a more comprehensive analysis of how urbanization affects carbon emissions.

(2) This study builds on selected variables from previous literature and, more importantly, includes the variable of city size distribution. In past research, the urbanization variable was denoted by the urbanization rate only (Fang et al., 2015; Xu and Lin, 2014; Farhani and Ozturk, 2015; Zhang and Lin, 2012), which reflects only one aspect of the urbanization process and may adversely affect the result. In addition to the rate of urbanization, an important related question is whether changes in city size distribution affect national or regional strategies for reducing

Table 1: Some representative literature reviews

Researchers	Geographic range	Dependent variables	Independent variables	Study model and method	Basic results
Poumanyvong and Kaneko (2010)	99 countries	E, C	P, A, T, S, UR	Extended STIRPAT model	Carbon emission effect of urbanization is positive.
Cole and Neumayer (2004)	86 countries	C	P, P^2, A, T, S, HS, UR	EKC and Extended STIRPAT model	Carbon emission effect of urbanization is positive.
Lantz and Feng (2006)	Canada	C	$P, P^2, A, A^2, T, T^2, UR$	EKC	Carbon emission effect of urbanization is positive.
Farhani and Ozturk (2015)	Tunisia	C	C^2, A, E, F, TR, UR	ARDL co-integration method, Extended STIRPAT model and EKC	Carbon emission effect of urbanization is positive.
Sharma (2011)	69 countries	C	C^2, A, TR, UR	Dynamic panel data model	Carbon emission effect of urbanization is negative.
Martínez−Zarzoso and Maruotti (2011)	88 developing countries	C	lagged C, P, A, T, S, UR, UR^2	Extended STIRPAT model and EKC	There is an inverted-U shaped relationship between urbanization and carbon emission.
Yu et al. (2014)	Chinese regions	C, CE	$P, A, T, S, ES, EP, TR, UR$	Extended STIRPAT model and Spatial econometric analysis models	Carbon emission effect of urbanization is negative, and spillover effect of urbanization is positive.
He et al.(2017)	Chinese regions	C	P, A, T, S, ES, UR, UR^2	Extended STIRPAT model and EKC	There is an inverted-U shaped relationship between urbanization and carbon emission.

Note: C refers to carbon emissions. P refers to population. A refers to economic income. T refers to technology. S represents industry structure. UR refers to urbanization level. HS refers to the variable of household size. E refers to the variable of energy consumption. F refers to the variable of financial development. ES refers to the variable of energy consumption structure. EP refers to the price of energy and TR refers to trade openness. The expressions of variables in different research are not identical.

energy consumption and carbon emissions during the urbanization process. Another possible variable of interest is average commuting distance, which may significantly contribute to the relationship between greenhouse gas emissions and city size (Bento et al., 2006; Brownstone and Golob, 2009; Glaeser and Kahn, 2010). An example of this logic is that compact cities might be greener because shorter average commutes may be the norm. Also, there are conflicting results regarding the relationships among city size, CO_2 emissions, and the environmental footprints of cities (Dodman, 2009; Glaeser and Kahn, 2010; Fragkias et al., 2013; Oliveira et al., 2014). In fact, it is unclear if large cities are more energy efficient and environmentally friendly than the small ones. Two recent studies of North American cities reached different conclusions regarding scaling relationships between city size and CO_2 emissions (Fragkias et al., 2013; Oliveira et al., 2014). In this paper, city size distribution—but not city size—is selected in order to measure the holistic level of city size during urbanization within a provincial scope. Obviously, if this important factor is overlooked, the results may be adversely affected.

(3) Our research contributes to existing literature by being the first application of the Dynamic Spatial Durbin Panel Data Model in this field. Models currently used in this specific area are non-dynamic for spatial panel or dynamic for non-spatial panel data. The Dynamic Spatial Durbin Panel data models we use have the advantages of panel data and spatial econometric approach, so they cover spatial and temporal characteristics as well as spatial effects. We also include the spatial effects of both dependent and independent variables, making our investigation more applicable to global or local scope. Lastly, our methodology is dynamic, which has the potential to more realistically express the statistical relationship to changes in the continuity of carbon emissions.

3 Methods

3.1 Empirical models

3.1.1 Extended STIRPAT model

In the 1970s, IPAT model ($I = P \times A \times T$) was put forward by Ehrlich and Holden (1971), where I is environment impact, P stands for population, A denotes average wealth and T refers to technology level. In order to supply the gap that the IPAT equation could only be used to analyze the concerned factors impacting the environment proportionally, the STIRPAT model ($I = aP^bA^cT^de$) was set up by York et al. (2003). In the expression, a represents the model coefficient; b, c and d are the coefficients for population, wealth and technology, respectively. And e is an error term.

The STIRPAT model permits the addition of other variables to investigate the impact of urbanization on carbon emission. So its logarithmic extended form can be:

$$lnI_{it} = lna + b(lnP_{it}) + c(lnA_{it}) + d(lnT_{it}) + f(lnUR_{it}) + g(lnUS_{it}) + lne_{it} \tag{1}$$

In Eq. (1), I denotes carbon emission, *UR* refers to urbanization rate, and *US* represents city size distribution. f and g are the coefficients for *UR* and *US* respectively; i and t denote the year and the region, respectively. The definitions of these variables are shown in Table 2.

In addition to urbanization rate level, the new variable of urban size distribution evolves with the growth of urbanization. In our paper, the effect of urbanization on carbon emissions will be discussed from the new perspective of urban size distribution. Goldstein and Gronberg (1984) considered that a large city is efficient because urban public facilities and services are shared by a higher percentage of citizens. Also, they indicated the economies within large cities are better for highly specialized and socialized production and service systems. Hence these economies achieve greater production and life cost reductions. The new urbanization state plan (2014–2020) issued by the Chinese government emphasizes that there are still many contradictions between the population concentration in some large cities and environmental carrying capacity at present. Presently, many small cities have weak service systems, which may carry both economic and environmental costs. Therefore, a quandary exists regarding the actual and dominant impact of urban size distribution on carbon emissions, which requires further empirical analysis.

In general, urban size can be measured directly by city's population size, economic size or land size, but the method of measuring urban size distribution is different from this. In his pioneering article, Jefferson (1939) proposed the Law of the Primate City as a generalization of urban size distribution in a country. In order to show city size distribution, he developed the urban primary index, the ratio of the size of the largest urban population to that of the second largest urban population in a country or region. This index has been widely used in the field of philosophy of urban geography. A higher value indicates a super center city encompassing more people and resources than other regional cities. In contrast, a lower value—sometimes near the minimum of 1—indicates two central cities within a region that have very similar populations, thus weakening the degree of agglomeration of the largest city.

Table 2: Definitions of all relevant variables

Variables	Definition	Unit of measurement
y	Total carbon emission	10,000 tons
P	Population at the end of a year	10,000 people
A	GDP per capita	Yuan per capita
T	Energy intensity	Ton of standard coal per 10,000 yuan
UR	Urbanization level (proportion of urban population in total population)	Percent
US	Urban primary index (ratio of the first and second largest urban population size)	Percent

3.1.2 Static spatial panel data models with fixed effects

There are three most classical static models of spatial econometrics, including Spatial Lag Model (SLM), Spatial Error Model (SEM) and Spatial Durbin Model (SDM) (Anselin, 1988; Anselin et al., 2008). When based on panel data we bring the fixed effects into the tree models, they could be set up as follows.

Spatial Lag Panel Data Model (SLPDM) with fixed effects:

$$y = \rho(H_T \otimes W)y + X\beta + \eta + \delta + \varepsilon \tag{2}$$

Spatial Error Panel Data Model (SEPDM) with fixed effects:

$$y = X\beta + \eta + \delta + \mu\mu = \lambda(H_T \otimes W)\mu + \varepsilon \tag{3}$$

Spatial Durbin Panel Data Model (SDPDM) with fixed effects:

$$y = \rho(H_T \otimes W)y + X\beta_1 + (H_T \otimes W)X\beta_2 + \eta + \delta + \mu + \varepsilon \tag{4}$$

y is a dependent variable matrix of $NT \times 1$and $X$is an independent variable matrix of $NT \times k$, in which k is the number of independent variables influencing carbon emission. $H_T \otimes W$ stands for Kroneker product of matrix $H_T$and W, H_T is the unit matrix of $T \times T$, W is the spatial weight matrix of $N \times N$, and λ is the space error coefficient measuring the spatial dependence of sample observations. N and T respectively stand for the number of provinces and years. Here, $\eta = i_T \otimes sF$ and $\delta = tF \otimes i_N$ both denote Kroneker product of matrix, the former represents the individual effect, and the later denotes the time-specific effect. i_T and i_N are respectively the column vector of dimension T and N . $sF = (\alpha_1, \alpha_2, \cdots, \alpha_N)^T$ and $tF = (\delta_1, \delta_2, \cdots, \delta_T)^T$ respectively stand for the column vector of dimension N for region fixed effects and the column vector of dimension T for time fixed effects. ε is the random error term vector, β and β_1 reflects the X's effect on$y$, and β_2 denotes spatial spillover effects. μ is the random error term vector with $E(\mu) = 0$ and $Cov(\mu) = \sigma^2 H$.

In the formulae above, if η is omitted, the Spatial Lag, Error Model or Durbin Model with time fixed effects is formed, while if δ omitted, the Spatial Lag, Error Model or Durbin Model with individual or regional fixed effects is got.

3.1.3 Generalized dynamic spatial panel data model and Dynamic Spatial Durbin Panel Data Models

When the dynamic items of time dimension are added to the spatial panel data models, their forms become more complex. Many different forms of dynamic spatial panel models have been adopted, and the most generalized dynamic model can be expressed in vector form as

$$y_t = \tau y_{t-1} + \delta W y_t + \eta W y_{t-1} + X_t\beta_1 + W X_t \beta_2 + X_{t-1}\beta_3 + W X_{t-1}\beta_4 + Z_t \pi + \upsilon_t \tag{5}$$

$$\upsilon_t = \rho \upsilon_{t-1} + \lambda W \upsilon_t + \mu + \xi_t \iota_N + \varepsilon_t \tag{6}$$

$$\mu = \kappa W \mu + \zeta \tag{7}$$

where y_t represents a dependent variable matrix of $N \times 1$, which consists of one observation of the dependent variable for every spatial unit ($i = 1, \cdots, N$) in the sample at time t ($t = 1, \cdots, T$); X_t is an independent variable matrix of $N \times k$, in which k is the number of independent variables, Z_t is an exogenous explanatory variable matrix of $N \times L$ and W denotes the spatial weight matrix of $N \times N$. A vector or a matrix with subscript $t-1$ denotes its serially lagged value that, when premultiplied by W indicates its spatially lagged value. The parameters τ, δ, and η denote the response coefficients of y_{t-1}, Wy_tandWy_{t-1}. The $K \times 1$ vectors, β_1,β_2,β_3 and β_4, indicate response parameters of the endogenous explanatory variables, and π is the coefficient of Z_t. Besides, υ_t is the error term vector of $N \times 1$, assumed to be serially and spatially correlated; ρ and λ are, respectively, the serial autocorrelation coefficient and the spatial autocorrelation coefficient. The $N \times 1$ vector, $\mu = (\mu_1, \cdots, \mu_N)^T$, representing spatial specific effects, is used to control for all spatial specific, time-invariant variables whose omission could bias the estimates in a typical cross-sectional study (Baltagi, 2005). Similarly, $\xi_t$denotes time-period specific effects, and ι_N as a $N \times 1$ vector of ones, means to control for all time-specific, unit-invariant variables whose omission could bias the estimates in a typical time-series study. The spatial specific effects are assumed to be spatially autocorrelated with spatial autocorrelation coefficient κ. Finally, ε_t and ζ are vectors of disturbance terms, whose elements both show zero mean and, respectively, have finite variance σ^2 and σ_ζ^2.

However, the general model of the dynamic spatial panel has identification problems and thus cannot be directly used for empirical research. Based on the STRPAT Model, by assigning different parameter values zero, various nested models are formed, including some basic spatial panel models such as the Spatial Lag Panel Data Model(SLPDM), Spatial Error Panel Data Model (SEPDM), and Spatial Durbin Panel Data Model (SDPDM). Although real data conform to the spatial lag or error model, the SDPDM estimation is still unbiased, which gives it a significant advantage over the others. In addition, the model does not limit the size of spatial spillover effects, is applicable to global and local scope, and also considers the spatial correlation of both dependent and independent variables (Elhorst, 2010). In addition, its dynamic format covers the time lagged dependent variable, space-time lagged dependent variable, or both, all of which cannot be performedby the other models.

If set as $\beta_3 = \beta_4 = \lambda = \pi = \kappa = 0$ in Eq. (5), the full form of the dynamic SDPDM (Elhorst et al., 2010) is as follows:

$$y_t = \tau y_{t-1} + \delta W y_t + \eta W y_{t-1} + X_t \beta_1 + W X_t \beta_2 + \alpha + \gamma + \upsilon_t \tag{8}$$

In the model, vectors α and γ denote individual fixed effects and time-fixed effects, respectively, which may exist at the same time. In addition, two common forms of SDPDM are shown below.

Suppose $\beta_3 = \beta_4 = \lambda = \pi = \kappa = \eta = 0$,

$$y_t = \tau y_{t-1} + \delta W y_t + X_t \beta_1 + W X_t \beta_2 + \alpha + \gamma + \upsilon_t \tag{9}$$

and in the event of $\beta_3 = \beta_4 = \lambda = \pi = \kappa = \tau = 0$,

$$y_t = \delta W y_t + \eta W y_{t-1} + X_t \beta_1 + W X_t \beta_2 + \alpha + \gamma + \upsilon_t \tag{10}$$

From the extended STRPAT model (see Eq. (1)), which expresses the basic relationship among all variables, our study develops the Dynamic Spatial Durbin Panel Data Models for empirical investigation. If in Eq. (8)–(10) set $y_t = (lnI_{1t}, lnI_{2t}, \cdots, lnI_{Nt})^T$ and

$X_t = \begin{bmatrix} lnP_{1t} & lnA_{1t} & lnT_{1t}\, lnUR_{1t}\, lnUS_{1t} \\ \cdots & \cdots & \cdots \quad \cdots \quad \cdots \\ lnP_{Nt} & lnA_{Nt} & lnT_{Nt} lnUR_{Nt} lnUS_{Nt} \end{bmatrix}$, where $t = 1,2,\cdots,T$, the three different dynamic SDPDMs are built for empirical analysis.

3.1.4 Direct and indirect (spatial spillover) effects of dynamic SDPDM

In recent years, more attention has been paid to direct, indirect, and spatial spillover effects of the independent variables in the field of spatial econometrics (Yu et al., 2014). Thus, such effects analysis is applied to the specific research area of carbon emission factors for the first time. The brief derivation process is as follows:

By rewriting the model as

$$y_t = (I - \delta W)^{-1}(\tau I + \eta W)y_{t-1} + (I - \delta W)^{-1}(X_t\beta_1 + WX_t\beta_2) + (I - \delta W)^{-1}v_t + (I - \delta W)^{-1}(\alpha + \gamma) \quad (11)$$

and the matrix of partial derivatives of y for the kth independent variable in matrix X from individual 1 to N at a time point can be

$$\left[\frac{\partial y}{\partial x_{1k}}, \cdots, \frac{\partial y}{\partial x_{Nk}}\right]_t = (I - \delta W)^{-1}(\beta_{1k}I_N + \beta_{2k}W) \quad (12)$$

In Eq. (12) the partial derivatives represent, in the short-term, the effects of a changing X in a particular spatial unit on the dependent variables of all other units. In the same manner, the long-term effects are seen as

$$\left[\frac{\partial y}{\partial x_{1k}}, \cdots, \frac{\partial y}{\partial x_{Nk}}\right] = [(1 - \tau)I - (\delta + \eta)W]^{-1}(\beta_{1k}I_N + \beta_{2k}W) \quad (13)$$

In Eq. (12), when $\delta = \beta_{2k} = 0$, there are no short-term indirect effects.And in Eq. (13) the long-term indirect effects do not exist when both $\delta = -\eta$ and $\beta_{2k} = 0$. So the Dynamic Spatial Durbin Model can be utilized to ascertain short- and long-term direct or indirect (spatial spillover) effects, and in this respect, it is an ideal model. Although the direct and indirect effects are different for various units of the sample, LeSage and Pace (2009) showed that the direct effect can be calculated by the mean diagonal elements and the indirect effect by the mean row sum of non-diagonal elements. So there are further equations to express the effects. The equations of short-term direct and indirect effects are $[(I - \delta W)^{-1}(\beta_{1k}I_N + \beta_{2k}W)]^{\overline{d}}$ and$[(I - \delta W)^{-1}(\beta_{1k}I_N + \beta_{2k}W)]^{\overline{rsum}}$ respectively. And the equations of long-term direct and indirect effects are $[((1 - \tau)I - (\delta + \eta)W)^{-1}(\beta_{1k}I_N + \beta_{2k}W)]^{\overline{d}}$ and $[((1 - \tau)I - (\delta + \eta)W)^{-1}(\beta_{1k}I_N + \beta_{2k}W)]^{\overline{rsum}}$ respectively. In the expressions above, $\overline{d}$ denotes the average value of diagonal elements and $\overline{rsum}$ indicates the average row sum of non-diagonal elements.

3.2 Spatial econometric methodology

3.2.1 Spatial autocorrelation test

In order to test whether the attribute value of a certain element is associated with that of the adjacent space point significantly, the global spatial index (Moran's I) is used to describe the overall spatial distribution of carbon emissions. And the local spatial index (LISA) is applied to grasp the heterogeneity of spatial elements.In essence, LISA, named local Moran's Iby Anselin (1995), divides Moran's I into each region unit.

3.2.2 Spatial weight matrix

We chose the spatial matrix with the inverse distance square method,

$$W_{ij} = \begin{cases} 1/d^2 & i \neq j \\ 0 & i = j \end{cases}$$

which denotes that the decrease in mutual influence accelerates with the increase of interlocal distance. Here, d stands for Euclidean distance between the centers of the provinces i and j, which can be measured using Geoda software according to the electronic map of 1:4,000,000 provided by National Geographic Information System website. W is standardized after every element value being divided by the sum of its row, which makes the sum of element value in every row 1.

3.3 Data sources and estimation method of CO_2 emissions

With reliability, integrity and consistency of primary concern, this research casts China as a test case and utilizes its panel data of 29 provincial administrative regions from 2002 to 2013 (Hong Kong, Macao, Taiwan, Qinghai, and Tibet not being included because of their incomplete data). These data are collected from China Statistical Yearbooks, China Energy Statistical Yearbooks, and the provincial statistical yearbooks published by the China National Bureau of Statistics.

In addition, the panel data focus only on carbon emissions caused by human activities, which is approximately 90% of the total. Three methods for calculating fossil fuel combustion emissions of stationary and moving sources have been introduced by IPCC, and in this paper the first method is used to measure CO_2 emissions because of its universal acceptance despite its (more or less) lack of accuracy. This technique is based on fuel quantity and the default emission factor.

3.4 Estimator of empirical models

A number of methods for estimating dynamic spatial panel data models are available (i.e., bias-correct the maximum likelihood (ML) or quasi-maximum likelihood (QML) estimator, instrumental variables or generalized method of moments (IV/GMM), Bayesian Markov Chain

Monte Carlo (MCMC) method, etc.). However, in these methods the bias of δ, which is the coefficient of Wy_t in the model, becomes a problem. Not every method can deal with the bias effectively, but the ML and QML estimators can be widely considered to be bias-correct. Yu et al. (2008) constructed one bias corrected estimator for the Dynamic Spatial Panel Data model with y_{t-1}, Wy_t, Wy_{t-1} and spatial fixed effects. The research was extended to include fixed-time effects by Lee and Yu (2010).

This paper takes 29 provincial administrative regions' datafrom 2002 to 2013 in China as sample. And its finite sample property may affect the validity and consistency of parameter estimation, which has been proved by some researchers (Lee and Yu, 2010). In this case, by reparameterization and data transformation, Yu et al. (2012) developed the consistency and asymptotics of the QML estimators and also proposed bias correction for QML estimates. For the QML estimators, Yu et al. see that they have some biases, but the bias corrected estimators reduce those biases onaverage, even when T is relatively small. It has been proved by a Monte Carlo experiment (Yu et al., 2012). Therefore such kind of method has been used in our research.

Furthermore, supposing that there is significant spatial correlation, the finite sample properties of fixed effect test still need to be improved. In order to enhance the performance of fixed effect test, it is necessary carry out both LM test and Robust LM test for the panel models at the same time.

4 Results and discussion

4.1 Multicollinearity test for panel data

A variance inflation factor (IF) was utilized to test the multicollinearity. Freund et al. (2006) indicated that if 0<VIF<10, multicollinearity is acceptable; if 10 <VIF<100, it implies multicollinearity; and if VIF<100, there is strong multicollinearity. Because the VIF of all variables in Eq. (1)are less than 4, the multicollinearity in our model is acceptable.

4.2 Non-spatial panel model test

4.2.1 Panel unit root test and panel co-integration test

In order to determine whether the selected sample data is suitable for the spatial econometric model, we should carry out a series of tests based on the assumed non-spatial forms of our models firstly and then check whether the residuals are spatially correlated. This would be ‘good practice’ as Gibbons and Overman (2012) put it.

In order to avoid the pseudo-regression and ensure the validity of estimated results, it is necessary to verify the stationarity of each panel sequence. Based on the four most common methods of panel unit root test, the results are shown in Table 3, which indicate that the original hypothesis of the unit root is rejected. And so all the sequences are stable.

Since all the variables were stationary at the first difference, Pedroni test (1999, 2004) and Kao test (1999) are used to estimate panel cointegration. Table 4 shows the cointegration test results. All statistical tests are significant, rejecting the null hypothesis (that is, without cointegration).

Table 3: Results of the panel unit root test on main variables

Variable	Test type (C，t，k)	LLC test		Fisher-ADF test		Breitungtest		IPS test	
		Statistic	P	Statistic	P	Statistic	P	Statistic	P
y	(C, 0, 0)	-10.3436	0.0000	14.6035	0.0000	-5.6289	0.0000	-4.2902	0.0000
P	(C, 0, 0)	-7.1905	0.0000	12.8851	0.0000	-6.0671	0.0000	-6.3841	0.0000
A	(C, 0, 0)	-6.2665	0.0000	11.4679	0.0000	-5.9118	0.0000	-8.5837	0.0000
T	(C, 0, 0)	-8.5393	0.0000	13.0215	0.0000	-3.7166	0.0001	-2.9247	0.0017
US	(C, 0, 0)	-6.4734	0.0000	12.3430	0.0000	-6.9260	0.0000	-8.6858	0.0000
UR	(C, 0, 0)	-3.0666	0.0011	10.4081	0.0000	-6.6694	0.0000	-10.6946	0.0000

Note: C, t and k indicate respectively constant term, time trend term and lag length k; the optimal lag lengths are obtained automatically with the Schwarz information criteria (SIC).

Table 4: Panel cointegration test results

Test method		Statistic	P
Pedroni test	Modified Phillips-Perron statistic	6.9947	0.0000
	Phillips-Perron statistic	-4.4246	0.0000
	Augmented Dickey-Fuller statistic	-4.2923	0.0000
Kao test	Augmented Dickey-Fuller statistic	-4.6937	0.0000

4.2.2 F test and Hausman test

The panel data model usually comes in three forms, including Pooled Regression Model, Fixed Effects Regression Model and Random Effects Regression Model. On the one hand, in this section F test was used to determine whether our model may belongto Pooled Regression Model or Fixed Effects Regression Model. And its test result (F=544.59, P=0.0000) indicates that the latter model is more reasonable. On the other hand, according to the Hausman test result (chi-square=25.02, P=0.0001), it can be proved that Fixed Effects Regression Model is more suitable for our research than Random Effects Regression Model.

4.3 Spatial panel data model identification

4.3.1 LM test

Table 5: LM test and Robust LM test for the panel models

Test method	Time fixed effect	Regional fixed effect	Time and regional fixed effect
LM-lag	4.2412***	1.1705	3.9853**
Robust LM-lag	5.6230***	6.5400***	4.0477**
LM-err	2.3115*	4.4362***	2.7228*
Robust LM-err	2.9933**	7.8057***	2.7852*

Note: * indicates significance at 10% level; ** indicates significance at 5% level; *** indicates significance at 1% level.

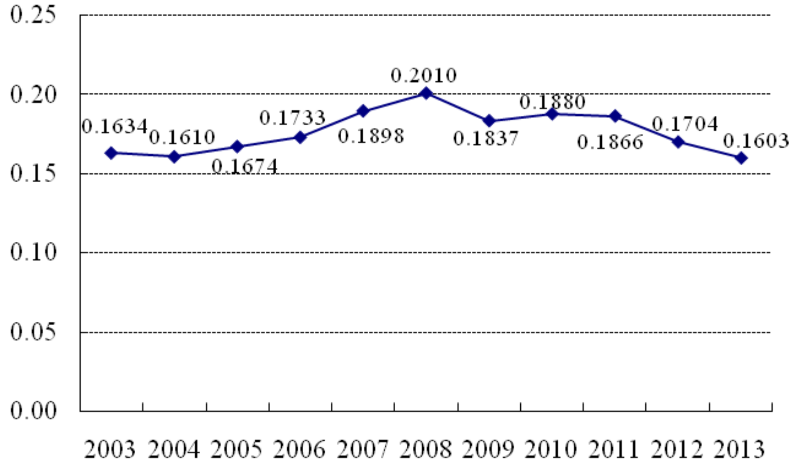
From the above, it can be concluded that the assumed non-spatial panel models belong to Fixed Effects Regression Models.And then they may have three basic forms, which respectively cover time fixed effect, regional fixed effect, and time and regional fixed effect. Based on the three kinds of models, classic LM test and Robust LM test both are utilized to ascertain whether the spatial correlation is involved in the models (Anselin et al., 2008). As shown in Table 5, almost every test is passed significantly and so we reject the null hypothesis that there is no spatial lagged term or spatial error term for the panel data. It can be seen that the spatial lagged and spatial error models are more appropriate for data analysis than the non-spatial panel models.

4.3.2 Spatial autocorrelation test

As shown in Figure 2, the Moran's I indexes did not fluctuate significantly and remained above 0.15 from 2003 to 2013; their significance levels are always less than 5%. Total carbon emissions of provinces have a relatively strong positive correlation as a whole. That is, the provinces with higher emissions are closer to each other, as are the provinces with lower emissions. Also, the spatial scatters of carbon emissions are not fully independent, and the carbon emissions of one province can be influenced by those of its neighboring regions.

We use Geoda to draw LISA clustering maps of carbon emissions for each of the provinces in 2000, 2005, 2010, and 2013, as shown in Figures 3–6. P-values for the colored regions in the four LISA clustering maps are all less than 0.01 except the blank regions don't pass the significance test. Figures 3–6 show, to some extent, heterogeneity and dependence of spatial dimension between the carbon emissions of provinces (which cannot be ignored). The provinces with substantial local spatial correlation present a characteristic of obvious regularity. The emissions distributions (HH, HL, LH and LL agglomeration areas) have changed little through-

Figure 2: Moran's I indexes of provinces' carbon emissions from 2003 to 2013



out the period. More specifically, most of the hot spots with higher local Moran's I indexes are located in the provinces of Jiangsu, Shandong, Hebei, Shanxi, Henan, Liaoning, and Inner Mongolia. They are relatively concentrated geographically—located mainly in thenorth, northeast, and east of China. These provinces and their surrounding regions all have relatively high carbon emissions. Meanwhile, the blind spots of the LL agglomeration area are largely distributed in Qinghai, Guizhou, Guangxi, and Hainan. These provinces and their neighboring regions all have low carbon emissions. Provinces within the hot spots or blind spots have smaller spatial differences and stronger positive correlations for carbon emissions than the others. Provinces such as Jilin and Tianjin (surrounded by the hot spots) are in the LH agglomeration area and, in most years, have lower carbon emissions than regions adjacent to them. Guangdong, because of its faster economic development, emits more carbon than its neighboring regions of Guangxi, Jiangxi, and Hunan (HL agglomeration). HL agglomeration and LH agglomeration show a negative spatial autocorrelation. For the other blank regions in the LISA, clustering maps don't pass the significance test, which means the correlations of carbon emissions between the provinces and their neighbors are weak for a number of reasons. For example, energy data for Tibet is unavailable, which is partly responsible for the (statistically) non-significant results of its surrounding provinces. Also, Jiangxi, Fujian, Hubei, and Hunan border on provinces with much higher or lower carbon emissions, so there are no clear or significant correlations between them. The root cause may be the imbalance of economic development and energy consumption within these areas.

4.3.3 LR test and Wald test

In fact, according to the test results in Table 5, not only the existence of spatial correlation in the empirical models can be verified, but also the choice of model between SLPDM and SEPDM can be made. Despite all that, it is still not confirmed that the following estimated results can be very satisfactory for the empirical research, and sometimes the spatial lagged term and spatial

Figure 3: LISA clustering map of provinces' carbon emissions in 2000

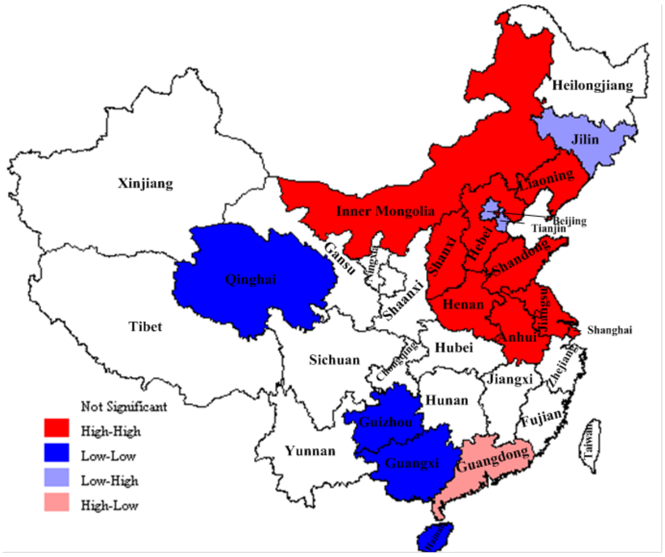


Figure 4: LISA clustering map of provinces' carbon emissions in 2005

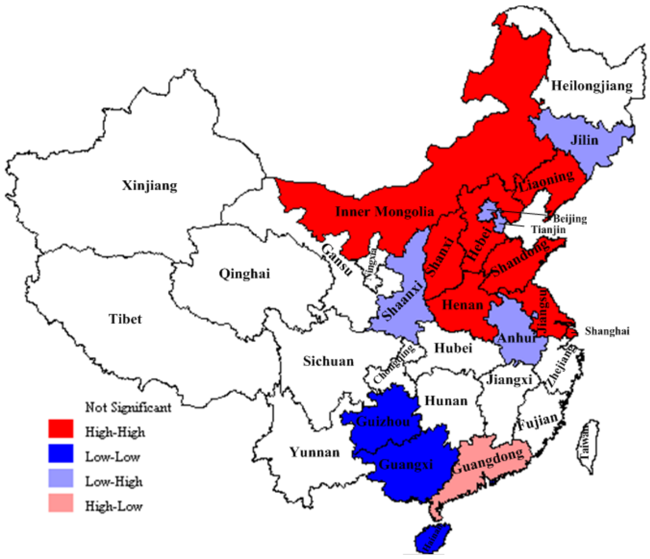


Figure 5: LISA clustering map of provinces' carbon emissions in 2010

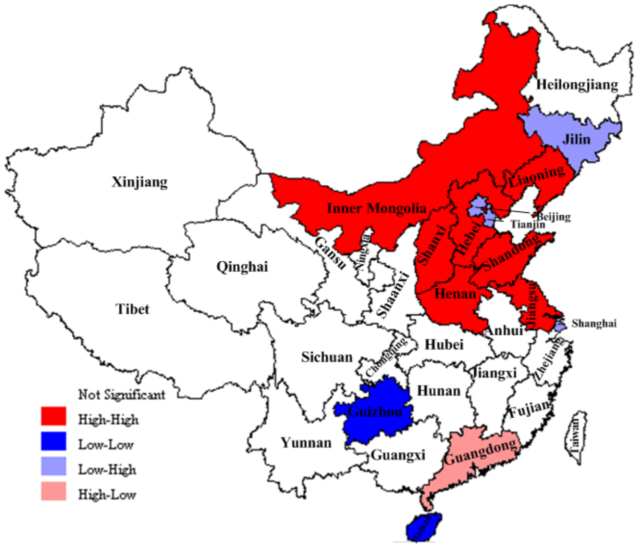
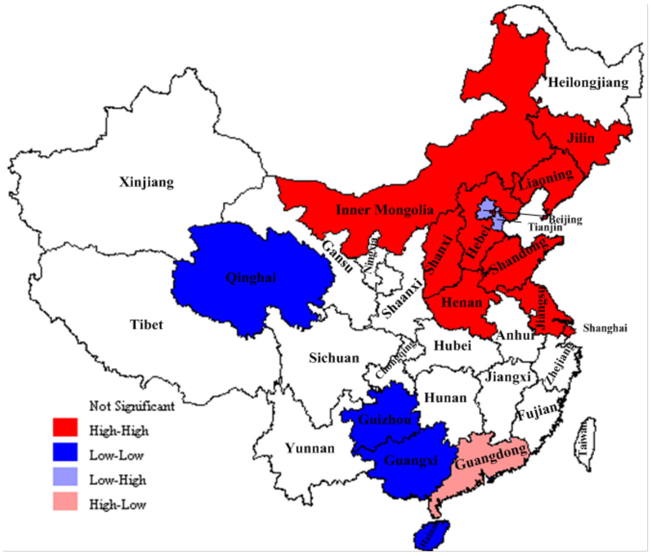


Figure 6: LISA clustering map of provinces' carbon emissions in 2013



Note: Every map above is not a complete map of the People's Republic of China, only those provinces used for this research analysis; the energy data for Tibet is unavailable.

error term can be coexisting. In such case, since SLPDM and SEPDM are nested in SDPDM, SDPDM could be estimated beforehand and then by LR and Wald test it is determined whether the model can be simplified to the form of SLPDM or SEPDM. Such a kind of econometric modeling process adopts the "general-to-specific approach". In contrast, there is another one- "Specific-to-General approach."

In addition, besides the static form as shown by Eq. (4), SDPDM has the dynamic forms, which should also be taken into consideration in order to reinforce the selected models' explanatory power. The three kinds of dynamic forms have been expressed by Eq. (8)–(10). So for the following study there are four kinds of static or dynamic Durbin Models to be estimated. As shown in Table 6, the results of joint significance test (LR test) denote that all the models should only cover time effect. And then based on the selected models with time fixed effect, depending on the LR and WALD test results shown in Table 7, it is determined that SDPDM for the paper cannot be simplified to the form of SLPDM or SEPDM. In other words, for the following empirical analysis, the four kinds of SDPDMs with time fixed effect are more appropriate than the others.

The empirical analysis was conducted by estimating the four Spatial Durbin models, with results reported in Table 8. Looking first at R^2 and log-likelihood of the models, the fit to models (2), (3) and (4) is slightly better than to Model (1). Moreover, when comparing all the estimated coefficients and significance levels, the Dynamic Spatial Durbin Panel Data Model with time fixed effect and time lagged dependent variable (i.e., Model (2)), is better than Model (3) and (4). Thus only its results will be discussed below.

Table 6: Joint significance test (LR test) for regional or time effect

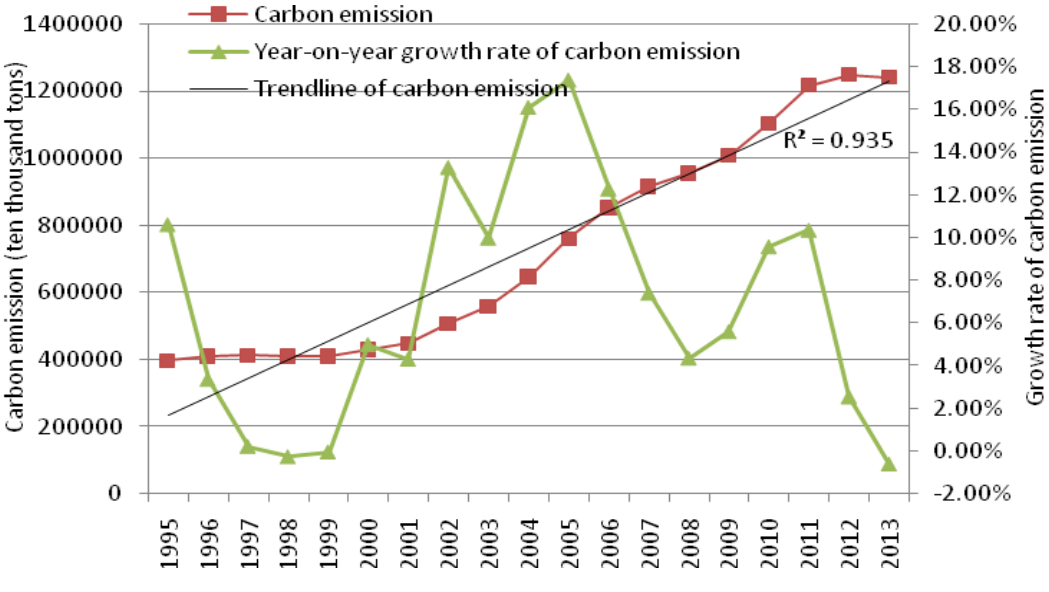
Model type	Fixed effect type	T-stat	DOF	P
Static Spatial Durbin Panel Data Model	Regional fixed effect	12.14	29	0.2760
	Time fixed effect	58.39	12	0.0000
Dynamic Spatial Durbin Panel Data Model with time lagged dependent variable	Regional fixed effect	10.45	29	0.4017
	Time fixed effect	45.21	12	0.0000
Dynamic Spatial Durbin Panel Data Model with space-time lagged dependent variable	Regional fixed effect	11.55	29	0.3166
	Time fixed effect	53.78	12	0.0000
Dynamic Spatial Durbin Panel Data Model with both time lagged and space-time lagged dependent variable	Regional fixed effect	10.30	29	0.4142
	Time fixed effect	44.92	12	0.0000

Table 7: LR and WALD test results of static and dynamic SDPDMs

Model type	LR-Spatial-Lag T-stat	LR-Spatial-Error T-stat	Wald-Spatial-Lag T-stat	Wald-Spatial-Error T-stat
Static Spatial Durbin Panel Data Model	23.02***	21.13***	25.98***	24.19***
Dynamic Spatial Durbin Panel Data Model with time fixed effectand time lagged dependent variable	15.12***	—	16.10***	55.72***
Dynamic Spatial Durbin Panel Data Model with time fixed effectand space-time lagged dependent variable	21.44***	—	21.95***	73.87***
Dynamic Spatial Durbin Panel Data Model with time fixed effectand both time lagged and space-time lagged dependent variable	15.39***	—	16.37***	59.37***

4.3.4 Dependent variable of carbon emissions

Figure 7: The growth rate of carbon emissions in China from 1995 to 2013



Source: The total carbon emissions are calculated using data from the China Statistical Yearbook published by Chinese government.

Table 8: Estimates of static or dynamic SDPDMs with time fixed effect

Variable	Model (1) Static Spatial Durbin Panel Data Model		Model (2) Dynamic Spatial Durbin Panel Data Model with time fixed effect and time lagged dependent variable		Model (3) Dynamic Spatial Durbin Panel Data Model with time fixed effect and space-time lagged dependent variable		Model (4) Dynamic Spatial Durbin Panel Data Model with time fixed effect and both time lagged and space-time lagged dependent variable	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
$ln(I)_{-1}$	-	-	0.089***	4.82	-	-	0.087***	4.720
$W*ln(I)_{-1}$	-	-	-	-	0.048	0.810	-0.027	-0.460
$W*ln(I)$	-0.291***	-2.430	0.260***	2.080	0.312***	2.450	0.254***	2.020
$ln(P)$	0.971***	46.930	0.938***	41.890	0.975***	44.910	0.938***	41.860
$ln(A)$	1.069***	31.910	1.029***	29.580	1.063***	30.260	1.034***	29.14
$ln(T)$	1.217***	35.140	1.155***	31.080	1.201***	32.570	1.158***	30.810
$ln(UR)$	-0.301***	-4.660	-0.315***	-4.850	-0.304***	-4.560	-0.319***	-4.89
$ln(US)$	0.139***	3.150	0.106***	2.370	0.123***	2.700	0.107**	2.390
$W*ln(P)$	0.259**	2.020	0.242**	1.830	0.254**	1.890	0.248**	1.870
$W*ln(A)$	0.613***	3.800	0.481***	2.880	0.582***	3.460	0.494***	2.930
$W*ln(T)$	0.639***	3.260	0.491***	2.440	0.581***	2.840	0.508***	2.500
$W*ln(UR)$	-0.643***	-3.680	-0.614***	-3.410	-0.702***	-3.800	-0.605***	-3.340
$W*ln(US)$	0.487***	3.090	0.399***	2.450	0.440***	2.590	0.415***	2.490
σ^2	0.0458		0.0479		0.0503		0.0480	
R^2	0.9645		0.9714		0.9655		0.9719	
log-likelihood	40.1977		51.3215		45.6062		51.1148	

Note: * indicates significance at 10% level; ** indicates significance at 5% level; *** indicates significance at 1% level; subscript -1 indicates the variable's serially lagged value.

The estimated coefficient for $ln(I)_{-1}$equals 0.089 and is statistically significant at the 1% level, which indicates that previous carbon emission shave a positive and significant impact on current carbon emissions. To be more precise, with 1% change of I_{-1} the carbon emission moves 0.089%. In Figure 7, despite declining for a very few years, carbon emissions in China grew from 4.06 to 12.46 billion tons at an average annual rate of 6.54%. Its year-on-year growth rate fluctuated between 0% and 10%, although it did reach 16.07% in 2004 and 17.35% in 2005. The trend line shows a continuous, progressive, and stable growth of carbon emissions over time, clearly showing that energy conservation and emissions reduction activities are continuous and cumulative, and their effect exhibits different pathways both in the current and following periods.

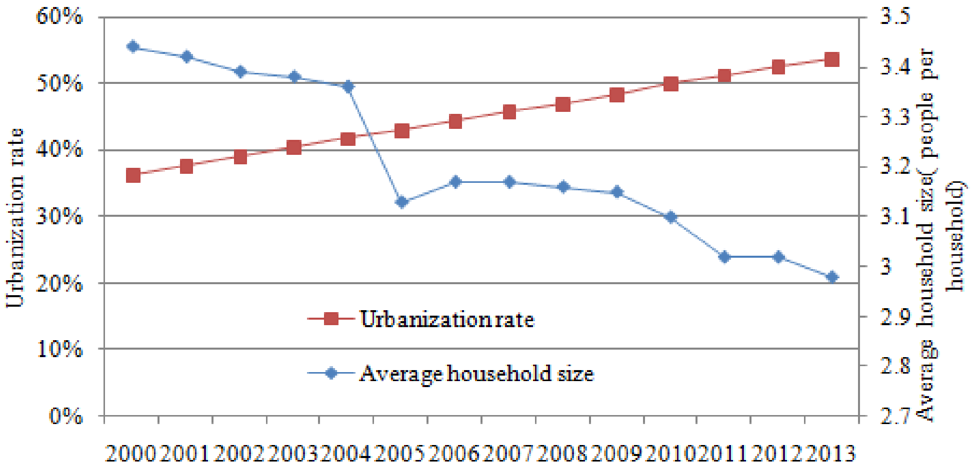
In addition, the coefficient for $\boldsymbol{W} * \boldsymbol{ln}(\boldsymbol{I})$ is 0.260 at the significance level of 1%, indicating that increasing the carbon emissions of one province may lead to more carbon emissions in neighboring provinces. Carbon emissions of adjacent regions are correlated with each other, and successfully controlling carbon emissions in one province also drives the control of carbon emissions in neighboring provinces.

4.3.5 Independent variable of urbanization rate

The estimated coefficient for $ln(UR)$ is –0.315 and is statistically significant at the 1% level, implying that 1% increase of URmay lead to 0.315% reduction in carbon emission. In fact, eachcoefficient of independent variables in Eq. (1) is interpreted as an elasticity between its corresponding independent variableand the dependent variable of carbon emission.Besides, the coefficient for $W * ln(UR)$ is –0.614 at the same significance level. In general, accelerating the rate of urbanization limits the increase of carbon emissions in both the local and neighboring regions. This result does not mean we forecast that an increase in the rate of urbanization will always be followed by a reduction in carbon emissions; urbanization is a complex construct having many factors, with the urbanization ratio being just one measurement of the aggregation of urban population. Many urbanization factors either directly or indirectly inhibit or promote carbon emissions in local or adjacent regions. These can be formed into a complete effect as shown by the statistical results.

The urbanization rate has increased from 17.92% in 1978 to an all-time high of 54.77% in 2014, accelerating significantly from the end of 1995 (Figure 8). In addition, urbanization may lead to higher or lower energy consumption and carbon emissions in different areas including household, production, and government policy. The final displayed effects depend on the balance between positive and negative effects. According to ecological modernization theory, researchers considered the existence of an inverted U-shape relationship between pollution per capita and urbanization (Ehrhardt-Martinez et al., 2002; York et al., 2003), and with increased urbanization, the correlation will change from positive to negative. The relationship between urbanization and carbon emissions may be positive or negative at certain stages depending on the resultant from different impacts of promoting or reducing carbon emissions caused by differentiated factors, some of which have strong spatial spillover effects.

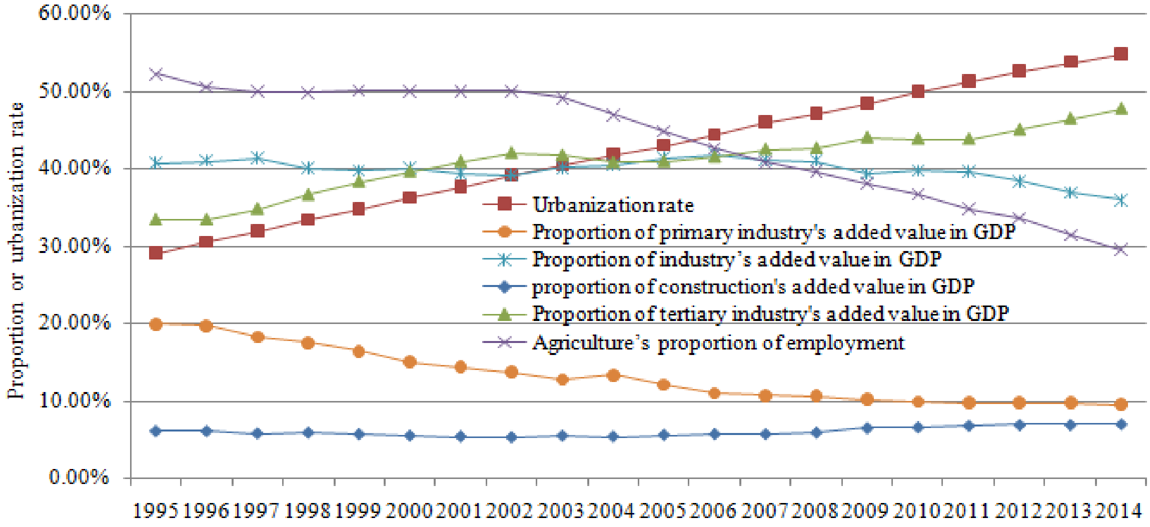
Figure 8: Urbanization rate and average family size in Chinafrom 2000 to 2013



First, household size is trending downward in China, with the average household size falling from 3.44 in 2000 to 2.98 in 2013 (Figure 8). In contrast, the urbanization rate always shows rapid growth. Household size is generally thought of as an important determinant of household carbon emissions because larger household size tends to create economies of scale (Dey et al. 2007; Baiocchi and Minx, 2010; Jones and Kammen, 2011; Weber and Matthews, 2008; Tukker et al., 2010; Gough et al., 2011). When more people share a dwelling, they also share energy consuming appliances, thus consuming less energy for heating, cooling, and cooking than single occupants (Tukker et al., 2010).

Second, urbanization could influence the development of some industries and industrial structure. The co-evolving movement of people from rural to urban areas is associated with industrialization. Figure 9 shows that the proportion of primary industry's added value to GDP has declined from 19.9% in 1995 to 9.5% in 2014, with a similar reduction in agriculture's proportion of employment. The change in the proportion of industry’s added value to GDP is relatively small and stable, fluctuating around 40%, despite a slightly declining trend after 2006. This does not diminish industry’s dominance constrained by the present developing stage of urbanization. In contrast, the proportion of tertiary industry has increased from 33.4% in 1995 to 47.7% in 2014. The rising trend of construction’s added value to GDP has been more noticeable in recent years. Overall, tertiary industry has the lowest energy intensity when compared to industry and construction. Industrial adjustment, which is partly related to urbanization, affects carbon emissions in different ways. With the increase of industrial employment, agriculture's share of employment has dropped from 52.22% in 1995 to 29.50% in 2014 (Figure 9). On one hand, agricultural operations are mechanizing, resulting in a need for fewer employees. Modern industry and manufacturing is becoming less labor intensive and consumes more energy per unit of output (Jones, 1991). On the other hand, the movement of people and industry to cities has

Figure 9: Industrial structure and agriculture's proportion of employment in China from 1995 to 2014



Source: China Statistical Yearbook

resulted in rapid urbanization (both in acreage and number of cities) most likely promoting construction of industrial and residential housing, urban infrastructure and municipal conveyance projects, and increasing investment in, and demand for, building materials, metallurgy, and equipment, real estate, finance, and insurance and logistics. This is partly explained by the proportion of construction and tertiary industry increasing at different rates. Clearly, the development of the service industry (partly driven by urbanization) has and will continue to play an increasingly-important role in energy-saving work.

Third, urbanization may result in lower levels of energy consumption since cities benefit from energy efficiencies via economies of scale by providing and encouraging people to live in high-rise buildings and use public transit networks or less energy intensive modes of transportation.

Fourth, urbanization may help to increase the incomes of both urban and rural residents, thus encouraging the consumption of more energy. The concentration of rural population, information, capital, technology and other factors of production in cities has resulted in remarkable development of the factor market (e.g., labor market) due to scaling effects. Urban residents have more job opportunities and higher income, especially with expansion of urban service industries. Moreover, the transfer of surplus rural labor to cities and towns helps grow consumer markets for agricultural products. On the other hand, upgrading the consumption structure and expanding the consumption area are accompanied by the disposable income growth, all of which affects energy consumption and carbon emission in different ways.

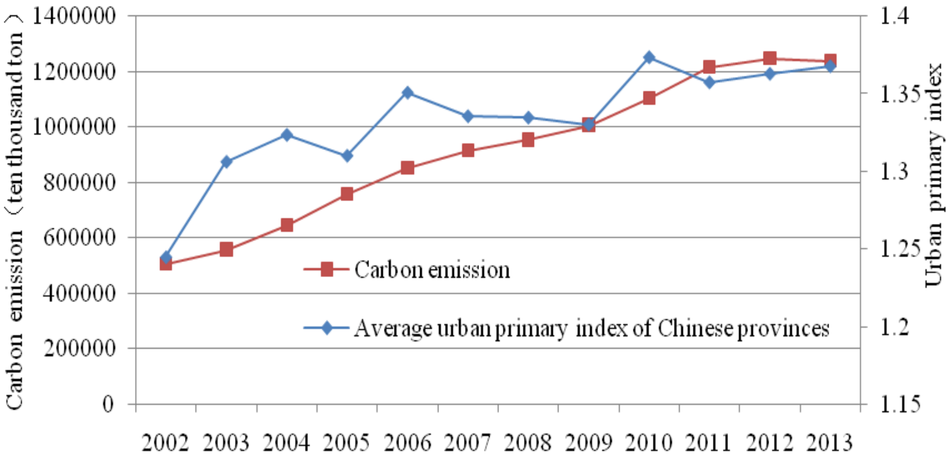
Fifth, during periods of accelerated urbanization, the government can make enterprises reduce carbon emissions by crafting and implementing corporate and public policies governing the environment and industrial development. Moderately stable environmental control policies can strengthen technical innovation, and enterprise production can evolve into clean production in order to reduce carbon emissions.

4.3.6 Independent variable of urban primary index

The estimated coefficient of $ln(US)$ is 0.106 at a significance level of 1%, while that of $W * ln(US)$ is 0.399 at 1%, showing that the urban primary index is positively correlated with carbon emissions, and also showing positive spatial spillover effects. In Figure 10, both carbon emissions and the average urban primary index increased from 2002 to 2013. Specifically, the increase of the urban primary index means the agglomeration effect is being fully exerted in the largest city, which may positively and/or negatively affect local and adjacent carbon emissions. In accordance with its estimated result, the increasing city size distribution in provinces overall indicate negative environmental impacts in local and surrounding regions. On one hand, the large urban primary index helps to promote technology innovation, the diffusion of knowledge, and the speed at which industry upgrades, and reduces transaction costs, risk of labor mismatch, and cost of services, contributing to an aggregate reduction in carbon emissions. Conversely, a primary city that cannot support its population may lead to high cost of living, heavy traffic, and a huge gap between big and small cities in technology and service facilities. Small cities may not be able to support technology diffusion, knowledge spillover, and transfers effectively resulting in negative externalities, i.e., environmental degradation and rising carbon emissions. The related socio-economic influences of local urbanization mentioned above also play a role in surrounding carbon emissions. Lastly, whether the effect on emission is positive or negative depends on which effect is dominant.

Increasing urban scale is not necessarily better from the standpoint of energy savings and emissions reduction. China, with its continually rising carbon emissions, implies that the negative externality of urban scale is dominant; therefore, controlling and optimizing urban scale is important to global policymakers. Promoting urbanization does not mean simply to foster urban population increase. Cities should be maintained at optimal and reasonable sizes to ensure that the eco-friendly effects are greater than the polluting effects on the premise of urban progress and economic development.

Figure 10: Carbon emissions and average urban primary index of Chinese provinces from 2002 to 2013



4.3.7 Other independent variables

First, the estimated coefficient for $ln(P)$ is 0.938 at a significance level of 1%, and the coefficient for $W * ln(P)$ is 0.242 at a significance level of 5%. This indicates that Chinese population growth increases energy demand, which in turn increases carbon emissions. Moreover, there are obvious spatial spillover effects in the provinces. When facing an aging population and steady population growth rate, advocating a low carbon lifestyle is one feasible way to achieve energy conservation and emissions reduction targets.

Second, the estimated coefficient for $ln(A)$ is 1.029 at a significance level of 1% while the coefficient of $W * ln(A)$ is significant (0.481). A nation's energy consumption may reflect its level of economic activity and ability to meet the living standards of its citizens. Traditionally, economic growth leads to inevitable increases in carbon emissions; however, economic growth in one region has positive and strong spillover effects on the carbon emissions of surrounding areas mainly because of its driving force for economic improvement. Leaders should carefully consider the tradeoffs among reducing carbon emissions, increasing economic development, and improving their citizens' standard of living.

Third, the estimated coefficient of $ln(T)$ is 1.155 at a significance level of 1% while the coefficient of $W * ln(T)$ is 0.491 at 1% significance, indicating that a reduction in energy intensity can help cut carbon emissions. Doing so is dependent on factors such as technological innovation and local leaders who promote technology to optimize energy consumption. A reduction in energy intensity associated with the elements mentioned above can reduce carbon emissions in one province and have the same effect on its neighboring provinces.

4.3.8 Regarding direct and indirect effects

In Table 9, in the short run, with the exception that the indirect effect of $ln(P)$ is not significant, the direct, indirect, and total effects are all significant and have the same signs as those of the estimated coefficients in Table 8. These results indicate that, in the short term, the growth of economic income, energy intensity, and urban primary index in one province increases carbon emissions in the local area and in adjacent provinces. Also, in the short-term, a rising urbanization rate in a local area can constrain carbon emissions in both local and adjacent regions. In the long-term, however, indirect effects are not as significant as those in the short term (i.e., indirect effects of $ln(P)$ and $ln(T)$). Their spillover effects on carbon emissions are very hard to maintain due to long-term uncertainty caused by interference from adjacent areas. The situation in the long-term is more complex; however, there are steady influences of $ln(P)$, $ln(A)$, $ln(T)$ and $ln(UR)$ on local carbon emissions in the future. It should be noted that the signs of direct and indirect effects of $ln(UR)$ are positive in the long-term; this is different from those exhibited in the short-term. From the foregoing, to some degree, our test result on the carbon emission effect of urbanization corresponds with He's research conclusion that there is an inverted U relationship between urbanization and CO_2 emission (He et al., 2016). But more than that, our research also found that the indirect effects of $ln(UR)$ show a negative sign in the short-term but a positive sign in the long-term. This implies that one region's urbanization

Table 9: Estimated effects of Model (2)

Variable	Short term			Long term		
	Directeffect	Indirecteffect	Total effect	Directeffect	Indirecteffect	Total effect
$ln(P)$	0.940*** (41.32)	-0.005 (-0.09)	0.935*** (16.20)	0.971*** (20.72)	-0.024 (-0.43)	0.947*** (12.78)
$ln(A)$	1.019*** (34.81)	0.185*** (2.69)	1.204*** (34.81)	1.148*** (17.39)	0.182*** (2.41)	1.330*** (12.71)
$ln(T)$	1.152*** (31.70)	0.155* (1.47)	1.307*** (11.23)	1.465*** (15.89)	0.166 (1.25)	1.631*** (9.19)
$ln(UR)$	-0.300*** (-4.64)	-0.450*** (-3.44)	-0.750*** (-4.97)	0.108*** (2.31)	0.153*** (2.75)	0.261*** (2.84)
$ln(US)$	0.100*** (2.24)	0.308*** (2.13)	0.408*** (2.81)	0.014 (1.36)	0.037* (1.67)	0.051* (1.77)

Note:* indicates significance at 10% level; ** indicates significance at 5% level; *** indicates significance at 1% level; t-values are in parentheses.

effect on its neighboring CO_2 emission shows the same directional change as its urbanization effect on its local CO_2 emission does. It should be noted that promoting the development of urbanization does not result in energy conservation and emissions reductions indefinitely; the high urbanization rate reaches a saturation point and begins to result in adverse environmental consequences.

5 Conclusions

This research investigates the effect of urbanization on carbon emissions empirically via the extended STIRPAT and Dynamic Spatial Durbin Panel Data Models. The Durbin model has been applied to a local microeconomic context (city and regional) for the first time, resulting in an analysis with a regional perspective and a dynamic feature. The analysis also reflects another effect of urbanization on carbon emissions by adding the variable of city size distribution to the model. It can enable the conclusions to provide mayors and policymakers with more useful methods for developing low-carbon urbanization strategies, especially in the field of regional coordination and controlling city size.

(1) The effects of urbanization on carbon emissions are continuous and changing in both the short- and long-term. In the short-term, the urbanization rate increase and the shorter distance between cities or towns contribute to energy conservation and emissions reductions in local and adjacent regions. In the long-term, an uncontrolled increase in urbanization can hamper emissions control. Therefore, we should employ both long- and short-term strategies when selecting and implementing low-carbon pathways to urbanization. In the same way, it is very important to take maximum advantage of scale and agglomeration effects on reducing carbon emissions in both the short and long term.

(2) Spatial autocorrelation and heterogeneity in carbon emissions between adjacent provinces exist. The carbon emissions of adjacent provinces are correlated, and the successful

control of carbon emissions in one province drives the control of carbon emissions in neighboring provinces. Provincial urbanization strategies to conserve energy and reduce emissions should not be separated from the overall regional environment. Each province should strive to coordinate the development of urban systems within its region to achieve lower carbon emissions. In addition, national low-carbon urbanization processes, procedures, and regulations should be diverse and changeable because of potential regional differences.

(3) Further research, focusing on how regional and provincial policymakers can successfully differentiate, coordinate, and harmonize the goals of both long- and short-term strategies to achieve low-carbon urbanization, can be advantageous. During the complex and multifaceted process of urbanization, the different spillover effects of implemented technologies should be exploited to the most efficient and effective extent possible within the numerous provincial areas, and the entire regional area, to maximize the conservation of energy and reduce emissions.

(4) The overall effect of an increasing rate of urbanization on carbon emissions has been examined. Urbanization increases resident income, accelerates industrialization, produces public transit networks or energy-free transport modes, and decreases household size, which affects carbon emissions in various ways. Therefore, we should not simply increase the rate of urbanization, but focus instead on achieving beneficial results via optimizing industrial structures—especially promoting low-carbon industries, advocating a low carbon lifestyle, and taking advantage of urbanization to strengthen innovation in low-carbon technologies.

(5) As city size distribution changes with urbanization, leaders and policymakers should be aware of the potential negative effects within their local areas, as they have similar effects throughout the region. Promoting urbanization does not mean to simply foster an increase in urban population. During the urbanization process, city leaders should maintain population at optimum levels and cities at reasonable sizes to keep the eco-friendly effects larger than the polluting effects.

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