Spatiotemporal variations of energy-related CO₂ emissions in China and its influencing factors: An empirical analysis based on provincial panel data

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A B S T R A C T

This paper examines carbon dioxide (CO₂) emissions from the perspective of energy consumption, detailing an empirical investigation into the spatiotemporal variations and impact factors of energy-related CO₂ 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 CO₂ 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 CO₂ 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 CO₂ Kuznets Curve (CKC), which describes the relation between CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions, as constituting the main cause of global warming. Despite this knowledge, global emissions of CO₂ from fossil fuel combustion and cement production continue to rise at a staggering rate, and a large amount of CO₂ 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 CO₂ emitter in the world, the country is now facing fossil energy supply crises and mounting international pressure to curb its CO₂ releases [4]. As a result, the Chinese government has implemented a bold national strategy for energy saving and CO₂ emissions reduction. At the 2009 Copenhagen climate conference, China set a goal to reduce its carbon intensity (that is, CO₂ 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 CO₂ emissions. Taking Beijing as an example and using an improved STIRPAT model [24], Wang et al. [28] examined the key influencing factors in relation to CO₂ emissions, finding urbanization level, economic level, and industry proportion to all positively impact on CO₂ 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...
CO₂ 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, Jayanthakumar 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions in China’s 30 provinces over the period 1995–2011, employing spatial analysis techniques in order to examine the spatiotemporal variations of CO₂ emissions according to Tobler’s first law of geography [47]. Using an extended STIRPAT model, we then examined the impact of human factors on CO₂ emissions. Finally, we also investigated the CO₂ 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 CO₂ 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 CO₂ emissions in China’s provinces

With reference to Du et al. [46], we calculated CO₂ emissions for China’s 30 provinces for the period 1995 to 2011 using the CO₂ emissions coefficients published by the Intergovernmental Panel on Climate Change (IPCC) [48], and the National Coordinating Committee Office on Climate Change and the Energy Research Institute under the National Development and Reform Commission [49]. Energy-related CO₂ emissions can be calculated using:

\[
I = \sum_{i=1}^{n} (E_i \times F_i) + Q \times C
\]

where \(I\) represents the total CO₂ 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 \(i\)th kind of primary energy consumption; \(F_i\) is the CO₂ emissions coefficient of fossil fuels; \(Q\) represents the quantity of cement production; and \(C\) is the CO₂ 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:

\[
I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})^2}
\]

where \(x\) is a variable measured in each of the \(i = 1, 2, ..., n\) locations, and \(w_{ij}\) 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 \(Z = (I - E(I))/\sqrt{\text{Var}(I)}\).

##### 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:

\[
I_i = \frac{z_i \sum_{j=1}^{n} w_{ij} z_j}{\sum_{j=1}^{n} w_{ij}^2}
\]

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:

\[
z_i^* = \sum_{j=1}^{n} w_{ij} z_j
\]

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

<table>
<thead>
<tr>
<th>Sources</th>
<th>Coal</th>
<th>Coke</th>
<th>Gasoline</th>
<th>Kerosene</th>
<th>Diesel</th>
<th>Fuel oil</th>
<th>Natural gas</th>
<th>Cement</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO₂ emissions coefficient</td>
<td>1.647</td>
<td>2.848</td>
<td>3.045</td>
<td>3.174</td>
<td>3.150</td>
<td>3.064</td>
<td>21.670</td>
<td>0.527</td>
</tr>
</tbody>
</table>
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 (HL): 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 popula-
tion, A is affluence, and T is technology level. After many
improvements, the IPAT model has some derivative forms, includ-
ing ImPACT model, which decomposes T into T and C (con-
sumption 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:

\[
I_i = aP_i A_i T_i r_i,
\]

(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 \( r \) denotes the random error. The IPAT model can thus be re-
written as a particular form of STIRPAT, when \( a = b = c = d = 1 \).
In empirical studies, Eq. (4) may be converted to logarithmic form:

\[
\ln I_i = \ln a + bP_i + cA_i + dT_i + \ln r_i
\]

(6)

where \( \ln(\cdot) \) 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 para-
meter 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 lit-
erature based on the original model in order to carry out a range of
new empirical research studies [24,52]. Considering the char-
acteristics 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 relation-
ship 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 rela-
tionship between economic growth and CO\(_2\) emissions [53–55].
The extended STIRPAT model can thus be established as follows:

\[
\ln I_i = a_0 + a_1 \ln A_i + a_2 (\ln A_i)^2 + a_3 (\ln A_i)^3 + a_4 \ln P_i + a_5 \ln T_i + a_6 \ln ES_i + a_7 \ln EI_i + a_8 \ln IP_i + a_9 \ln TIP_i
\]

(7)

where \( I \) denotes per capita CO\(_2\) emissions; \( P \) represents urban-
ization 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 con-
sumption to total energy consumption); \( EI \) denotes energy inten-
sity (expressed as energy consumption per Yuan GDP); \( IP \) repre-
sents 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 con-
sumption 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
propopotion, 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 consump-
tion, 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

Table 3: Summary statistics of the variables.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Symbol</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per capita CO(_2)</td>
<td>( I )</td>
<td>ton</td>
<td>4.33</td>
<td>2.20</td>
<td>0.94</td>
<td>12.91</td>
</tr>
<tr>
<td>Economic level</td>
<td>( P )</td>
<td>%</td>
<td>43.33</td>
<td>16.40</td>
<td>17.19</td>
<td>89.30</td>
</tr>
<tr>
<td>Technology level</td>
<td>( T )</td>
<td>ton/10(^4) Yuan</td>
<td>3.77</td>
<td>1.99</td>
<td>0.97</td>
<td>11.32</td>
</tr>
<tr>
<td>Energy intensity</td>
<td>( EI )</td>
<td>ton/10(^4) Yuan</td>
<td>1.73</td>
<td>0.98</td>
<td>0.21</td>
<td>7.66</td>
</tr>
<tr>
<td>Energy structure</td>
<td>( ES )</td>
<td>%</td>
<td>66.08</td>
<td>16.67</td>
<td>24.16</td>
<td>92.10</td>
</tr>
<tr>
<td>Industry proportion</td>
<td>( IP )</td>
<td>%</td>
<td>45.28</td>
<td>7.90</td>
<td>19.81</td>
<td>60.13</td>
</tr>
<tr>
<td>Tertiary industry</td>
<td>( TIP )</td>
<td>%</td>
<td>39.62</td>
<td>7.16</td>
<td>20.22</td>
<td>76.14</td>
</tr>
</tbody>
</table>

Table 2: Local Moran classifications.

Source: Rey [45].

<table>
<thead>
<tr>
<th>Class</th>
<th>Own value ( z_i )</th>
<th>Neighbor’s value ( z_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH</td>
<td>Above average</td>
<td>Above average</td>
</tr>
<tr>
<td>HL</td>
<td>Above average</td>
<td>Below average</td>
</tr>
<tr>
<td>LH</td>
<td>Below average</td>
<td>Above average</td>
</tr>
<tr>
<td>LL</td>
<td>Below average</td>
<td>Below average</td>
</tr>
</tbody>
</table>

### Table 2

Local Moran classifications.

Source: Rey [45].

<table>
<thead>
<tr>
<th>Class</th>
<th>Own value ( z_i )</th>
<th>Neighbor’s value ( z_i )</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH</td>
<td>Above average</td>
<td>Above average</td>
</tr>
<tr>
<td>HL</td>
<td>Above average</td>
<td>Below average</td>
</tr>
<tr>
<td>LH</td>
<td>Below average</td>
<td>Above average</td>
</tr>
<tr>
<td>LL</td>
<td>Below average</td>
<td>Below average</td>
</tr>
</tbody>
</table>
3. Results and discussion

3.1. The temporal evolution characteristics of per capita CO\textsubscript{2} emissions

The per capita CO\textsubscript{2} emissions in China over the period 1995–2011 were calculated using Eq. (1), as indicated in Fig. 1. Per capita CO\textsubscript{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\textsuperscript{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\textsubscript{2} emissions during the study period. From Fig. 1, 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\textsubscript{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\textsubscript{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\textsubscript{2} emissions in provincial China does not illustrate a trend of balanced development with respect to CO\textsubscript{2} emissions; rather, it simply reflects the spatial variations of CO\textsubscript{2} emissions at the provincial level.

3.2. The spatial pattern evolution characteristics of per capita CO\textsubscript{2} emissions

Fig. 3 plots the distributions of Moran scatter of per capita CO\textsubscript{2} emissions in Chinese provinces according to the temporal characteristics of global Moran’s I, showing the local spatial correlation of per capita CO\textsubscript{2} emissions in Chinese provinces spatially and geographically. The right section of Fig. 3 shows the quadrant distributions of per capita CO\textsubscript{2} emissions: the left section shows the corresponding spatial patterns of per capita CO\textsubscript{2} emissions. Fig. 3 reveals characteristics of significant local spatial agglomeration in the distribution of per capita CO\textsubscript{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 capita CO\textsubscript{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\textsubscript{2} emissions had weakened markedly between 1995 and 2000. Further, spatial inequalities in provincial per capita CO\textsubscript{2} emissions in 2005 and 2011 decreased since 2000. From these findings, we can conclude that the pattern

---

\( \sigma \) is a measure of the dispersion of a distribution. It is defined as the ratio of the standard deviation (\( \sigma \)) to the mean (\( \mu \)). The larger the CV, the larger the disparity among provinces.

---

Fig. 1. Per capita CO\textsubscript{2} emissions in China, 1995–2011.

Fig. 2. Per capita CO\textsubscript{2} emissions in China, 1995–2011.
evolution of emissions therefore displays a certain path dependency effect.

To further understand the spatial agglomeration characteristics of CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 (ln² 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 (ln³ A) terms are shown to be significantly positive. This indicates that the relationship between CO₂ 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 CO₂ 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 CO₂ emission and economic level takes the form

![Figure 3](image_url)  
**Fig. 3.** Moran scatter plot of per capital CO₂ in 1995, 2000, 2005, and 2010. The right part shows quadrant distributions of per capital CO₂ and the left part shows the corresponding spatial patterns of per capita CO₂.
The coefficients of \( I_{\alpha-1} \) generated through this study indicate that CO2 emissions in the last period maintain a significant positive correlation in relation to CO2 emissions in the current period, indicating that CO2 emissions are in fact characterized by a continuous and dynamic process of adjustment. The urbanization level was also found to positively correlate with CO2 emissions (Table 5), indicating that CO2 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 CO2 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 CO2 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 CO2 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 CO2 emissions. Rapid development through industrialization promotes increased energy consumption and further results in rapid increases in CO2 emissions. Despite this, the present study found industry proportion to be less significant in relation to CO2 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 CO2 emissions. Different kinds of energy sources have different CO2 emission coefficients, with coal ranking first. As such, the larger the percentage of coal consumption to total energy consumption, the larger CO2 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 CO2 emissions.

Results show energy intensity and carbon emission intensity to be negatively correlated with CO2 emissions during the study period (Table 5), reflecting the existence of inhibitory effects in relation to CO2 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 CO2 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 4
Space-time transition matrices.

<table>
<thead>
<tr>
<th></th>
<th>HH</th>
<th>LH</th>
<th>LL</th>
<th>HL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995–2000</td>
<td>IV (5)</td>
<td>I (0)</td>
<td>III (0)</td>
<td>II (0)</td>
</tr>
<tr>
<td></td>
<td>LH</td>
<td>LL</td>
<td>HL</td>
<td></td>
</tr>
<tr>
<td>2000–2005</td>
<td>HH</td>
<td>IV (7)</td>
<td>I (1)</td>
<td>III (0)</td>
</tr>
<tr>
<td></td>
<td>LH</td>
<td>I (0)</td>
<td>IV (3)</td>
<td>II (0)</td>
</tr>
<tr>
<td></td>
<td>LL</td>
<td>III (0)</td>
<td>II (0)</td>
<td>IV (12)</td>
</tr>
<tr>
<td>2005–2011</td>
<td>HH</td>
<td>II (2)</td>
<td>III (0)</td>
<td>I (2)</td>
</tr>
<tr>
<td></td>
<td>LH</td>
<td>I (0)</td>
<td>IV (5)</td>
<td>III (0)</td>
</tr>
<tr>
<td></td>
<td>LL</td>
<td>III (0)</td>
<td>II (0)</td>
<td>IV (11)</td>
</tr>
<tr>
<td></td>
<td>HL</td>
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<td>III (0)</td>
<td>I (0)</td>
</tr>
<tr>
<td>1995–2011</td>
<td>HH</td>
<td>IV (5)</td>
<td>I (0)</td>
<td>III (0)</td>
</tr>
<tr>
<td></td>
<td>LH</td>
<td>I (2)</td>
<td>IV (1)</td>
<td>II (0)</td>
</tr>
<tr>
<td></td>
<td>LL</td>
<td>III (0)</td>
<td>II (3)</td>
<td>IV (12)</td>
</tr>
<tr>
<td></td>
<td>HL</td>
<td>II (3)</td>
<td>III (0)</td>
<td>I (0)</td>
</tr>
</tbody>
</table>

Note: Number of transition provinces in parentheses.
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 CO2 emissions between various Chinese provinces. Using the conventional evolution model of CV, we found per capita CO2 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 CO2 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 CO2 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 CO2 emissions in Chinese provinces over time. Many factors – including the urbanization level, the economic level, and industry proportion – were found to positively increase CO2 emissions at the provincial level. The urbanization level in particular was identified as the main positive influencing factor of CO2 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 CO2 emissions, amongst which tertiary industry proportion was found to constitute the key inhibiting factor. Importantly, the CO2 Kuznets Curve, which describes the relationship between CO2 emissions and economic growth, was found to take the form of an N-shape in the medium- and long-term, rather than the classical inverted-U shape (EKC). Specifically, an additional inflection appeared after the U-shape relationship between economic growth and CO2 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 CO2 emissions.

### Table 5

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Model I</th>
<th>Model II</th>
<th>Model III</th>
<th>Model IV</th>
<th>Model V</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln $E_I$</td>
<td>0.727080 (0.011090)</td>
<td>0.625439 (0.012543)</td>
<td>0.615673 (0.014695)</td>
<td>0.643132 (0.021224)</td>
<td>0.687645 (0.024731)</td>
</tr>
<tr>
<td>ln $A$</td>
<td>0.161267 (1.192871)</td>
<td>0.174532 (1.237794)</td>
<td>0.182269 (1.18493)</td>
<td>0.155322 (1.122382)</td>
<td>0.161768 (1.163575)</td>
</tr>
<tr>
<td>ln ($A^2$)</td>
<td>-0.054664 (0.122146)</td>
<td>-0.014343 (0.230529)</td>
<td>-0.040112 (0.129756)</td>
<td>-0.022094 (0.106526)</td>
<td>-0.051815 (0.140719)</td>
</tr>
<tr>
<td>ln ($A^3$)</td>
<td>0.016744 (0.003938)</td>
<td>0.00843 (0.003018)</td>
<td>0.012122 (0.005017)</td>
<td>0.016283 (0.004678)</td>
<td>0.017561 (0.006984)</td>
</tr>
<tr>
<td>ln $P$</td>
<td>0.444016 (0.013027)</td>
<td>0.381914 (0.023052)</td>
<td>0.423578 (0.037190)</td>
<td>0.448153 (0.129756)</td>
<td>0.410622 (0.015589)</td>
</tr>
<tr>
<td>ln $T$</td>
<td>-0.095324 (0.024183)</td>
<td>-0.104330 (0.020604)</td>
<td>-0.097654 (0.020783)</td>
<td>-0.098942 (0.235382)</td>
<td>-0.106547 (0.029809)</td>
</tr>
<tr>
<td>ln $ES$</td>
<td>-0.200234 (0.00560)</td>
<td>-0.197939 (0.00572)</td>
<td>-0.217114 (0.012343)</td>
<td>-0.160454 (0.013278)</td>
<td>-0.343478 (0.010878)</td>
</tr>
<tr>
<td>ln $EI$</td>
<td>0.059432 (0.013492)</td>
<td>0.087636 (0.014783)</td>
<td>0.156752 (0.016345)</td>
<td>0.148324 (0.014322)</td>
<td>0.148324 (0.014322)</td>
</tr>
<tr>
<td>ln $IP$</td>
<td>0.165297 (0.051522)</td>
<td>0.179395 (0.00572)</td>
<td>0.211714 (0.012343)</td>
<td>0.160454 (0.013278)</td>
<td>0.343478 (0.010878)</td>
</tr>
<tr>
<td>ln $TIP$</td>
<td>0.343478 (0.010878)</td>
<td>0.343478 (0.010878)</td>
<td>0.343478 (0.010878)</td>
<td>0.343478 (0.010878)</td>
<td>0.343478 (0.010878)</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>CKC type</th>
<th>N</th>
<th>N</th>
<th>N</th>
<th>N</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inflation</td>
<td>0.556453 (1.414445)</td>
<td>0.604533 (1.536721)</td>
<td>0.512456 (1.40712)</td>
<td>0.621890 (1.473218)</td>
<td>0.608257 (1.154672)</td>
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<tr>
<td>AR (1)</td>
<td>-1.675342 (0.034444)</td>
<td>-1.686758 (0.096597)</td>
<td>-1.502975 (0.051522)</td>
<td>-1.642618 (0.041777)</td>
<td>-1.675425 (0.044693)</td>
</tr>
<tr>
<td>AR (2)</td>
<td>1.362532 (0.301662)</td>
<td>1.376754 (0.222342)</td>
<td>1.362534 (0.341564)</td>
<td>1.381232 (0.223221)</td>
<td>1.363241 (0.200932)</td>
</tr>
<tr>
<td>Hansen test (p)</td>
<td>32.342133 (0.044561)</td>
<td>33.302319 (0.087345)</td>
<td>32.332458 (0.091435)</td>
<td>34.665463 (0.048234)</td>
<td>28.543694 (0.040453)</td>
</tr>
</tbody>
</table>

| Observations | 510 | 510 | 510 | 510 | 510 |

4. Conclusions and policy implications

This paper has investigated the spatiotemporal variations and impact factors of energy-related CO2 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 CO2 emissions at the provincial level. The study found per capita energy-related CO2 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 CO2 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 CO2 emissions, this paper also corresponds to other scholars’ interests in the impact factors of CO2 emissions from an evolutionary and comparative perspective [28,29]. Finally, the estimation of a CO2 Kuznets Curve between economic growth and CO2 emissions was also performed and discussed through this study.
However, our study provided evidence that the relationship between CO₂ 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 CO₂ 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, CO₂ 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 CO₂ emissions. After the financial crisis, the government promoted economic recovery by investing large scale infrastructure projects, leading an increase of CO₂ emissions. Thus, the relationship between CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions. Our empirical analysis of Chinese provinces also demonstrates the appropriateness of the spatial method and the extended STIRPAT model for analyzing CO₂ 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 CO₂ emissions in any country or region.

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References