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

Honglei Niu and William Lekse

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 Model to empirically examine aspects of developing low-carbon strategies for the rapidly expanding size and number of the world's urban areas. Their 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 error model; panel data

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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) and UN Habitat III (2016). 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, relative to carbon emissions, unplanned and 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 (Fig. 1).

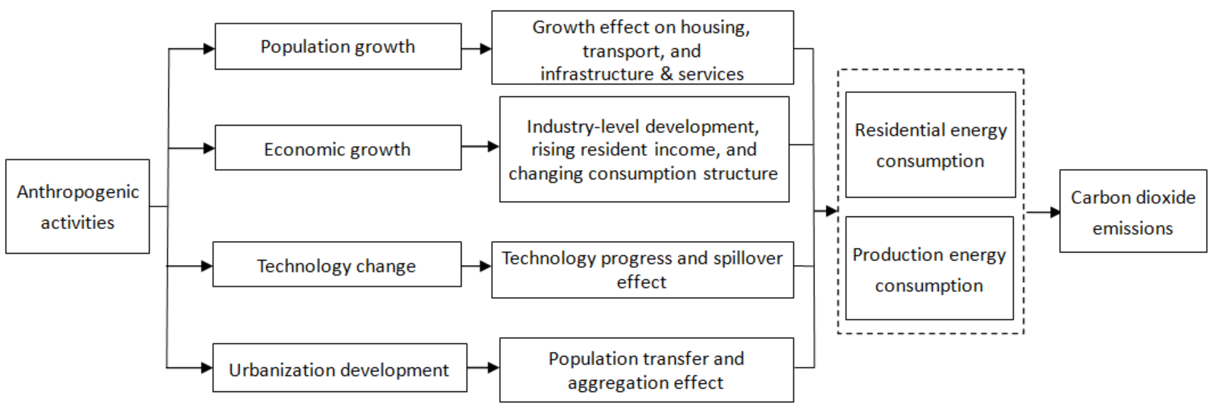

Fig. 1. Conceptual framework of factors influencing carbon emissions

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). 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.

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. In our model, 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 and the spillovers of provincial government environmental regulation produce free-riding effect, the correlation between provincial carbon emissions are strengthened. Therefore spatial correlation should be taken into account or else the estimation of model parameter is biased. Our research investigates the spatial correlation among these areas using the spatial econometric model which is the most common and widely put into use in this field.

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

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; and (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 one study has a regional focus without a dynamic focus. 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 KS, et al., 2013; Xu SC, et al., 2014; He KB, et al., 2005), input-output analysis (Liang QM, et al., 2007), or Granger Causality Test (Sahbi Farhani and Ilhan Ozturk, 2006) 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. In addition, results regarding the effect of urbanization on carbon emissions are not entirely consistent (see Table 1).

Table 1. Some representative literature reviews

Researchers	Geographic range	Dependent variables	Independent variables	Study model and method	Basic results
Phetkeo Poumanyvong and Shinji Kaneko (2010)	99 countries	E, C	P, A, T, S, UR	Extended STIRPAT model	Carbon emission effect of urbanization is positive.
Cole MA and Neumayer E (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.
Sahbi Farhani and Ilhan 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
Martinez-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 Liu 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

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.

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 (Chuanglin Fang, et al., 2012; Bin Xu and Boqiang Lin, 2014; Sahbi Farhani and Ilhan Ozturk, 2015; Zhang CG and Lin Y, 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 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. Empirical models

3.1 Extended STIRPAT model

Our basic model is an extended form of the STIRPAT model, which originated from the IPAT model (I=P×A×T) advanced by Ehrlich and Holden (1971), where I is environmental impact, P stands for population, A denotes average wealth, and T refers to technology level. The STIRPAT model ($I_i = aP_i^b A_i^c T_i^d e^{e_i}$) was developed by Dietz and Rose (2003) to resolve the shortcoming that the IPAT equation could be used only to analyze factors impacting the environment proportionally. In its expression, a represents model coefficient; b, c, and d are the coefficients for population, wealth, and technology, respectively. And e^{e_i} is an error term and i represents time or region.

The STIRPAT model permits the addition of other variables to investigate the impact of urbanization on carbon emissions, and so its logarithmic extended form is:

$$\ln I_{it} = \ln a + b(\ln P_{it}) + c(\ln A_{it}) + d(\ln T_{it}) + e(\ln UR_{it}) + f(\ln US_{it}) + e_{it} \qquad (1)$$

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

Table 2. Definitions of all relevant variables

Variab	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

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 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.

3.2 Dynamic Spatial Durbin Panel Data Models

From the extended STRPAT model, which expresses the basic relationship among all variables, our study develops the dynamic Spatial Durbin Panel Data Models for empirical investigation. Many different forms of dynamic spatial panel models have been adopted, and the most generalized dynamic model can be expressed in vector form as

$$y_{\mathrm{t}} = \tau y_{t-1} + \delta W y_{\mathrm{t}} + \eta W y_{\mathrm{t-1}} + X_t \beta_1 + W X_t \beta_2 + X_{t-1} \beta_3 + W X_{t-1} \beta_4 + Z_t \pi + \nu_t \quad (2)$$

$$\nu_t = \rho \nu_{t-1} + \lambda W \nu_t + \mu + \xi_t \iota_N + \varepsilon_t \quad (3)$$

$$\mu = \kappa W \mu + \zeta \quad (4)$$

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 $(i = 1, \ldots, N)$ in the sample at time t $(t = 1, \ldots, T)$; 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}, Wy_{t} and $Wy_{\mathrm{t-1}}$. 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 ν_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, $\mu = (\mu_1, \ldots, \mu_N)$, 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, ξ_t denotes time-period specific effects, and ι_N as an $N \times 1$ vector of ones, meant 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 $\sigma_\zeta{}^2$.

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 performed by the other models. Therefore, this research builds on the SDPDM.

If set as $\beta_3 = \beta_4 = \lambda = \pi = \kappa = 0$ in Eq. (2), the full form of the dynamic SDPDM（Elhorst et al., 2010）is as follows:

$$y_{\mathrm{t}} = \tau y_{t-1} + \delta W y_t + \eta W y_{t-1} + X_t \beta_1 + W X_t \beta_2 + \alpha + \gamma + \nu_t \quad (5)$$

In this case, the samples of Chinese provinces are not random but limited to certain individual provinces, and so the models with fixed effects should be better (Baltagi, 2001). 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 $\beta_3 = \beta_4 = \lambda = \pi = \kappa = \eta = 0$, $y_{\mathrm{t}} = \tau y_{t-1} + \delta W y_t + X_t \beta_1 + W X_t \beta_2 + \alpha + \gamma + \nu_t$ (6)

and in the event of $\beta_3 = \beta_4 = \lambda = \pi = \kappa = \tau = 0$, $y_{\mathrm{t}} = \delta W y_t + \eta W y_{t-1} + X_t \beta_1 + W X_t \beta_2 + \alpha + \gamma + \nu_t$.(7)

If in Model set $y_t = (\ln I_{1t}, \ln I_{2t}, \ldots, \ln I_{Nt})^T$ and $X_t = \begin{pmatrix} \ln P_{1t} & \ln A_{1t} & \ln T_{1t} & \ln UR_{1t} & \ln US_{1t} \\ \ln P_{2t} & \ln A_{2t} & \ln T_{2t} & \ln UR_{2t} & \ln US_{2t} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \ln P_{Nt} & \ln A_{Nt} & \ln T_{Nt} & \ln UR_{Nt} & \ln US_{Nt} \end{pmatrix}$,

where $t = 1, 2, \ldots, T$, the three different dynamic SDPDMs are built for empirical analysis.

3.3 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 Liu 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

$$y_t = (I-\delta W)^{-1}(\tau I+\eta W)y_{t-1} + (I-\delta W)^{-1}(X_t\beta_1 + WX_t\beta_2) + (I-\delta W)^{-1}v_t + (I-\delta W)^{-1}(\alpha+\gamma) \quad (8)$$

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

$$\left[\frac{\partial y}{\partial x_{1k}}, \cdots, \frac{\partial y}{\partial x_{Nk}}\right]_t = (I-\delta W)^{-1}(\beta_{1k}I_N + \beta_{2k}W) \quad (9)$$

In Eq. (9) 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

$$\left[\frac{\partial y}{\partial x_{1k}}, \cdots, \frac{\partial y}{\partial x_{Nk}}\right]_t = [(1-\tau)I - (\delta+\eta)W]^{-1}(\beta_{1k}I_N + \beta_{2k}W) \quad (10)$$

In Eq. (10), when $\delta = \beta_{2k} = 0$, there are no short-term indirect effects, and 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 $[(I-\delta W)^{-1}(\beta_{1k}I_N+\beta_{2k}W)]^{\bar{d}}$ 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 $[(1-\tau)I-(\delta+\eta)W)^{-1}(\beta_{1k}I_N+\beta_{2k}W)]^{\bar{d}}$ and $[(1-\tau)I-(\delta+\eta)W)^{-1}(\beta_{1k}I_N+\beta_{2k}W)]^{\overline{rsum}}$ respectively. In the expressions above, $\bar{d}$ denotes the average value of diagonal elements and $\overline{rsum}$ indicates the average row sum of non-diagonal elements.

4. 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.

5. Spatial econometric methodology

5.1 Spatial autocorrelation test

5.1.1 Moran's I index and LISA map

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 $Moran's\ I$ by Anselin (1995), divides $Moran's\ I$ into each region unit.

5.1.2 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.

5.2 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. Because the ML and QML estimators can be widely considered to be bias-correct, they have been chosen as the estimators for this research. 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. Research was extended to include fixed-time effects by Lee and Yu (2010).

6. Empirical results

6.1 Spatial autocorrelation test

As shown in Fig. 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.

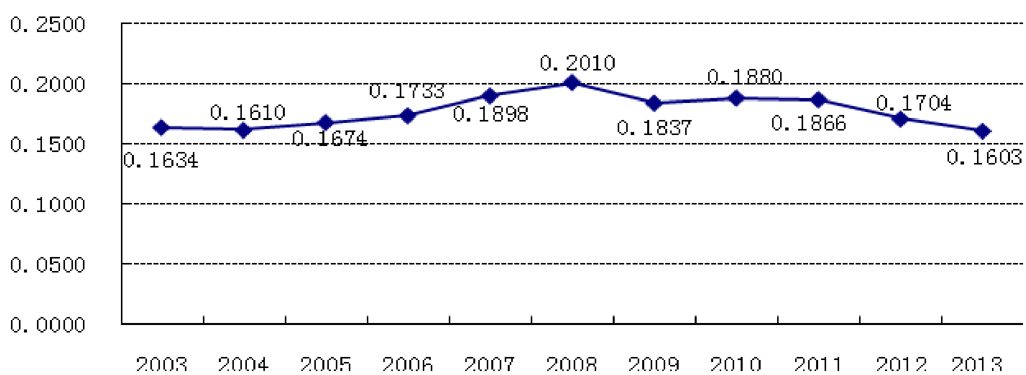

Fig. 2. Moran's I indexes of provinces' carbon emissions from 2003 to 2013

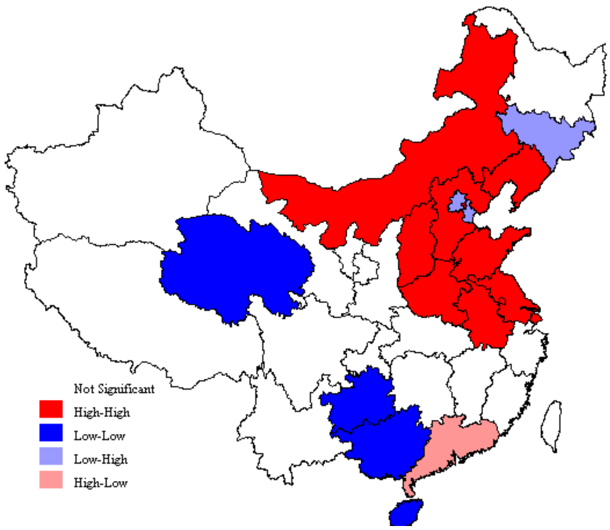

Fig. 3. LISA clustering map of provinces' carbon emissions in 2000

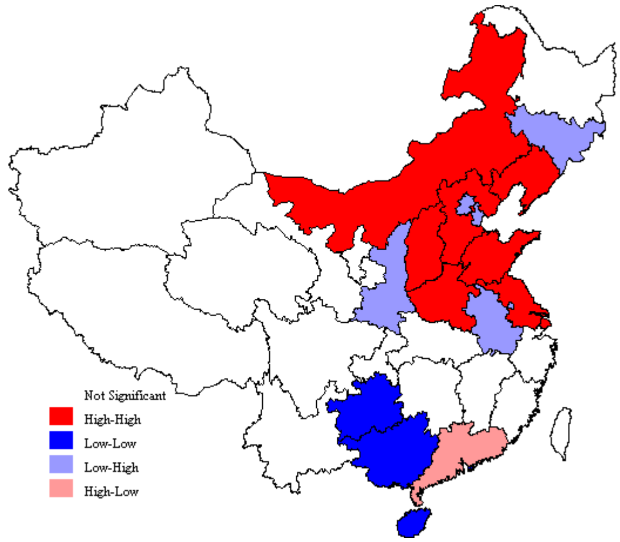

Fig. 4. LISA clustering map of provinces' carbon emissions in 2005

Note: This 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.

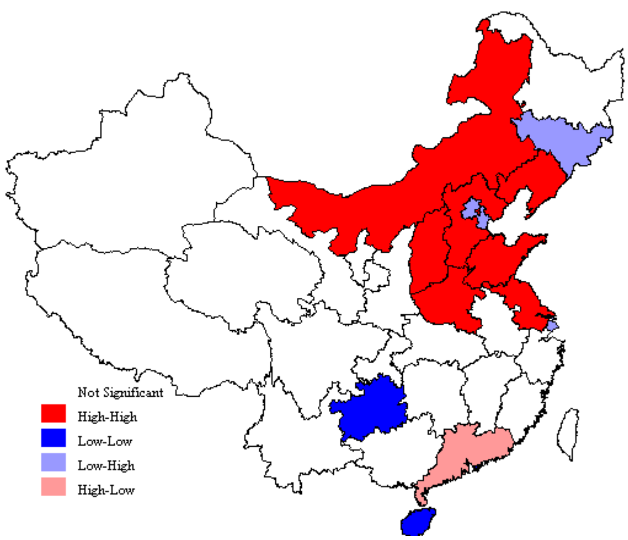

Fig. 5. LISA clustering map of provinces' carbon emissions in 2010

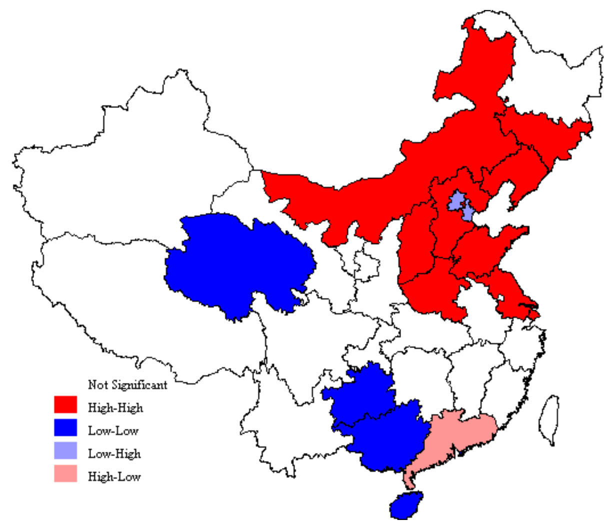

Fig. 6. LISA clustering map of provinces' carbon emissions in 2013

Note: This 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.

We use Geoda to draw LISA clustering maps of carbon emissions for each of the provinces in 2000, 2005, 2010, and 2013. Fig. 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 throughout 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 the north, 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. 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.

Table 3. Estimates of three dynamic spatial Durbin models

Variable	Model (1)		Model (2)		Model (3)	
	Dynamic Spatial Durbin Model with both time lagged and space-time lagged dependent variable		Dynamic Spatial Durbin Model with time lagged dependent variable		Dynamic Spatial Durbin Model with space-time lagged dependent variable	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
$ln(I)_{-1}$	0.070^{***}	3.620	0.069^{***}	3.600	-	-
$W*ln(I)_{-1}$	0.028^{***}	0.460	-	-	0.096^{*}	1.600
$W*ln(I)$	0.178	1.480	0.168^{*}	2.420	0.223^{***}	1.840
$ln(P)$	0.936^{***}	41.900	0.935^{***}	42.080	0.958^{***}	43.080
$ln(A)$	0.990^{***}	25.620	0.989^{***}	25.590	0.994^{***}	25.380
$ln(T)$	1.130^{***}	27.820	1.131^{***}	27.910	1.156^{***}	28.670
$ln(UR)$	-0.345^{***}	-5.490	-0.344^{***}	-5.480	-0.337^{***}	-5.280
$ln(US)$	0.094^{**}	2.120	0.094^{**}	0.034	0.100^{**}	2.230
$W*ln(P)$	0.168	1.320	0.163	1.290	0.163	1.270
$W*ln(A)$	0.523^{***}	2.900	0.514^{***}	2.870	0.565^{***}	3.100
$W*ln(T)$	0.393^{**}	2.000	0.400^{**}	2.030	0.425^{**}	2.140
$W*ln(UR)$	-0.584^{***}	-3.680	-0.569^{***}	-3.670	-0.651^{***}	-4.050
$W*ln(US)$	0.255^{*}	1.780	0.266^{*}	1.890	0.271^{*}	1.880
sigma^2	0.0441		0.0441		0.0452	
R^2	0.9535		0.9557		0.9443	
log-likelihood	57.8870		57.8113		52.1154	

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.

6.2 Estimation results

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

(1) Dependent variable of carbon emissions

The estimated coefficient for $ln(I)_{-1}$ equals 0.069 and is statistically significant at the 1% level, which indicates that previous carbon emissions have a positive and significant impact on current carbon emissions. In Fig. 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.

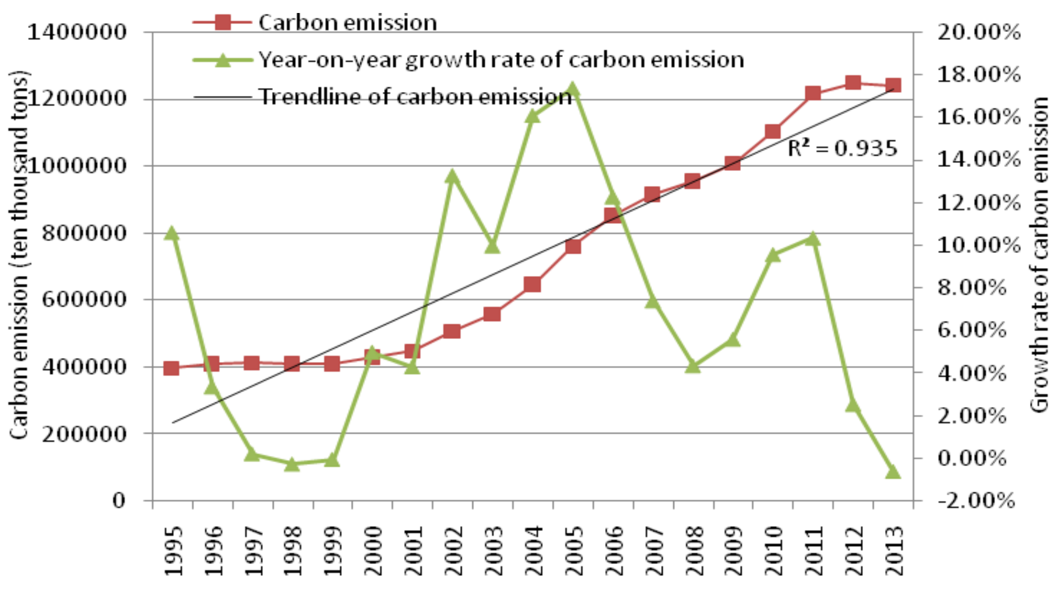

Fig. 7. The growth rate of carbon emissions in China from 1995 to 2013

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

In addition, the coefficient for $W * ln(I)$ is 0.168 at the significance level of 10%, 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.

(2) Independent variable of urbanization rate

The estimated coefficient for $ln(UR)$ is -0.344 and is statistically significant at the 1% level; similarly, the coefficient for $W * ln(UR)$ is -0.584 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.

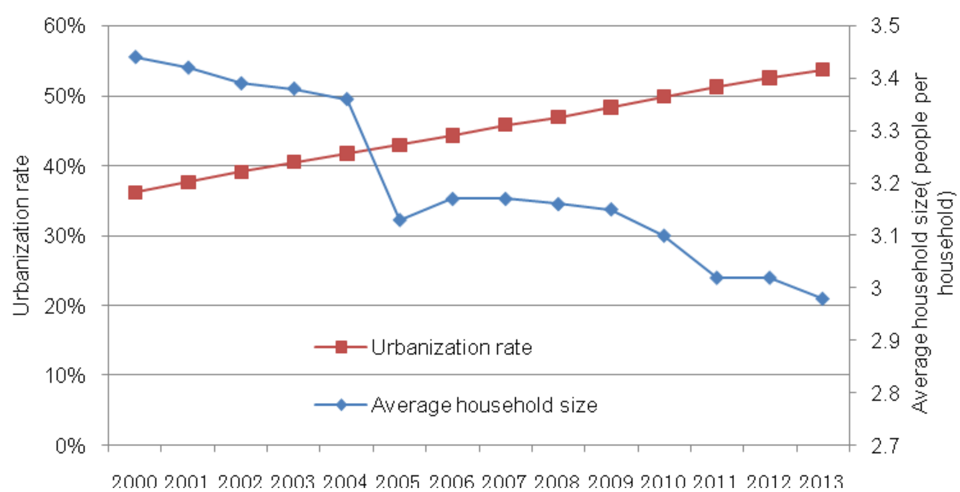

Fig. 8. Urbanization rate and average family size in China from 2000 to 2013

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 (Fig. 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.

First, household size is trending downward in China, with the average household size falling from 3.44 in 2000 to 2.98 in 2013 (Fig. 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. 2003; Baiocchi et al. 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).

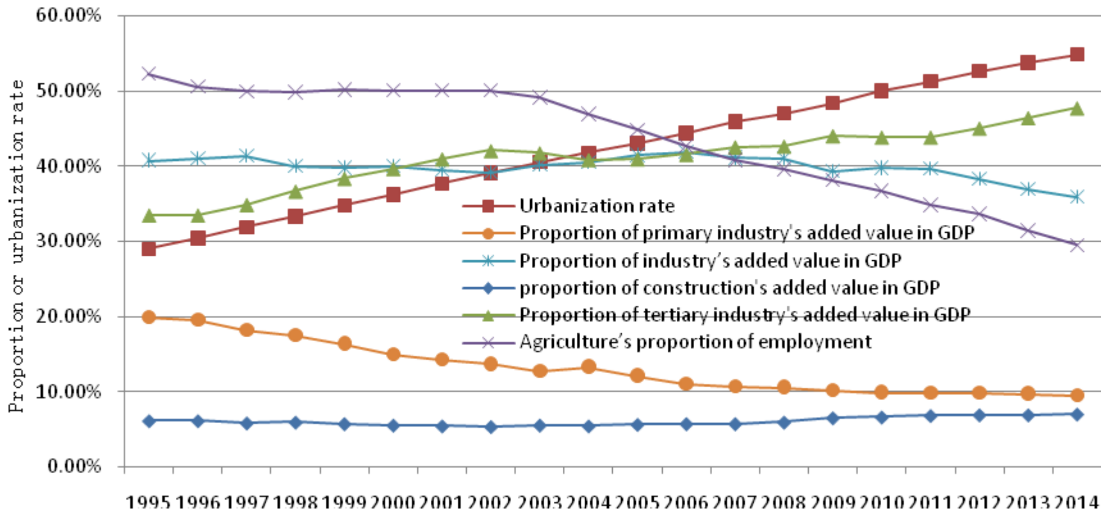

Fig. 9. Industrial structure and agriculture's proportion of employment in China from 1995 to 2014

Source: China Statistical Yearbook

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. Fig. 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 (Fig. 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 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 disposable growth and the Engel Index, the decline 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.

(3) Independent variable of urban primary index

The estimated coefficient of $ln(US)$ is 0.094 at a significance level of 5%, while that of $W * ln(US)$ is 0.266 at 10%, showing that the urban primary index is positively correlated with carbon emissions, and also showing positive spatial spillover effects. In Fig. 10, both carbon emissions and the average urban primary index increase 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 variable 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 emissions is positive or negative depends on which effect is dominant.

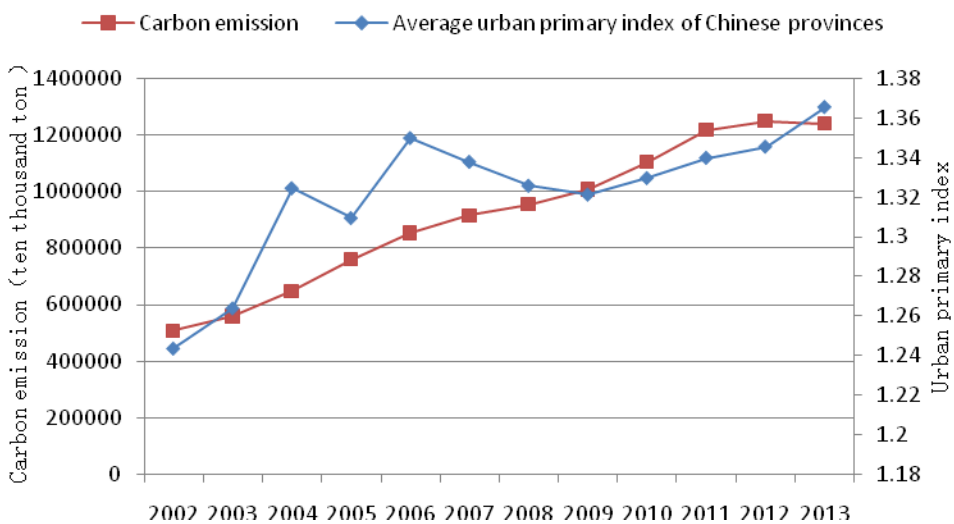

Fig. 10. Carbon emissions and average urban primary index of Chinese provinces from 2002 to 2013

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.

(4) Other independent variables

First, the estimated coefficient for $ln(P)$ is 0.935 at a significance level of 1%, but the estimated result for $W*ln(P)$ is not significant. This indicates that Chinese population growth increases energy demand, which in turn increases carbon emissions. However, there are no 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 0.989 at significance level of 1% while the coefficient of $W*ln(A)$ is significant (0.514). 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 1.131 at a significance level of 1% while the coefficient of $W*ln(T)$ is 0.400 at 5% 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.

(5) Regarding direct and indirect effects

In Table 4, in the short run, with the exception that the indirect effect of $ln(P)$ is not significant, the direct, indirect, and total effects are significant and have the same signs as those of the estimated coefficients in Table 3. 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 $ln(P)$, $ln(T)$ and $ln(US)$). 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; this is different from those exhibited in the short-term. 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.

Table 4. Estimated effects of Model (2)

Variable	Short term			Long term		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
$ln(P)$	0.933***	0.003	0.940***	0.943***	-0.006	0.937***
	(39.72)	(0.06)	(14.68)	(19.86)	(-0.11)	11.42
$ln(A)$	0.985***	0.309***	1.294***	1.051***	0.316***	1.367***
	(23.31)	(3.38)	(12.83)	(11.59)	(3.21)	9.59
$ln(T)$	1.129***	0.178*	1.306***	1.376***	0.201	1.577***
	(27.19)	(1.63)	(10.71)	13.65	(1.52)	8.67
$ln(UR)$	-0.326***	-0.453***	-0.780***	0.121***	0.160***	0.282***
	(-5.79)	(-3.64)	(-6.00)	(2.98)	(3.10)	(3.57)
$ln(US)$	0.096**	0.225*	0.321***	0.013	0.024	0.036
	(2.08)	(1.86)	(2.58)	(1.21)	(1.38)	(1.47)

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

7. Conclusion

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, enabling the conclusions as shown to provide mayors and policymakers with more useful methods for developing low-carbon urbanization strategies, especially methods for 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 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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