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Spatiotemporal variations of energy-related CO_2 emissions in China and its influencing factors: An empirical analysis based on provincial panel data

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ABSTRACT

This paper examines carbon dioxide (CO_2) emissions from the perspective of energy consumption, detailing an empirical investigation into the spatiotemporal variations and impact factors of energy-related CO_2 emissions in China. The study, which is based on a provincial panel data set for the period 1995–2011, used an extended STIRPAT model, which was in turn examined using System-Generalized Method of Moments (Sys-GMM) regression. Results indicate that while per capita CO_2 emissions in China were characterized by conspicuous regional imbalances during the period studied, regional inequality and spatial autocorrelation (agglomeration) both decreased gradually between 1995 and 2011, and the pattern evolutions of emissions evidenced a clear path dependency effect. The urbanization level was found to be the most important driving impact factor of CO_2 emissions, followed by economic level and industry proportion. Conversely, tertiary industry proportion constituted the main inhibiting factor among the negative influencing factors, which also included technology level, energy consumption structure, energy intensity, and tertiary industry proportion. Importantly, the study revealed that the CO_2 Kuznets Curve (CKC), which describes the relation between CO_2 emissions and economic growth, in fact took the form of N-shape in the medium- and long-term, rather than the classical inverted-U shape of the environmental Kuznets Curve (EKC). Specifically, an additional inflection appeared after the U-shape relationship between economic growth and CO_2 emissions, indicating the emergence of a relink phase between the two variables. The findings of this study have important implications for policy makers and urban planners: alongside steps to improve the technology level, accelerate the development of tertiary industry, and boost recycling and renewable energies, the optimization of a country's energy structure that can in fact reduce reliance on fossil energy resources and constitute an effective measure to reduce CO_2 emissions.

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1. Introduction

Global warming has in recent years become an indisputable fact. Through deepening research into and analysis of the phenomenon, most climate scientists now identify greenhouse gases, most notably CO_2 emissions, as constituting the main cause of global warming. Despite this knowledge, global emissions of CO_2 from fossil fuel combustion and cement production continue to rise at a staggering rate, and a large amount of CO_2 continues to be spilled into the atmosphere each day. China is the largest developing country in the world; its economy has undergone rapid and continuous expansion since the Chinese economic reform in 1978, with an annual growth rate of 9.9% [1,2]. However, behind this economic success lies the reality that China is entering the energy-intensive stages of economic development [3]. As the largest energy consumer and CO_2 emitter in the world, the country is now facing fossil energy supply crises and mounting international pressure to curb its CO_2 releases [4]. As a result, the Chinese government has implemented a bold national strategy for energy saving and CO_2 emissions reduction. At the 2009 Copenhagen climate conference, China set a goal to reduce its carbon intensity (that is, CO_2 emissions per unit of gross domestic product, or GDP) by 40–45% of 2005 levels by 2020. This target would be binding, through its inclusion in China's national economic and social development and long-term plans. In addition, through the 12th Five-Year Plan, the Chinese government plans to achieve a reduction of 16% in energy intensity (energy consumption per unit of GDP) and 17% in carbon intensity. All of these actions demonstrate the strategic adjustments currently being undertaken by the Chinese government in order to deal with the country's high carbon intensity. In meeting these goals, China faces the additional challenges of not only radically curbing fossil-energy use and emissions, but also doing so in an equitable manner, and whilst maintaining economic growth [5]. China is a vast country, and marked regional inequalities exist between its provinces, not only in terms of their population size, economic scale, and industry structure, but also (and more significantly) in terms of their energy structure. Given these inequalities and the framework of the national carbon reduction targets now in play, it is essential that an analysis be performed of the spatiotemporal variations of CO_2 emissions and, further, that key impact factors which will effectively inhibit the rapid growth of emissions be identified.

A number of previous studies have analyzed the distribution of CO_2 emissions, from a range of different perspectives and with various methods. The literature addressing inequality in carbon emissions can broadly be divided into two general types. The first group of studies is primarily concerned with the use and development of measures of inequality – for instance, working with concentration measures such as the Gini coefficient and coefficient of variation (CV), or entropy measures such as the Theil and Atkinson indices [6–11]. One example of such scholarship lies in Heil and Wodon's [6] group decomposition of the Gini coefficient in order to study inequality in carbon emissions, which found inequality in per capita CO_2 emissions to, on a global level, be directly related to per capita GDP. Heil and Wodon's [6] findings also appear to hold true in the context of China. Using data on China's provincial energy consumption and energy-related carbon emissions, Yue et al. [12] conducted a study, based on the Theil index, which found that carbon emissions and per capita emissions were significantly higher in China's eastern region than in the country's middle and western regions. Mussini and Grossi [13] analyzed the change in per capita CO_2 emission inequality in Europe using a three-term decomposition of the Gini index. The within-group and between-group inequalities of CO_2 emissions were identified. Using similar analysis techniques, Grunewald et al. [14] decompose the inequalities of CO_2 emissions in the primary energy carriers and economic sectors of 90 countries. The second group of studies mainly focuses on the analysis of either retrospective (that is, involving historical emissions) or prospective (working with scenario simulation of future trends) data [10,15]. Almost all of the studies that have so far addressed the inequality of CO_2 emissions were conducted using conventional econometric measurement indexes, and as a result did not consider spatial effects. By treating research units as independent and homogeneous individuals, existing research has neglected the spatial autocorrelation of geographic data, an omission which can lead to biased results in terms of the distribution of research objects.

The factors affecting CO_2 emissions are complex. Research is increasingly being conducted into the major factors influencing CO_2 emissions in different countries and regions, and a range of different methods have been used in order to examine these impact factors, amongst which the SDA method [16], the LMDI method [17–20], the IPAT model [21–24], the STIRPAT model [24–29], the Panel Granger causality test [30–34], the ARDL model [35,36], and the Kaya equation [37] are the most popular. Using the SDA method Ang et al. [16] have examined factor changes in energy use and gas emissions in Singapore, China, and Korea. Similar studies were also taken in US by Feng et al. [38], in China by Guan et al. [39] and Feng et al. [40]. Using the LMDI model and working within the context of China, Wang et al. [18] were able to decompose CO_2 emissions into population, GDP per capita, energy consumption intensity, and energy consumption structure. Based on IPAT formulation, York et al. [23] found population, affluence, and technology to have different potentials for mitigating different types of impacts on environmental change, and that all the factors were equally important. Similar methods were used by York et al. [24]. Taking Beijing city as an example and using an improved STIRPAT model, Wang et al. [28] examined the key influencing factors in relation to CO_2 emissions, finding urbanization level, economic level, and industry proportion to all positively impact on CO_2 emissions, while tertiary industry proportion, energy intensity, and R&D output were identified as having a negative influence. This finding was supported by similar results in subsequent studies by Wang et al. in relation to Guangdong province [29], by Al-mulali [33] in relation to the Middle East, by Soytas et al. [41] in a study addressing the United States, and by Hamit-Haggar [42] in relation to Canada. Using a panel model, Al-mulali [33] found total primary energy consumption, foreign direct investment net inflows, GDP, and total trade to be important factors in increasing

Table 1
CO_2 emissions coefficients.
Sources: IPCC [43] and the National Coordination Committee Office on Climate Change and Energy Research Institute under the National Development and Reform Commission [44].

Sources	Coal	Coke	Gasoline	Kerosene	Diesel	Fuel oil	Natural gas	Cement
CO_2 emissions coefficient	1.647	2.848	3.045	3.174	3.150	3.064	21.670	0.527

CO_2 emission in Middle Eastern countries, a finding in turn supported by studies undertaken in relation to eight Asian-Pacific countries by Niu et al. [31], BRIC countries by Pao and Tsai [32], and G-7 countries by Kum et al. [34]. Further, Jayanthakumaran et al. [35] used the ARDL methodology to test long- and short-run relationships between growth, trade, energy use, and endogenously determined structural breaks in China and India, concluding that the factors influencing CO_2 emissions vary across both China and India. Similar studies have also been undertaken by Ang [43], Halicioglu [44], and Jalil and Mahmud [45]. Among the various methods reviewed above, the STIRPAT model has been widely used in recent research. Whilst this previous research has certainly enriched our understanding of the main impact factors for CO_2 emissions, a number of shortcomings are also evident in these previous studies. Importantly, existing research has to a large extent focused on population and economic and technology levels, and has, as a result, seldom directed attention towards energy intensity, energy consumption structure, industrial proportion, urbanization level, or tertiary industry proportion. These significant factors should, it is argued, be examined for their impacts on CO_2 emissions. In addition, most Chinese studies have either focused on the level of a single city, or else on the national level [28,29]; this has occurred at the exclusion of the provincial level. Finally, we note that most models used to examine the factors for CO_2 emissions have been based on time-series data or cross-sectional data. Whilst it is widely known that panel data sets have several major advantages over conventional cross-sectional or time series data sets [46], few studies have to date been based on panel data models.

Building on this previous research, this study firstly calculated CO_2 emissions in China's 30 provinces over the period 1995–2011, employing spatial analysis techniques in order to examine the spatiotemporal variations of CO_2 emissions according to Tobler's first law of geography [47]. Using an extended STIRPAT model, we then examined the impact of human factors on CO_2 emissions. Finally, we also investigated the CO_2 Kuznets curve (CKC), a measure based on an environmental Kuznets curve (EKC), which we generated using provincial panel data.

The remainder of the paper is organized as follows. Section 2 focuses on methods and data, presenting the spatial analysis methods, the extended STIRPAT model and the data used within the study. Section 3 presents the results of the study and discusses the ways in which the models proposed in Section 2 were used to analyze the spatiotemporal variations and impact factors of CO_2 emissions in China's provinces. Section 4 sets out the main conclusions and details a series of policy implications which can be drawn from the results of the study.

2. Methodology and research material

2.1. Estimating energy-related CO_2 emissions in China's provinces

With reference to Du et al. [46], we calculated CO_2 emissions for China's 30 provinces for the period 1995 to 2011 using the CO_2 emissions coefficients published by the Intergovernmental Panel on Climate Change (IPCC) [48], and the National Coordination Committee Office on Climate Change and the Energy Research Institute under the National Development and Reform Commission [49]. Energy-related CO_2 emissions can be calculated using:

$$I=\sum_{i=1}^{7}(E_i \times F_i)+Q \times C \tag{1}$$

where I represents the total CO_2 emissions; i denotes the different types of fossil fuel (including coal, coke, gasoline, kerosene, diesel, fuel oil, and natural gas); E_i refers to the ith kind of primary energy consumption; F_i is the CO_2 emissions coefficient of fossil fuels i; Q represents the quantity of cement production; and C is the CO_2 emissions coefficient of the cement production process (Table 1).

2.2. Spatial autocorrelation

2.2.1. Global spatial autocorrelation

Spatial autocorrelation is a spatial data analysis method that is used to estimate and analyze the degree of dependency among observational units in a geographic space. Spatial autocorrelation can reveal phenomena of spatial dependence and spatial heterogeneity in geographic data [50]. One of the most commonly used measures of spatial autocorrelation is Moran's I coefficient:

$$I=\frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}}\frac{\sum_{j=1}^{n}\omega_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\sum_{i=1}^{n}(x_i-\overline{x})^2} \tag{2}$$

where x is a variable measured in each of the $i=1, 2, \ldots, n$ locations, and ω_{ij} is the element in row i column j of a spatial weights matrix. At a given level of significance, if Moran's $I>0$, it denotes positive correlation; if Moran's $I<0$, this denotes negative correlation. The larger Moran's I is, the larger the correlation degree is. When Moran's $I=0$, this represents a random spatial distribution. Generally, the z value is used for Moran's I statistic test. The z value is calculated using $Z=(I-E(\mathrm{I}))/\sqrt{\mathrm{Var(I)}}$

2.2.2. Local spatial autocorrelation

Local Moran's I is a local indicator of spatial autocorrelation for the analysis of spatial clustering. Local Moran's I can provide more detailed insights into the location-specific nature of spatial dependence [50]. The specific formula of the local Moran statistic can be shown as follows:

$$I_i=\frac{z_i}{\sum_i z_i^2}\times z_i^{\circ} \tag{3}$$

where z_i expresses the observation for region i on a variable as a deviation from the mean, and z_i° is the spatial lag for location I, obtained as:

$$z_i^{\circ}=\sum_{j=1}^{n}\omega_{ij}z_j \tag{4}$$

In the local spatial autocorrelation implementation, each observation could be placed into one of four classes, as summarized in Table 2.

These classifications can be portrayed in a Moran's scatter plot. The scatter plot allows for the visualization of several geographical

Table 2
Local Moran classifications.
Source: Rey [45].

Class	Own value z_i	Neighbor's value z_i°
HH	Above average	Above average
HL	Above average	Below average
LH	Below average	Above average
LL	Below average	Below average

aspects of the distribution at one point in time [50]. According to the classifications, we can further divide a Moran scatter plot into four quadrants (I, II, III, and IV), corresponding to four different types of regional disparities:

(1) I quadrant (HH): high values surrounded by high values. The inequality is relatively small;
(2) II quadrant (LH): low values surrounded by high values. The disparity is relatively large;
(3) III quadrant (LL): low values surrounded by low values. The imbalance is relatively small; and
(4) IV quadrant (HL): high values surrounded by low values. The inequality is relatively large.

The definitions of High and Low are compared to the average for the whole study area.

2.2.3. STIRPAT model

Since the IPAT model has a concise form, it is widely used in analyzing the impact of human factors on environmental changes [21–23]. Here, I is the environmental impact, P represents population, A is affluence, and T is technology level. After many improvements, the IPAT model has some derivative forms, including ImPACT model, which decomposes T into T and C (consumption per unit of GDP) [51]. Since IPAT and ImPACT models do not allow non-monotonic and non-propositional changes in human factors, the utilization of the two is limited. To overcome this shortcoming, Dietz and Rosa [25] reformed the IPAT model into a random form, establishing the STIRPAT model:

$$I_i = aP_i^b A_i^c T_i^d e_i \tag{5}$$

where I, P, A and T have the same meaning as in the IPAT model; a is the constant term; b, c, and d are undetermined parameters; and e denotes the random error. The IPAT model can thus be rewritten as a particular form of STIRPAT, when $a=b=c=d=1$. In empirical studies, Eq. (4) may be converted to logarithmic form:

$$\ln I_i = \ln a + bP_i + cA_i + dT_i + lne_i \tag{6}$$

where ln(.) is a natural logarithm. In this form, b, c, and d can be seen as referring to the percentage change in environmental impact caused by a 1% change in an impact factor when the other influence factors remain unchanged, which is equivalent to the elastic coefficient in economics.

The STIRPAT model not only allows each coefficient as a parameter to estimate, but also allows the proper decomposition of each factor [25]. According to the characteristics of each study, corresponding improvements are often made in the relevant literature based on the original model in order to carry out a range of new empirical research studies [24,52]. Considering the characteristics of energy-related CO_2 emissions in China, and learning from the relevant literature, we expanded the STIRPAT model by incorporating urbanization level, industry proportion, tertiary industry proportion, energy intensity, and energy structure into the model. Additionally, we decomposed affluence into linear, quadratic, and cubic terms in order to fully portray the relationship between per capita CO_2 emissions and GDP per capita, and validate the EKC hypothesis. Existing studies indicate that an inverted-U curve relationship exists between economic growth and local pollutant emissions. However, whilst pollutants such as SO_2 and NO_x have local effects, CO_2 has a cross-period and cross-country global effect as such, it is essential research into CO_2 emissions think beyond the traditional inverted-U trend between economic growth and CO_2 emissions. This study therefore introduces a traditional cubic term into the STIRPAT model, called the “CKC relink effect.” A number of previous studies have in fact found the cubic term to be more effective portraying the relationship between economic growth and CO_2 emissions [53–55]. The extended STIRPAT model can thus be established as follows:

$$\begin{aligned}\ln I_{it} = {} & a_0 + a_1 \ln A_{it} + a_2(\ln A_{it})^2 + a_3(\ln A_{it})^3 + a_4 \ln P_{it} \\ & + a_5 \ln T_{it} + a_6 \ln ES_{it} + a_7 \ln EI_{it} \\ & + a_8 \ln IP_{it} + a_9 \ln TIP_{it}\end{aligned} \tag{7}$$

where I denotes per capita CO_2 emissions; P represents urbanization level (expressed as the percentage of the urban population in the total population); A denotes affluence (expressed as GDP per capita); T refers to technology level (expressed as carbon emission intensity); ES is energy structure (the percentage of coal consumption to total energy consumption); EI denotes energy intensity (expressed as energy consumption per Yuan GDP); IP represents industry proportion (expressed as a percentage of the increased value of secondary industry to GDP); and TIP denotes tertiary industry proportion (expressed as a percentage of the increased value of tertiary industry to GDP).

2.3. Data acquisition

All data used in this paper, with the exception of CO_2 emissions, were obtained from the China Statistical Yearbook and China Energy Statistical Yearbook, from 1995 to 2011. The data on the CO_2 emissions of provinces were derived from calculations using the method described previously. The total primary energy consumption and consumption of coal, coke, gasoline, kerosene, diesel, fuel oil, and natural gas were all converted into standard coal measures (units of 10^4 t). The urbanization level, economic level, technology level, energy intensity, energy structure, industrial proposition, and tertiary industry proportion were given as a percentage of the urban population, GDP per capita, carbon emission intensity (tons/10^4 Yuan), energy consumption intensity (tons/10^4 Yuan), fossil oil consumption to total energy consumption, percentage of the added value of secondary industry to GDP, added value of tertiary industry to GDP, respectively. To eliminate the price effect, GDP was deflated by the consumer price index in the year 2000, which was used to calculate per capita GDP in Yuan and CO_2 emissions intensity and energy intensity in tons per 10^4 Yuan. Table 3 shows the statistical description of the variables in 30 Chinese provinces from 1995 to 2011.

Table 3
Summary statistics of the variables.

Variables	Symbol	Unit	Mean	Std. Dev	Min	Max
Per capita CO_2	I	ton	4.33	2.20	0.94	12.91
Urbanization level	P	%	43.33	16.40	17.19	89.30
Economic level	A	Yuan	16224.63	14829.06	1853	85213
Technology level	T	ton/10^4 Yuan	3.77	1.99	0.97	11.32
Energy intensity	EI	ton/10^4 Yuan	1.73	0.98	0.21	7.66
Energy structure	ES	%	66.08	16.67	24.16	92.10
Industry proportion	IP	%	45.28	7.90	19.81	60.13
Tertiary industry proportion	TIP	%	39.62	7.16	20.22	76.14

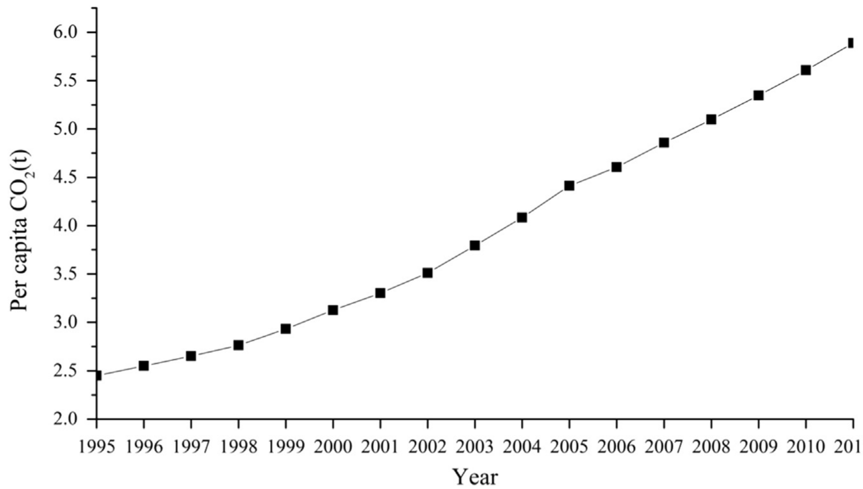

Fig. 1. Per capita CO_2 emissions in China, 1995–2011.

3. Results and discussion

3.1. The temporal evolution characteristics of per capita CO_2 emissions

The per capita CO_2 emissions in China over the period 1995–2011 were calculated using Eq. (1), as indicated in Fig. 1. Per capita CO_2 emissions in China were found to have increased annually during the study period, from 2.45 t in 1995 to 5.89 t in 2011. The annual growth rate was 5.3%.

Studies of temporal evolution characteristics often employ a variety of conventional evolution measurements, like the commonly utilized coefficient of variation (CV[1]). With the development of spatial data analysis, indexes explicitly taking into account spatial effects, such as Moran's *I* (both global and local) have also increasingly been employed [56]. This study intends to use both methods for the exploration of temporal evolution characteristics. As such, Fig. 2 plots the CV and Moran's *I* evolution path of per capita CO_2 emissions during the study period. From Fig. 2, we find that the CV index decreased gradually between 1995 and 2011, indicating that overall inter-province inequality steadily decreased over that period. The inequality of per capita CO_2 emissions in Chinese provinces has therefore shown persistent divergence, a change that can be attributed to energy conservation and emissions mitigation policies. In order to lessen regional disparities and realize balanced development, China has for a long time implemented regional compensation mechanisms and distinct development policies in relation to CO_2 emissions.

The conventional evolution method described above does not take into account spatial effects. For geographic data, a "coincidence of attribute similarity with locational similarity," or spatial autocorrelation, is almost inevitable [56]. Such autocorrelation, if ignored, can lead to biased or even misleading conclusions about temporal evolution characteristics [56]. From Fig. 2, we can clearly see two distinct trends of global Moran's *I* during study period. Specifically, global Moran's *I* increased gradually from 0.36 in 1996 to 0.44 in 2002, and then started to decrease from 0.44 in 2002 to 0.29 in 2011, all are significant at 95 percent confidence level via the randomization assumption. This indicates that a spatial agglomeration trend, which was not revealed through the application of conventional methods, in fact took place in Chinese provinces during the study period.

Whilst the CV index was found to decrease over time and Moran's *I* found to increase initially and then decrease during the same period, there is no contradiction between the two indexes. Whilst the CV index reflects the discrete degrees evidenced among regions, it does not address geographic variation. In comparison, the global Moran's *I* index takes into account spatial locations, and can therefore reflect spatial agglomeration or spread during a given period. Overall, the decrease of the regional inequality of per capita CO_2 emissions in provincial China does not illustrate a trend of balanced development with respect to CO_2 emissions; rather, it simply reflects the spatial variations of CO_2 emissions at the province level.

3.2. The spatial pattern evolution characteristics of per capita CO_2 emissions

Fig. 3 plots the distributions of Moran scatter of per capita CO_2 emissions in Chinese provinces according to the temporal characteristics of global Moran's *I*, showing the local spatial correlation of per capita CO_2 emissions in Chinese provinces spatially and geographically. The right section of Fig. 3 shows the quadrant distributions of per capita CO_2 emissions: the left section shows the corresponding spatial patterns of per capita CO_2 emissions. Fig. 3 reveals characteristics of significant local spatial agglomeration in the distribution of per capita CO_2 emissions. HH and LL clusters constitute the main types of agglomeration. Whilst provinces within the HH classification tend to be concentrated in northeast China, the provinces within the LL cluster were shown to be highly concentrated in central and southeast coastal China.

The number and the distribution of each cluster of provinces also display regional dynamic characteristics. For instance, in 1995, the numbers of provinces belonging to HH and LL cluster were 5 and 19 respectively, accounting for 80% of all Chinese provinces. Correspondingly, only 20% of all provinces conformed to the remaining HL and LH classifications. These results indicate the existence of a significant dual structure in the spatial distribution of Chinese per capital CO_2 emissions in 1995. However, by 2000, the number of HH and LL provinces had increased and decreased by 4 and 5 respectively, indicating that the spatial extent of agglomeration of per capita CO_2 emissions had weakened markedly between 1995 and 2000. Further, spatial inequalities in provincial per capita CO_2 emissions in 2005 and 2011 decreased since 2000. From these findings, we can conclude that the pattern

[1] CV is a measure of the dispersion of a distribution. It is defined as the ratio of the standard deviation (σ) to the mean (μ). The larger the CV, the larger the disparity among provinces.

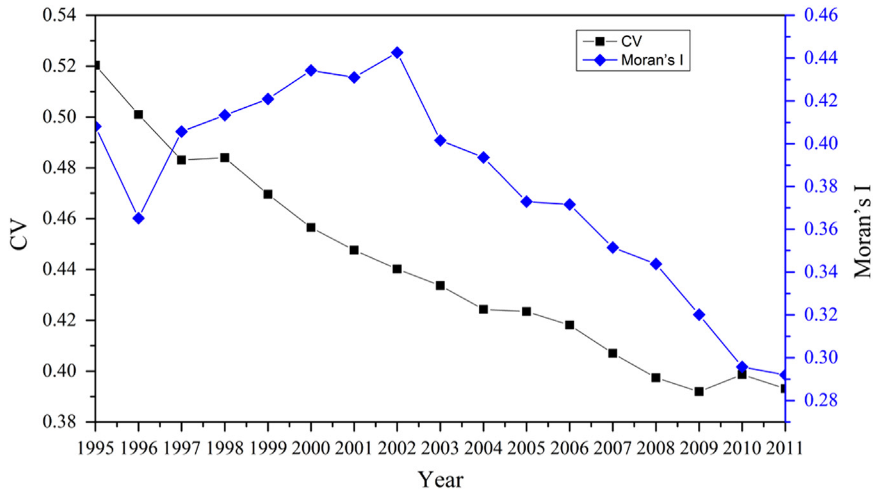

Fig. 2. Global Moran's *I* and CV of per capita CO_2 emissions in China's provinces, 1995–2011.

evolution of emissions therefore displays a certain path dependency effect.

To further understand the spatial agglomeration characteristics of CO_2 emissions, we calculated the space–time transition matrices (Table 4). In accordance with Rey's study [50], we subcategorized the 30 provinces into four types, based on the local Moran statistics of per capita CO_2 emissions, whereby Type I referred to a transition involving a relative move of only that province, and Type II involved a transition of only the neighbors in relative space (whilst the province in question remained in the previous state). Moreover, Type III referred to a transition of both a province and its neighbors to a different state, and Type IV denoted a transition of the province-neighbor pair remains at the same level. The space–time transition matrix enables the characterization of spatial-economic asymmetries, highlights the performance of each province, and provides an indication of the nature of its mobility (both upward and downward). From Table 4, we find that most of the diagonal numbers are higher than the non-diagonal numbers, meaning that it is more likely for each category to remain at the same level during the period studied. Further, all the diagonal elements are revealed as belonging to Type IV, with 77%, 77%, and 93% of all provinces being located in the diagonal during the periods 1995–2000, 2000–2005, and 2005–2011 respectively. This indicates that the distribution of per capita CO_2 emissions in Chinese provinces displays clear path-dependency and self-reinforcing agglomeration characteristics. On the other hand, the results detailed in Table 4 also show that 47%, 47%, and 37% of all provinces transited to Type LL during the above corresponding periods. This illustrates a weakening trend in terms of the degree of concentration witnessed amongst provinces with relatively low per capita CO_2 emissions.

Note: HH=high values surrounded by high values; LH=low values surrounded by high values; LL=low values surrounded by low values; HL=high values surrounded by low values.

3.3. *Factors influencing CO_2 emissions*

Multicollinearity refers to a situation in which two or more independent variables in a multiple regression model are strongly and linearly related [29]. It is essential to test whether multicollinearity exists among explanatory variables in a study like the present one. As such, we performed a multicollinearity test, based on pooled regression. None of the variables reported VIFs higher than 10 in this test, indicating that the independent variables did not suffer from the problem of multicollinearity. The System-Generalized Method of Moments (Sys-GMM) was subsequently employed in order to estimate Eq. (6) [57]. When conducting the Sys-GMM, we used the Hansen test in order to check the reliability of the variables. Accordingly, if the estimators were found to be relatively smaller (i.e., to have a higher p value), we would not reject the null hypothesis of unsuitable for the variables. Sys-GMM allows variable correlation at first difference, but not at second difference. AR (1) and AR (2) were utilized to test whether a serial correlation existed among random disturbances. The Sys-GMM regression analysis was performed using Stata11.0 software, and the results are reported in Table 5 and discussed below.

Among the five models listed in Table 1, only model I reviews the regression results of GDP per capita, urbanization level, and carbon emission intensity. To test the robustness of model I, we added a number of control variables based on the three independent variables-energy structure, energy intensity, industry proposition, and tertiary industry proportion, which were put into models II–V sequentially. Given that the consistency of the Sys-GMM estimator is based on the hypothesis that no second-order serial correlation exists for the disturbances of the first-differenced equation, we followed Roodman's [52] method in order to test this hypothesis. On the basis of the test results for AR (1) and AR (2), which are listed in Table 3, we could not reject the null hypothesis that no second-order serial correlation was present for the first-differenced disturbance. Thus, the Sys-GMM estimator was consistent. In addition, the Hansen test was also unable to reject the null hypothesis. As such, the selected variables were therefore considered reliable, and the Sys-GMM test effective.

The results at Table 5 indicate that urbanization level, GDP per capita, and industry proposition had positive effects on CO_2 emissions in Chinese provinces in the study period. On the other hand, carbon emission intensity, energy consumption structure, energy intensity, and tertiary industry proportion were found to have negative effects. Once we controlled for the effects of the new added variables, we found that the impact of the former variables mix changed. This is consistent with studies conducted by Wang et al. [28], Wang et al. [29], Siddiqi [58], Shi [59], and others. From Table 5, the coefficients of the quadratic term ($\ln^2 A$) are shown to be negative (not significantly), which is consistent with the study of Du et al. [46]; however, the coefficients of the linear ($\ln A$) and cubic ($\ln^3 A$) terms are shown to be significantly positive. This indicates that the relationship between CO_2 emission and economic level takes the form of an N-shape curve. On the basis of the obvious inflection that is present in the curve, we can conclude that a significant relink effect exists between CO_2 emission and economic level. These results are consistent with the empirical conclusions arrived at by researchers studying a number of industrialized countries. For instance, deBruyn and Opschoor [53] argued that whilst environmental pressure and economic growth perform an inverted-U curve (classical EKC) in the short- and medium-term, from a medium- and long-term perspective, environmental pressure and economic growth enter a relink period due to technological progress and an inadequate rate of change in industry structure. This constitutes their famous "relinking hypothesis": in the long run, environmental pressure and economic growth perform an N-shape curve, not an inverted U-shape curve. A large number of empirical studies have subsequently verified this hypothesis [54,55]. In relation to the present study, we can provide a dual explanation for the way in which the relationship between CO_2 emission and economic level takes the form

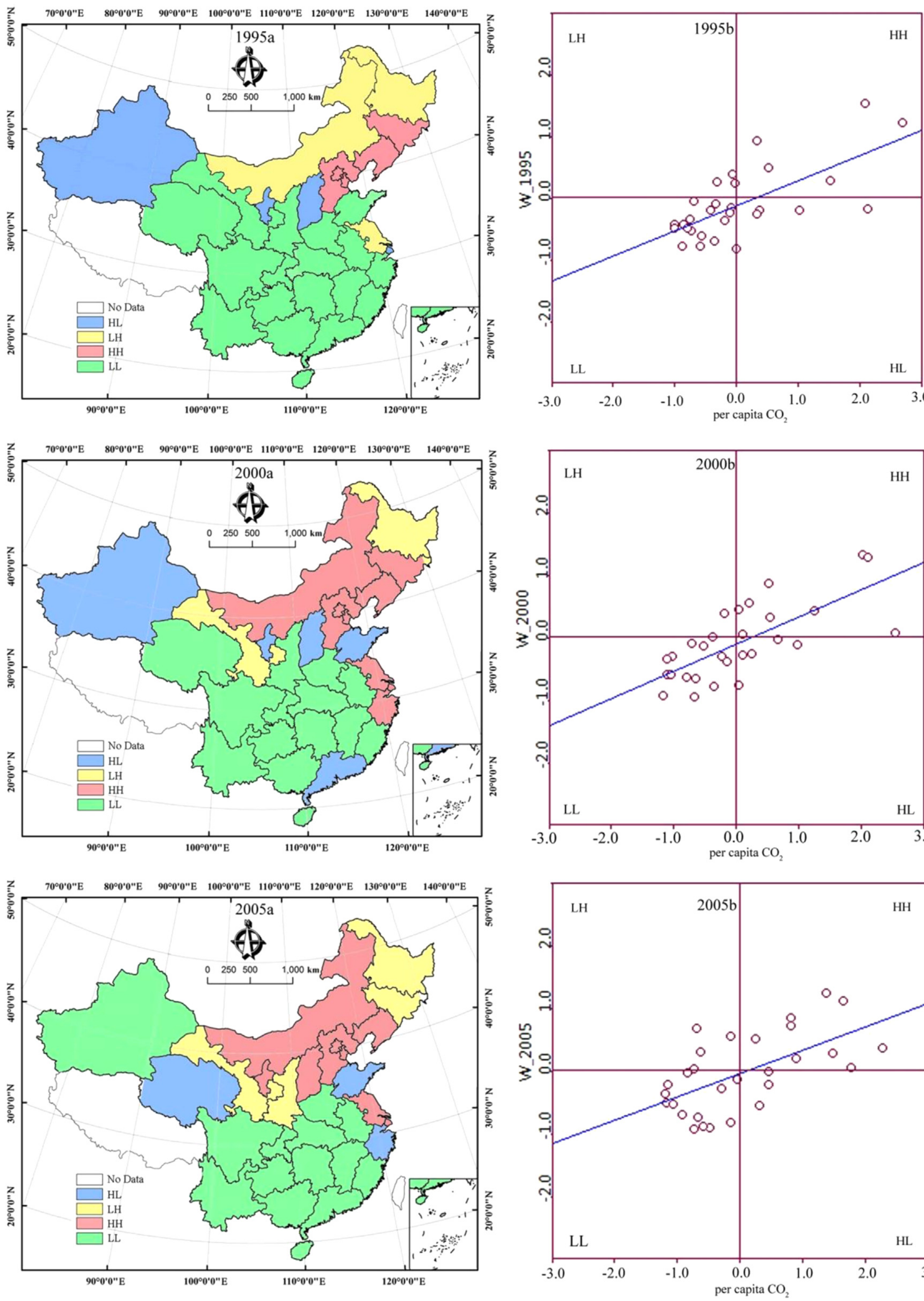

Fig. 3. Moran scatter plot of per capital CO_2 in 1995, 2000, 2005, and 2010. The right part shows quadrant distributions of per capital CO_2, and the left part shows the corresponding spatial patterns of per capita CO_2.

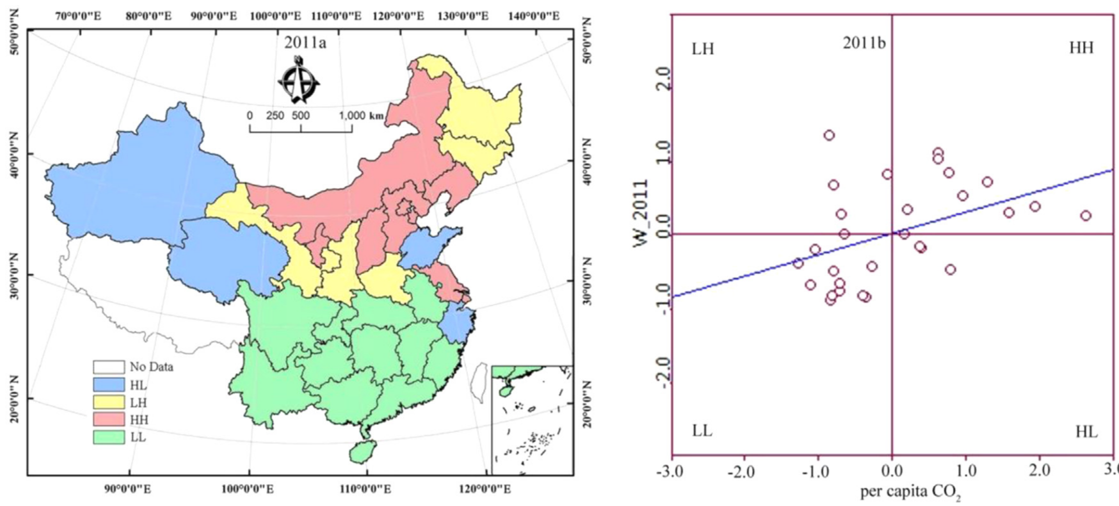

Fig. 3. (*continued*)

Table 4
Space–time transition matrices.

		HH	LH	LL	HL
1995–2000	HH	IV (5)	I (0)	III (0)	II (0)
	LH	I (2)	IV (1)	II (0)	III (0)
	LL	III (1)	II (1)	IV (14)	I (2)
	HL	II (1)	III (0)	I (0)	IV (3)
2000–2005	HH	IV (7)	I (1)	III (0)	II (1)
	LH	I (0)	IV (3)	II (0)	III (0)
	LL	III (0)	II (0)	IV (12)	I (1)
	HL	II (2)	III (0)	I (2)	IV (1)
2005–2011	HH	IV (9)	I (0)	III (0)	II (0)
	LH	I (0)	IV (5)	II (0)	III (0)
	LL	III (0)	II (1)	IV (11)	I (1)
	HL	II (0)	III (0)	I (0)	IV (3)
1995–2011	HH	IV (5)	I (0)	III (0)	II (0)
	LH	I (2)	IV (1)	II (0)	III (0)
	LL	III (0)	II (3)	IV (12)	I (3)
	HL	II (3)	III (0)	I (0)	IV (1)

Note: Number of transition provinces in parentheses.

of an N-shape curve in China in the period 1995–2011. Firstly, the slowness of both the shift in industrial restructuring and of progress in the development of environmental and other technologies plays a significant role in determining the relink rate of CO_2 emissions and economic growth: essentially, the heavy nature of certain industries may necessitate high energy consumption and high carbon emissions. At the same time, the slowness of the advance of green technology may directly affect the ability to improve energy efficiency. Secondly, relaxation of environmental regulations and failure of regulatory policies will also both result in the relink. Energy conservation policy should therefore take into comprehensive consideration aspects like industry structure, technology progress, and environmental regulation. The relationship between the environment and economic growth is complex, and it varies definitively in different regions, in response to different measurement indices, and across different observation periods. At the same time, it is also affected by social and political factors [28].

The coefficients of $I_{it\text{-}1}$ generated through this study indicate that CO_2 emissions in the last period maintain a significant positive correlation in relation to CO_2 emissions in the current period, indicating that CO_2 emissions are in fact characterized by a continuous and dynamic process of adjustment. The urbanization level was also found to positively correlate with CO_2 emissions (Table 5), indicating that CO_2 emissions increased in line with the urbanization of Chinese provinces. Similar results were found by Al-mulali et al. [60]. Over the last decade of rapid economic growth, China has witnessed equally fast-paced urban development, with the country's level of urbanization rising from 29.04% in 1995 to 51.27% in 2011. At the same time, energy consumption increased by almost 187% and CO_2 emissions increased by 50%. On the one hand, urbanization can be understood to promote economic growth and improve living standards. On the other, it can also increase energy consumption and CO_2 emissions, and, in turn, produce energy crises [61,62]. Therefore, China should continue to control population size, promote stable and moderate urbanization and pay attention to optimizing population structure and quality. More important, it is essential to enhance inhabitants' low-carbon awareness, and strengthen the generalization of low-carbon urbanization [29]. This conclusion is consistent with results produced by Wang et al. [28].

Industry proportion and energy structure were also found to have positive impacts on CO_2 emissions, a finding which is consistent with both our initial expectations and with common sense (Table 5). Industrialization is widely known to be a key engine of economic growth. In addition, secondary industry is more energy-intensive than other types of industry, and thus produces greater CO_2 emissions. Rapid development through industrialization promotes increased energy consumption and further results in rapid increases in CO_2 emissions. Despite this, the present study found industry proportion to be less significant in relation to CO_2 emissions than either GDP per capita or urbanization level. Energy consumption is another important positive factor for economic growth; it is also a source of environmental pollution and CO_2 emissions. Different kinds of energy sources have different CO_2 emission coefficients, with coal ranking first. As such, the larger the percentage of coal consumption to total energy consumption, the larger CO_2 emissions will be. In recent years, however, low-carbon energy technologies have developed rapidly in China and clean and renewable energy, such as wind power, is beginning to have some inhibitory effect on CO_2 emissions.

Results show energy intensity and carbon emission intensity to be negatively correlated with CO_2 emissions during the study period (Table 5), reflecting the existence of inhibitory effects in relation to CO_2 emissions. Further, energy intensity was found to have greater significance than carbon emission intensity. This suggests that decreases in energy intensity or in carbon emissions intensity do reduce CO_2 emissions (although the effect is relatively small compared to the promoting factors). Despite this, technological progress in terms of energy intensity and carbon emission

Table 5
Estimation results for different models.

Independent variables	Model I	Model II	Model III	Model IV	Model V
I_{it-1}	0.727080[a] (0.011090)	0.625439[a] (0.012543)	0.615673[a] (0.014695)	0.643312[a] (0.021224)	0.687645[a] (0.024731)
ln *A*	0.163267[a] (1.129871)	0.174532[a] (1. 237794)	0.182269[a] (1. 118493)	0.155322[a] (1. 122382)	0.161768[a] (1. 165375)
$(\ln A)^2$	−0.054664[b] (0.122146)	−0.014343[b] (0.230529)	−0.040112[b] (0.129756)	−0.022094[b] (0.106526)	−0.051815[a] (0.140719)
$(\ln A)^3$	0.011674 [a] (0.004398)	0.00843 [a] (0.003018)	0.012122[a] (0.005017)	0.016283[a] (0.004678)	0.017561[a] (0.006984)
ln *P*	0.444016[a] (0.013027)	0. 383194 [a] (0.023052)	0. 423578 [a] (0.051790)	0. 441815[a] (0. 129756)	0. 410622 [a] (0.015589)
ln *T*	−0.095324[a] (0.024183)	−0. 104330 [a] (0.020604)	−0.097654 [a] (0.020783)	−0.098942[a] (0.235582)	−0.106547[a] (0.029809)
ln *ES*		−0.200234[c] (0.00560)	−0.179395[c] (0.00572)	−0.211714[a] (0.012343)	−0.160454[a] (0.013278)
ln *EI*			−0.095432[c] (0.013492)	−0.087636[c] (0.014783)	−0.0772311[a] (0.016294)
ln *IP*				0.156725 (0.016345)	0.148324[b] (0.014322)
ln *TIP*					−0.343478[a] (0.010878)
CKC type	*N*	*N*	*N*	*N*	*N*
Inflection	0.556453 (1.414445)	0.604533 (1.536721)	0.512456 (1.40712)	0.621890 (1.473218)	0.608257 (1.154672)
AR (1)	−1.675342 (0.034444)	−1.686758 (0.096597)	−1.652975 (0. 051522)	−1.642168 (0.041777	−1.675425 (0.044693)
AR (2)	1.362532 (0.301162)	1.376754 (0.222342)	1.362543 (0.341564)	1.381232 (0.223221)	1.363241 (0.200932)
Hansen test (*p*)	32.342133 (0.044561)	33.302319 (0.087345)	32.332458 (0.091435)	34.665463 (0.048234)	28.543694 (0.040453)
Observations	510	510	510	510	510

Note: Standard errors in parentheses for factors. *p* values in parentheses for AR and Hansen test.

[a] Denotes significant at 1% level.
[b] Denotes significant at 10% level.
[c] Denotes significant at 5% level.

intensity has proven to be relatively slow in China, and its potential influence in inhibiting CO_2 emissions can as Wang et al. warn be offset by accompanying rapid increases in energy consumption [26].

Tertiary industry proportion was found to have a significant negative impact on CO_2 emissions during the study period (Table 5). The tertiary industries are light industries (i.e., the service industry) which produce less CO_2 emissions than heavy industry. The proportion of heavy industry in China has to some extent decreased in recent years. At the same time, China's gradual transition toward a green-oriented globalizing economy has generated spectacular development in the tertiary industries, especially in developed and wealthy cities [28,29]. In fact, China's tertiary industry development evidences a trend towards continual acceleration. With the implementation of energy conservation and emissions mitigation policies, industry structure is being gradually optimized in most Chinese cities, and this, we can conclude, is beginning to have bring about some inhibitory effects in relation to CO_2 emissions.

4. Conclusions and policy implications

This paper has investigated the spatiotemporal variations and impact factors of energy-related CO_2 emissions in one of the world's largest developing countries, China. Results confirm the applicability of spatial analysis techniques and the extended STIRPAT model in empirical research into China's CO_2 emissions at the provincial level. The study found per capita energy-related CO_2 emissions in China to have increased annually over the period 1995–2011, from 2.45 t in 1995 to 5.89 t in 2011, with an annual growth rate of 5.3%. Further, it concluded that CO_2 emissions are sensitive to rapid urbanization, industrialization, economic structural change, energy consumption structure, and other factors that are addressed by China's energy saving and emissions reduction policy. By emphasizing the complexity of the impact of human factors on CO_2 emissions, this paper also corresponds to other scholars' interests in the impact factors of CO_2 emissions from an evolutionary and comparative perspective [28,29]. Finally, the estimation of a CO_2 Kuznets Curve between economic growth and CO_2 emissions was also performed and discussed through this study.

The application of orthodox neoclassical approaches and spatial analysis techniques has enabled us to generate some important findings [63]. China's rapid development of urbanization and industrialization has generated considerable attention in relation to the issue of differences in the growth of CO_2 emissions between various Chinese provinces. Using the conventional evolution method of CV, we found per capita CO_2 emissions to have grown in all of China's provinces in the period 1995 to 2011. It is, however, worth noting that inequality among provinces in terms of regional CO_2 emissions actually decreased gradually during the period studied. Orthodox methods can detect changing trends in inequality, but they do not take into account spatial effects. Considering the "coincidence of attribute similarity with locational similarity," we calculated the global Moran's *I* index, allowing us to measure spatial autocorrelation. Findings showed that spatial agglomeration decreased at the provincial level during the study period. Combined with the local Moran's *I*, the results reveal that whilst provinces with either high or low values demonstrated a certain spatial dependence, spatial differences in fact decreased during study period. The space–time transition matrices of per capita CO_2 emissions supported the results of the Moran scatter plots.

The results generated from the application of the extended STIRPAT model are capable of better explaining the factors underlying changes in CO_2 emissions in Chinese provinces over time. Many factors – including the urbanization level, the economic level, and industry proportion – were found to positively increase CO_2 emissions at the provincial level. The urbanization level in particular was identified as the main positive influencing factor of CO_2 emissions during the period 1995–2011. Further, the study also identified a series of factors – technology level, energy consumption structure, energy intensity, and tertiary industry proportion – which could be linked to decreases in CO_2 emissions, amongst which tertiary industry proportion was found to constitute the key inhibiting factor. Importantly, the CO_2 Kuznets Curve, which describes the relationship between CO_2 emissions and economic growth, was found to take the form of an N-shape in the medium- and long- term, rather the classical inverted-U shape (EKC). Specifically, an additional inflection appeared after the U-shape relationship between economic growth and CO_2 emissions, demonstrating the emergence of a relink phase between the two variables. A growing literature has found that there was an inverted-U curve between economic growth and CO_2 emissions.

However, our study provided evidence that the relationship between CO_2 emission and economic level takes the form of an N-shape curve. The additional inflection appeared after the U-shape relationship between economic growth and CO_2 emissions, indicating the emergence of a relink phase between the two variables. We can provide an illustration for the phenomenon: First, in the early stage of economic growth, CO_2 emissions increased rapidly due to the slowness of progress in the development of technologies. However, macroeconomic fluctuations and strengthening environmental regulation will lead to the emergence of the relink effect. For example, the emergence of global financial crisis and simultaneous the Olympic Games held in 2008 made significant influence on CO_2 emissions. After the financial crisis, the government promoted economic recovery by investing large scale infrastructure projects, leading an increase of CO_2 emissions. Thus, the relationship between CO_2 emission and economic level takes the form of an N-shape curve in China during the period studied. This result is considered particularly significant. This result is considered particularly significant.

The findings detailed above contribute to the existing literature and suggest meaningful theoretical and policy implications [64]. China is urbanizing and industrializing at an unprecedented rate. Rapid economic growth has, however, been achieved through huge increases in energy consumption, leading to high CO_2 emissions, which in turn have placed significant pressure on the sustainable development of the country's economy, society, and environment [65,66]. Whilst China has made great efforts to cut CO_2 emissions, challenges still remain in curbing emissions while maintaining rapid economic growth. To achieve this goal, China must become a low-carbon economy. This paper proposes several measures which might be used to move China onto this low-carbon pathway. Firstly, China should continue to control the scale of urban populations in order to maintain healthy levels of population urbanization. Secondly, it is necessary to optimize the country's industrial structure, enhancing the proportion of tertiary industry and reducing the proportion of secondary industry. Thirdly, China should devote considerable effort to developing low-carbon technologies, boosting recycling and renewable energies, and reducing energy intensity. Fourthly, regional energy supply and demand must be balanced. Fifth, China should cut its reliance on fossil energy resources in order to optimize its energy structure.

From a methodological perspective, this paper underscores the promising aspects of employing spatial analysis techniques such as spatial autocorrelation (both global and local) and space–time transition matrices in understanding the spatiotemporal variations of CO_2 emissions. Our empirical analysis of Chinese provinces also demonstrates the appropriateness of the spatial method and the extended STIRPAT model for analyzing CO_2 emissions by addressing their spatial-temporal dynamic evolution process. The spatial analysis techniques and STIRPAT model are widely used in existing studies due to their high universalities. We believe that this analysis process is relevant not only to specific countries such as China and that in fact this analysis method constitutes a critical tool for building a more comprehensive understanding of the varied spatial patterns and dynamics of CO_2 emissions in any country or region.

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