

Original Research

Spatial Characteristics and Influencing Factors of Carbon Emissions from Energy Consumption in China's Transport Sector: An Empirical Analysis Based on Provincial Panel Data

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Abstract

This paper examines the CO₂ emissions from energy consumption in China's transport sector, conducting an empirical investigation into the spatial distribution characteristics and influencing factors of transport CO₂ emissions. This study, which is based on province-level panel data covering the 30 provincial regions during the period 2001-2016, used the methods of exploratory spatial data analysis (ESDA) and the extended STIRPAT model (examined by the method of system-generalized method of moments (Sys-GMM) regression). The results indicated that the amount of CO₂ emissions in China's transport sector has increased steadily during the observation period, but there was a noticeable disparity across the provinces and regions. From the perspective of spatial dimension, the spatial agglomeration characteristics of provincial transport CO₂ emissions tended to be strengthened, and the pattern evolutions of spatial distribution presented a path-dependence effect to some extent. The scale of population was found to be the most important influencing factor of transport CO₂ emissions, and followed by the per-capita GDP. Further, the improvement of energy efficiency was the key factor to controlling transport CO₂ emissions. Compared to freight transportation, passenger transportation was more important in transport CO₂ emissions reduction due to its lower efficiency of energy utilization and rapid growth. Meanwhile, electrification played an important inhibitory effect on transport CO₂ emissions because of its high fuel efficiency and less pollution. Importantly, we could not support the existence of the environmental Kuznets curve (EKC) hypothesis in China's transport sector during the observation period, which describes the relationship between the environmental pressures and economic development. These findings contain some meaningful implications for policy makers: confirm the priority transport CO₂ emissions reduction areas, improve transport energy

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efficiency, strengthen passenger transportation decarbonization policy, and highlight the model shift of fuel consumption.

Keywords: transport CO₂ emissions, spatial distribution characteristics, STIRPAT model, Sys-GMM regression, China

Introduction

The transport sector, the foundation of national economic and social development, has undergone a dramatic change since 2001 in China. According to China Statistical Yearbooks, the length of railways in operation increased from 7.01 ten thousand km in 2001 to 12.40 ten thousand km in 2016; the length of expressway increased by an average annual growth of 13.58%, from 1.94 ten thousand km to 13.10 ten thousand km during the same period. The dramatic development was not only reflected in the construction of transportation infrastructure, but also in the economic activities of transportation. The added value of China's transport sector has increased steadily during the period 2001-2016, from 0.69 trillion yuan to 3.31 trillion yuan (at current values), for an average annual growth of 11.04%. However, we must consciously realize that the rapid development of China's transport sector has also resulted in some environmental pressures, such as energy consumption and CO₂ emissions [1]. According to the estimates of the International Energy Agency (IEA, 2012) [2], the transport sector approximately accounts for 19% and 23% of global energy consumption and related CO₂ emissions, respectively. Furthermore, China will account for more than one-third of global energy consumption in 2035 in the field of transportation [3]. As a basis fact, China has been the largest greenhouse gas emitter since 2007, and surpassed the United States in 2010 to become the largest energy consumer in the world (with 3079 million ton standard coal equivalent (Mtce)) [4]. The transport sector, as a high energy consuming sector, is a major contributor of CO₂ emissions in China [5, 6]. The resulting environmental deterioration not only affects the health of the people, but also threatens the sustainable development of China in the future.

As a result, environmental pressures have drawn nationwide concern in China. In order to save energy and conduct CO₂ emissions abatement, the Chinese government has implemented a series of relevant policies [7]. For example, in 2009 China promised to reduce the carbon intensity by 40-45% in 2020 compared to the level of 2005. In addition, through the 12th Five-Year Plan, China planned to reduce the energy intensity by 16% compared to the level of 2010. Objectively, the efforts of the Chinese government have been remarkable [8]. However, it is worth noting that the provinces in China have remarkable inequality, such as geographical characteristics, the scale of population, the level of national economic and social development,

and the structure of energy consumption. As pointed out by Wang et al. [9], in order to effectively control the CO₂ emissions in China, it is necessary to understand the spatial distribution characteristics of CO₂ emissions due to the noticeable differences among the provinces and regions. This not only applies to China's overall situation, but also to transportation CO₂ emissions in China. Moreover, the policies on CO₂ emissions reduction of the Chinese government mainly focus on energy conservation and efficiency, and there are some driving factors that do affect the increase in China's transport CO₂ emissions. However, more influencing factors may exist. Therefore, it is necessary to establish the analytical framework with key impact factors to analyze the CO₂ emissions in China's transport sector.

At present, most existing studies have analyzed the distribution characteristics of transport CO₂ emissions from the perspective of descriptive statistics analysis. For example, Alonso et al. [10] investigated the distribution of air transport traffic and CO₂ emissions within the European Union. Yuan et al. [11] found that the distribution of CO₂ emissions in China's transport sector were significantly directly related to the level of economic development, and presented the characteristics of "high in eastern region and low in the western region". Song et al. [12] confirmed the above findings, and further found that the distribution characteristics of north-south direction showed an inverted-U curve. However, as far as we know, there is little literature that considers the spatial effects in transport CO₂ emissions. By regarding the research units as the independent individuals, the existing studies have ignored the spatial autocorrelation and agglomeration characteristics of geographic data. Namely, the spatial distribution characteristics of transport CO₂ emissions are seldom discussed in existing literature. As pointed out by LeSage et al. [13], the characteristics of a local region will be affected by the adjacent regions to some extent. In other words, the spatial autocorrelation theory shows that the interaction obviously exists among the different research units; the transport CO₂ emissions in different research units are not independent of each other. Furthermore, according to the study of Dhakal [14], the 35% cities with 18% of the total population in China approximately accounted for 40% of the total amount of CO₂ emissions. This finding indicates that CO₂ emissions in China has obvious tendency to aggregate together. The same characteristics also are reflected in China's transport CO₂ emissions. As pointed out by Li et al. [15], the provinces in China with high transport CO₂ emissions were mainly distributed in

the eastern economically developed areas. The geography is an important issue that cannot be neglected in the research of CO₂ emissions in China's transport sector. Therefore, in order to achieve the target of transport CO₂ emission abatement, it is necessary to explore the spatial distribution patterns of transport CO₂ emissions among different research units. In this paper, we attempt to fill this research gap. This will help policy makers formulate the different transport CO₂ emissions reduction policies in accordance with the spatial distribution characteristics of different regions.

Meanwhile, the existing studies have paid extensive attention to the transport CO₂ emissions, and the relevant research methods can be divided into four categories. [16]. The first research method is the index decomposition method, which is also the most commonly used. Mazzarino [17] found that growth in the economy was the main driving factor for Italy's transport CO₂ emissions during the period 1970-1993. Achour and Belloumi [18] found that the scale of economy and population, transportation intensity, and energy intensity played a positive effect on Tunisia's transport CO₂ emissions growth. Timilsina and Shrestha [19] found that economic development and the transportation energy intensity played a dominant role in 20 Latin American and Caribbean (LAC) countries' transport CO₂ emissions during the period 1980-2005. Andreoni and Galmarini [20] come to a similar conclusion in European water and aviation transport CO₂ emissions. Solaymani [21] found that electricity structure and economic output were the main drivers of transport CO₂ emissions in 7 top transport CO₂ emitter countries. The second research method is the bottom-up sector-based analysis. Sanjuan-Delmás et al. [22] proposed a top-down approach to evaluate waterway transport CO₂ emissions in Spain. Tarancón Morán and Del Río González [23] proposed an input-output methodology to analyze the structural factors affecting the land-transport CO₂ emissions in Europe. The third method is system optimization and is commonly used to forecast the demand of energy consumption and CO₂ emissions [24, 25] in analyzing the policy effect of transport CO₂ emissions reduction [26]. The fourth method is econometric estimation techniques. Liao et al. [27] found that the economic growth and oil price were responsible for carbon emissions growth for the inland container transport by using the multiple regression models. With the increase of environmental problem from the transport sector and the improvement of environmental awareness, transport CO₂ emissions abatement has attracted growing attention in mainland China. Using index decomposition analysis, Wang et al. [28] found that the per-capita GDP and transport modal shifts were the main driving factors for China's transport CO₂ emission during the period 1985-2009. Loo and Li [29] analyzed the influencing factor in passenger transportation carbon emissions in China since 1949; they found that per-capita income level was, firstly, responsible for carbon emissions

growth. Using the bottom-up methods, He et al. [30] estimated the energy consumption and CO₂ emissions from China's urban passenger transportation sector. Ou et al. [31], using the method of system optimization, analyzed the future trends of energy demand and greenhouse gas emissions in China's road transport sector. Using the method of econometric estimation techniques, Zhang and Ning [3] and Xu and Lin [16] analyzed the influencing factors of China's transport CO₂ emissions. Wu et al. [32] analyzed the main driving factors of transport CO₂ emissions in Gansu, China. Previous studies have enriched our understanding of the main influencing factors of transport CO₂ emissions. However, there may be two main shortcomings in the above studies. On the one hand, most models used to study transport CO₂ emissions were based on the time series or cross-sectional data. As pointed out by Du et al. [33], the panel data sets have significant advantages compared to the pure time series or cross-sectional data. On the other hand, we noted that most models used in the previous studies mainly focused on the linear relationship between the influencing factors. By regarding the relationship between economic variables as linear and monotonic, the existing studies have ignored the non-linear and non-monotonic relationships. For example, the environmental Kuznets curve (EKC) hypothesis points out that the relationship between per capita income and environmental pressures is non-linear and non-monotonic, but rather an inverted U-shaped curve.

Based on the above analysis, this study first estimated the CO₂ emissions from energy consumption in China's transport sector covering the 30 provinces during the period 2001-2016. Secondly, based on the method of exploratory spatial data analysis (ESDA), this study attempted to analyze the spatial distribution characteristics of province-level transport CO₂ emissions. Thirdly, based on an extended STIRPAT model, we investigated the main influencing factors of CO₂ emissions in China's transport sector. Finally, we further examined the existence of EKC hypothesis, which describes the relationship between environmental pressure and economic development. It is expected that the results of this study can provide the scientific references for the Chinese government to formulate the reasonable and specific environmental policies in transport sector to a certain extent.

Materials and Methods

Study Areas

The study areas of this paper contain 22 provinces, 4 municipalities and 4 special administrative regions in mainland China (excluding Tibet, which belongs to the special administrative region, due to the absence of energy data). While according to the level of economic development and geographical characteristics,

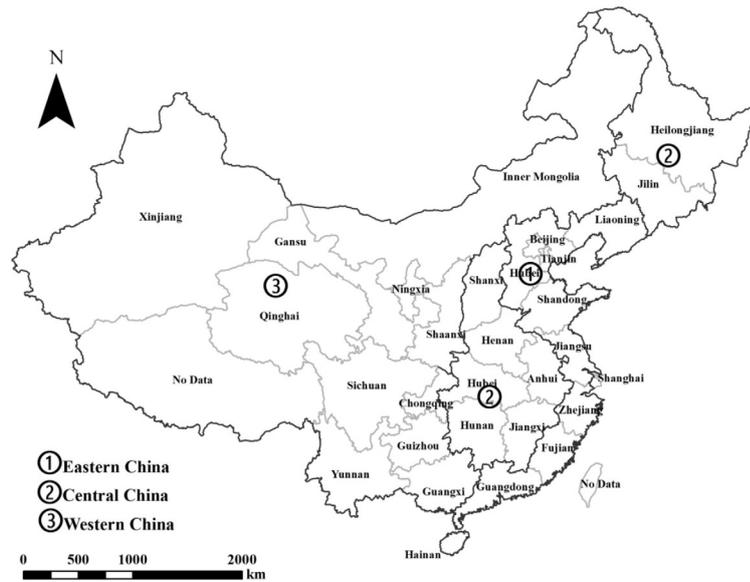


Fig. 1. Provinces in the three major regions.

the 30 provincial regions can also be divided into three major regions: Eastern China, Central China, and Western China, and the provinces in the three major regions are shown in Fig. 1.

Methods

Estimating CO₂ Emissions from Energy Consumption in the Transport Sector

At present, the measurement of transport CO₂ emissions mainly adopts the bottom-up and top-down approach proposed by IPCC [34, 35]. Due to China’s energy statistical department having adopted the top-down statistical system, from the availability of data we employed the top-down approach to estimate the energy-related CO₂ emissions in China’s transport sector. Concretely, the top-down approach can be expressed as follows:

$$C_{it} = \sum_i E'_{mi} \times K_m \tag{1}$$

...where C_{it} refers to the transport CO₂ emissions for province i at year t ; E'_{mij} refers to the amount of m th energy consumption in transport sector for province i at year t ; and K_m refers to the CO₂ emissions coefficient of m th energy type. Meanwhile, this study mainly chose eight energy types as the energy input: raw coal, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, natural gas and electricity. The chosen energy types not only include the primary energies, but also the secondary energies. Meanwhile, the energy consumption for all energy types are converted into standard coal equivalent (CE), and the conversion coefficients derive from the China Energy Statistical

Yearbook. Meanwhile, the CO₂ emissions coefficients of different energy types derive from the references [36, 37]. The corresponding conversion coefficients and the CO₂ emissions coefficients are shown in Table 1.

Spatial Autocorrelation Analysis Method

In this paper, we employed the exploratory spatial data analysis (ESDA) method to analyze the spatial autocorrelation of transport CO₂ emissions in China. Spatial autocorrelation is used to analyze the degree of dependency among the adjacent geographical units (the provincial regions), which reveals the phenomena of spatial correlation and heterogeneity for relevant elements in a geographic space [38]. Generally, spatial autocorrelation mainly includes the global and local spatial autocorrelation, and in practice, the spatial autocorrelation is commonly examined using Moran’s

Table 1. Conversion coefficient and CO₂ emissions coefficients.

Type of energy	Conversion coefficients to standard coal equivalent	CO ₂ emissions coefficients
Raw coal	0.7143 kg of CE/kg	1.9003 kg/kg
Gasoline	1.4714 kg of CE/kg	2.9251 kg/kg
Kerosene	1.4714 kg of CE/kg	3.0334 kg/kg
Diesel oil	1.4571 kg of CE/kg	3.0959 kg/kg
Fuel oil	1.4286 kg of CE/kg	3.1705 kg/kg
Liquefied petroleum gas	1.7143 kg of CE/kg	3.1013 kg/kg
Natural gas	12.143 t of CE/10 ⁴ m ³	2.1322 kg/m ³
Electricity	1.229 t of CE/10 ⁴ kWh	9.7402 t/10 ⁴ kWh

I index method [39]. Concretely, the global Moran's I index can be given as follows:

$$Moran's\ I = \frac{n \sum_{i=1}^n \sum_{j=1}^n \omega_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n \omega_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (2)$$

$$\omega_{ij} = \begin{cases} 1, & \text{if share a common border or a single common point} \\ 0, & \text{else} \end{cases} \quad (3)$$

...where ω_{ij} refers to the spatial weight matrix and describes the spatial relationship corresponding to the geographic districts (i, j), and Follow Long et al. [40] ω_{ij} can be described in equation (3). Namely, for provinces i and j , which are adjacent to each other, then the spatial weight matrix element ω_{ij} will be assigned a weight of 1, otherwise ω_{ij} will be assigned a weight of 0. Meanwhile, the global Moran's I index has values in the range [-1, 1], If $0 < Moran's\ I \leq 1$, it denotes that there is a positive spatial dependence; if $-1 < Moran's\ I < 0$, it denotes that there is a negative spatial dependence; and if $Moran's\ I = 0$, it denotes that there is no spatial dependence.

The local Moran's I index is the local indicator of spatial association (LISA) to reflect the spatial clustering. It makes up for the shortcomings of the overgeneralization of global spatial autocorrelation analysis [41]. Concretely, the local Moran's I index can be given as follows:

$$Z_i = z_i \sum_{j=1}^n \omega_{ij} z_j \quad (4)$$

$$z_i = (x_i - \bar{x}) / \sum_i (x_i - \bar{x})^2, \quad z_j = (x_j - \bar{x})$$

According to the value of Z_i and z_i , we can divided each province into four agglomeration areas: HH (high-high), LH (low-high), and LL (low-low) HL (high-low) agglomeration areas [41]. If $Z_i > 0$ and $z_i > 0$, then the

provincial region i belongs to HH agglomeration area (located in quadrant I in the Moran I scatter plot); if $Z_i < 0$ and $z_i > 0$, then the provincial region i belongs to the LH agglomeration area (locating in the quadrant II); if $Z_i > 0$ and $z_i < 0$, then the provincial region i belongs to LL agglomeration area (located in quadrant III); and if $Z_i < 0$ and $z_i < 0$, then the provincial region i belong to HL agglomeration area (locating in the quadrant IV). The specific meaning of four agglomeration areas is shown in Fig. 2 [41].

STIRPAT Model

Due to the simplicity of the IPAT ($I = PAT$) model, it has been widely used as an analytical framework for analyzing the driving forces of environmental change [42]. However, the application of the IPAT models is greatly limited because the model does not allow for the non-monotonic changes in influencing factors [43]. In order to overcome the limitation, Dietz and Rosa proposed the STIRPAT model [44]. Concretely, the STIRPAT model can be expressed as:

$$I_{it} = aP_{it}^b A_{it}^c T_{it}^d e_{it} \quad (5)$$

...where I, P, A, T refers to the environmental pressure, the scale of population, affluence degree and technology level, respectively; a refers to the coefficient of the model; b, c, d refers to the corresponding undetermined parameters of P, A and T , respectively; and e_{it} refers to the error term. Meanwhile, the base STIRPAT model can be improved or extended according to the respective research characteristics [45]. In this paper, we also establish an extended STIRPAT model to analyze the driving forces in transport CO₂ emissions.

(1) We regard the amount of CO₂ emissions in China's transport sector as environmental pressure. The affluence degree is represented by the per capita GDP. The technology level is represented by the energy intensity [1]. Meanwhile, we introduce transport activities (represented by passenger turnover and freight turnover) and the proportion of electricity consumption

<p>LH Agglomeration area</p> <p>Low value surrounded by high value. The disparity is relatively large, and there is a strong negative spatial correlation</p>	<p>HH Agglomeration area</p> <p>High value surrounded by high value. The inequality is relatively small, and there is a strong positive spatial correlation</p>
<p>LL Agglomeration area</p> <p>Low value surrounded by low value. The imbalance is relatively small, and there is a strong positive spatial correlation</p>	<p>HL Agglomeration area</p> <p>High value surrounded by low value. The inequality is relatively small, and there is a strong negative spatial correlation</p>

Fig. 2. Agglomeration areas parsing of Moran's I scatter plot.

Table 2. Judgment criteria for the relationship between transport CO₂ emissions and economic development.

β_1	β_2	β_3	Relationship
$\beta_1 > 0$	$\beta_2 = 0$	$\beta_3 = 0$	Monotonically increasing relationship
$\beta_1 < 0$	$\beta_2 = 0$	$\beta_3 = 0$	Monotonically decreasing relationship
$\beta_1 > 0$	$\beta_2 < 0$	$\beta_3 = 0$	Inverted U-shape relationship
$\beta_1 < 0$	$\beta_2 < 0$	$\beta_3 = 0$	U-shape relationship
$\beta_1 > 0$	$\beta_2 < 0$	$\beta_3 > 0$	N-shape relationship
$\beta_1 < 0$	$\beta_2 > 0$	$\beta_3 < 0$	Inverted N-shape relationship

as the key variables affecting transport CO₂ emissions.

(2) Importantly, in order to fully depict the relationship between transport CO₂ emissions and economic development, and validate the EKC hypothesis, we decomposed per capita GDP into linear, quadratic, and cubic terms in the extended STIRPAT model.

Based on the above analysis, the extended STIRPAT model in this paper can be expressed as:

$$I_{it} = \alpha I_{it-1} + \beta_1 \ln PGDP_{it} + \beta_2 (\ln PGDP_{it})^2 + \beta_3 (\ln PGDP_{it})^3 + \beta_4 \ln PO_{it} + \beta_5 \ln EI_{it} + \beta_6 \ln PT_{it} + \beta_7 \ln FT_{it} + \beta_8 \ln EL_{it} + e_{it} \tag{6}$$

...where I_{it} refers to the amount of transport CO₂ emissions; I_{it-1} refers to the one-period lagged term of transport CO₂ emissions and reflects the continuous and dynamic adjustment process of transport CO₂ emissions; $PGDP$ refers to the per capita GDP; PO refers to the scale of population; EI refers to the energy intensity in transport sector (the ratio of the energy consumption and the actual added value of transport sector); PT refers to passenger turnover (including railway, highway, waterway); FT refers to freight turnover (including railway, highway, waterway); and EL refers to the proportion of electricity consumption to the total energy consumption. Meanwhile, according to the value of β_1 , β_2 and β_3 , we can validate the existence of the environmental Kuznets hypothesis based on the relationship between economic development and transport CO₂ emissions (Table 2) [46].

Data Sources

The annual data of terminal energy consumption in the transport sector is derived from the China Energy Statistical Yearbooks (2002-2017). The annual data of added value of transport sector, per capita GDP, the scale of population, passenger turnover and freight turnover derive from China Statistical Yearbooks (2002-20017). Note that, according to China Statistical Yearbooks and China Energy Statistical Yearbooks, the data sources of the transport sector in China derive from the data of transport, storage, and post, so we will follow the method to collect the relevant data as most scholars did [4, 47, 48]. Meanwhile, the monetary indicators, including the GDP and added value of transport sector, are converted into 2001 constant price by using gross domestic product deflator and the third industry added value deflator, respectively. Table 3 shows the descriptive statistics of the variables in 30 provincial regions during the period 2001-2016.

Results and Discussion

General Trend of CO₂ Emissions in China's Transport Sector

Based on the above calculation method (formula 1) and energy consumption statistics, the transport CO₂ emissions in China from 2001 to 2016 were measured (Fig. 3). It can be seen that the amount of transport CO₂ emissions has increased steadily during the observation period, from 200.42 million tons in 2001 to 814.10 million tons in 2016, for an average annual growth of 8.37%. Meanwhile, according to the CO₂ emissions in transport sector by energy type (Fig. 4), petroleum products were the leading contributor to energy consumption and CO₂ emissions during the period 2001-2016, which is in line with the characteristics of energy consumption in transport activities.

Similarly, as shown in Fig. 3, the amount of transport CO₂ emissions for each province also was found to increase steadily from 2001 to 2016. However, there was a noticeable disparity in CO₂ emissions during the observation period. For example,

Table 3. Descriptive statistics of the variables.

Variables	Unit	Min	Max	Mean	Std. dev.
$PGDP$	10 ⁴ Yuan/person	0.2983	9.1979	2.2650	1.6184
PO	10 ⁴ persons	523	10999	4391	2642.2
EI	Ton/10 ⁴ Yuan	0.2669	6.3561	1.7465	0.854324
PT	100 million passenger-km	32.95	2998.23	654.98	489.17
FT	100 million ton-km	97.50	21801.65	3589.09	3947.51
EL	Percent	0.0077	0.1560	0.0438	0.028187

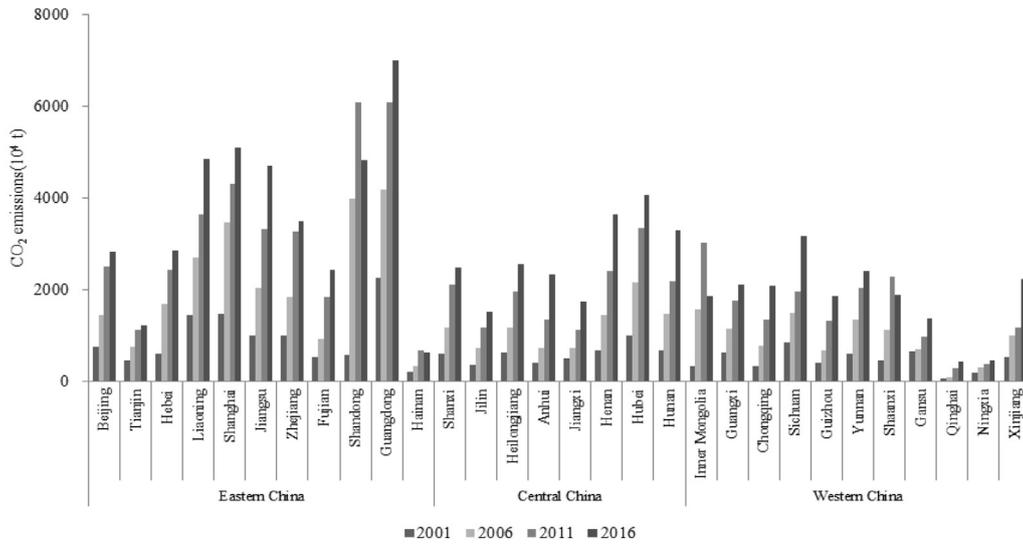


Fig. 3. Annual total CO₂ emissions in China's transport sector.

in 2016 the five provincial regions with the highest transport CO₂ emissions were Guangdong, Shanghai, Liaoning, Shandong, and Jiangsu. These provinces are mainly located in the eastern economically developed areas of China, and the corresponding transport CO₂ emissions in the transport sector were 70.15 Mt, 51.11Mt, 48.59 Mt, 48.20 Mt and 47.13 Mt, respectively. Conversely, the five provincial regions with the lowest transport CO₂ emissions were Qinghai, Ningxia, Hainan, Tianjin, Gansu, and the corresponding CO₂ emissions in the transport sector were 4.15 Mt, 4.43 Mt, 6.18 Mt, 12.24 Mt and 13.55 Mt, respectively. The results showed that the transport CO₂ emission in Guangdong were 16.90 times that of Qinghai in 2016.

Meanwhile, CO₂ emissions in the transport sector were also noticeably unequal across the three major regions. Eastern China accounted for approximately

average 51.86% (the largest portion) of the total transport CO₂ emissions during the period 2001-2016, and followed by Western China and Central China, average accounted for 24.25% and 23.89%, respectively. Moreover, the average amount of CO₂ emissions in Eastern China was consistently above the national average, but province-level differences in Eastern China were large (according to the coefficient of variation (CV) index, the CV index is widely employed to analyze regional inequality [49]) (Fig. 5). The main reason was that there were not only high CO₂ emissions provinces such as Guangdong, Shanghai, and Liaoning, but also the low CO₂ emissions provinces such as Hainan and Tianjin. The average transport CO₂ emissions in Central China and Western China were consistently below the national average level, and the average amount of CO₂ emissions in Central China was larger than in Western

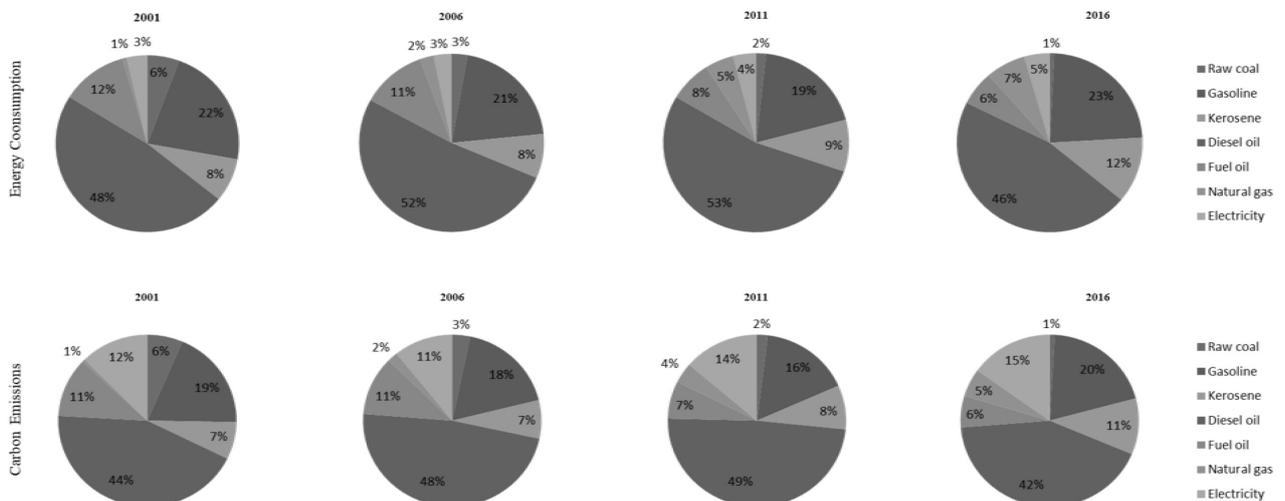


Fig. 4. Annual energy consumption and CO₂ emissions by energy types in China's transport sector.

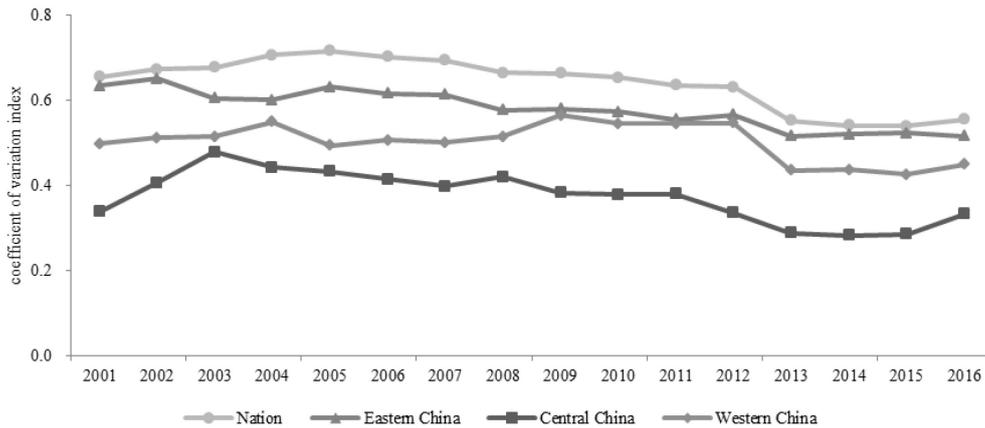


Fig. 5. CV index of CO₂ emissions at regional level.

China, but the province-level difference in Central China was smaller than Western China. The main reason was that in Western China there were not only the low CO₂ emissions provinces such as Qinghai, Ningxia, and Gansu, but also the high CO₂ emissions provinces such as Sichuan and Yunnan. Therefore, according to descriptive statistics analysis and the CV index, it can be seen that there was the great heterogeneity of transport CO₂ emissions among the provinces and regions during the study period.

Analysis of Spatial Agglomeration Characteristics in China’s Transport Sector

As shown in Fig. 6, global Moran’s I index indicated that the transport CO₂ emissions in China presented a significant positive spatial dependence during the period 2001-2016. Recalling that transport CO₂ emissions are calculated by a top-down approach, the significant positive spatial dependence refers to the spatial autocorrelation of energy consumption to some extent. This indicated that the geographic distribution of the transport CO₂ emissions tended to cluster together. Meanwhile, the value of global Moran’s I index overall showed an increasing trend, from 0.0214 in 2001 to 0.1685 in 2016 (with large fluctuations), which indicated that the spatial clustering degree had an increasing tendency. However, the global Moran’s I index can

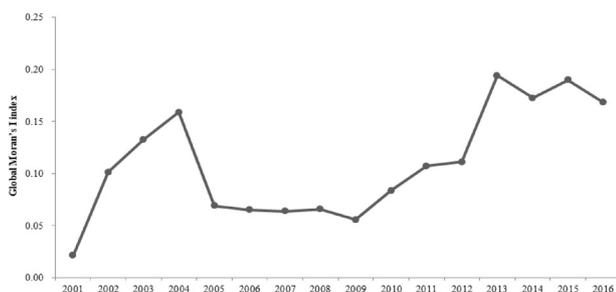


Fig. 6. Global Moran’s I index of CO₂ emissions.

just be used to examine the average correlation degree overall [40]. When some provinces show the positive effects, whereas the others present negative effects, the global Moran’s index may reveal non-spatial autocorrelation because the spatial effects may offset each other [50]. Therefore, we employ the method of local Moran’s I index (Moran’s I scatter plot) to further examine the spatial clustering characteristics of the CO₂ emissions in the transport sector in 2001, 2006, 2011, and 2016.

According to the local Moran’s I index, Fig. 7 plots the distribution of Moran scatter of CO₂ emissions in China’s transport sector. The left section of Fig. 7 presents the local spatial agglomeration patterns, and the right section presents the corresponding quadrant distributions. As shown in Fig. 7, in 2001, 2006, 2011, and 2016, there were 4 provinces, 7 provinces, 6 provinces, and 7 provinces located in quadrant I in Moran’s I scatter plot, respectively. Meanwhile, there were 10 provinces, 9 provinces, 9 provinces, and 10 provinces located in quadrant III, respectively. In other words, approximately half of the provinces belonged to the HH agglomeration area and LL agglomeration area, and showed the positive spatial autocorrelation. Meanwhile, the results showed that the provinces in quadrant I were mainly distributed in Eastern China, whereas the provinces in quadrant III were mainly distributed in Western China. This result further indicated that energy-related CO₂ emissions in China’s transport sector had a significant spatial clustering characteristic. Additionally, there were also some provinces that presented negative spatial autocorrelation during the observation period. For example, in 2016 Anhui, Jiangxi, Fujian, Guangxi, Jilin, Tianjin, and Chongqing belonged to the LH agglomeration area; and Hubei, Guangdong, Hainan, Liaoning, Beijing, and Sichuan belonged to the LH agglomeration area. Compared to 2001, in 2016 the number of provinces that belonged to quadrant I and quadrant III increased by 4, while the number of provinces that belonged to quadrant II and quadrant IV

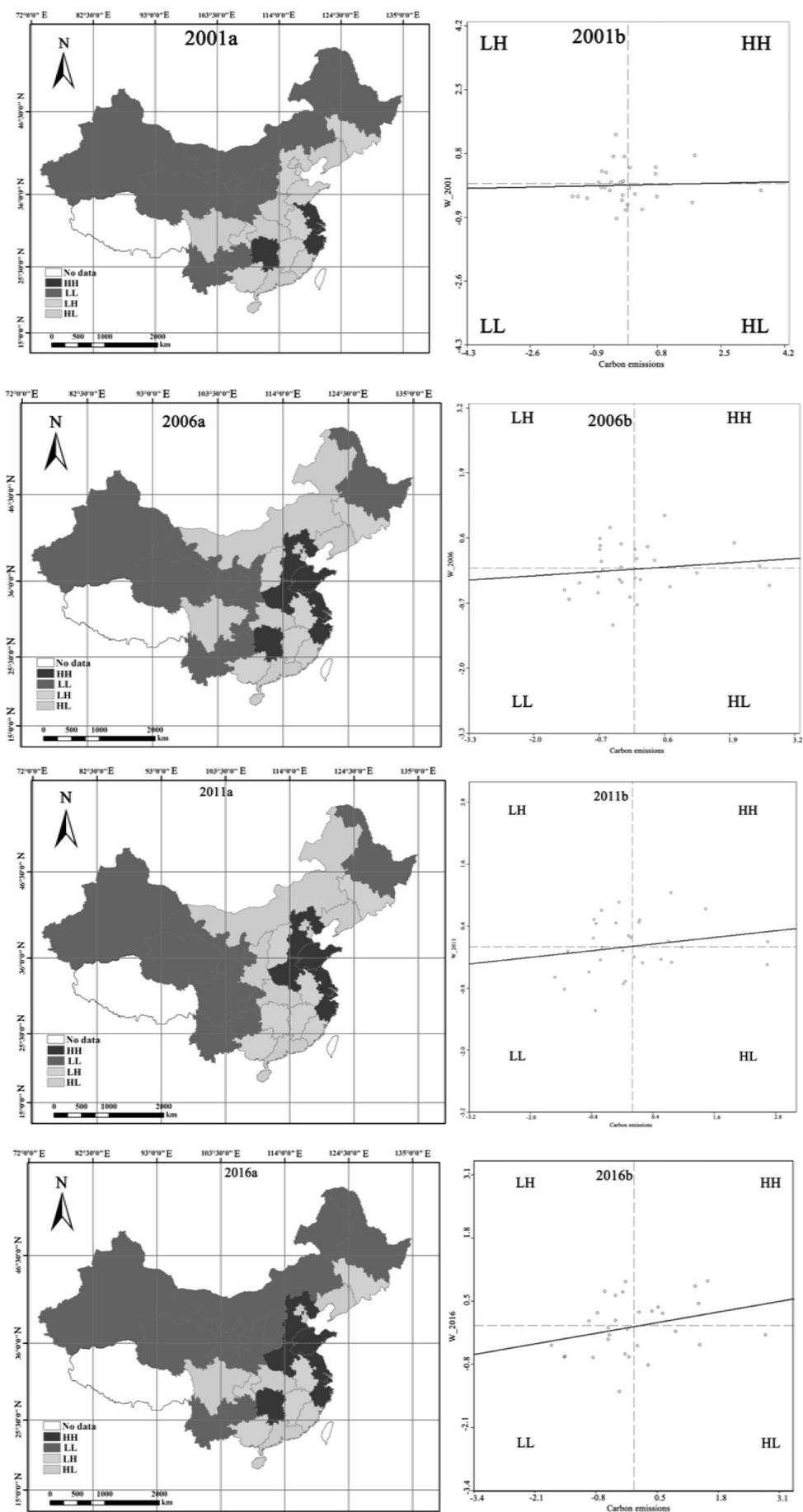


Fig. 7. Moran's I scatter plots of CO₂ emissions in China's transport sector.

decreased by 2 and 2, respectively. This showed that the distribution of each agglomeration area of provinces presented the regional dynamic characteristics, and the spatial clustering degree of the transport CO₂ emissions seemed to be strengthened during the period 2001-2016.

In order to further reveal the dynamic spatial distribution characteristics of transport CO₂ emissions in China. We employ the space-time transition method [51] to depict the transfer of Moran I scatter plots between the different local agglomeration areas. Generally, based on the way in which transition occurs, the space-time transition can be divided into 4 types [40]:

- Type I describes the transitions of the provincial unit itself, including $HH_t \rightarrow LH_{t+1}$, $HL_t \rightarrow LL_{t+1}$, $LH_t \rightarrow HH_{t+1}$, and $LL_t \rightarrow HL_{t+1}$.
- Type II describes the transitions of the neighboring provinces, but the state of the local provincial unit does not change, including $HH_t \rightarrow HL_{t+1}$, $HL_t \rightarrow HH_{t+1}$, $LH_t \rightarrow LL_{t+1}$, and $LL_t \rightarrow LH_{t+1}$.
- Type III includes Type IIIA and Type IIIB. Type IIIA describes the consistent direction of transition between the provincial unit itself and its neighboring provinces, including $HH_t \rightarrow LL_{t+1}$, $LL_t \rightarrow HH_{t+1}$. Type IIIB describes the opposite direction of the transition between the provincial unit itself and its neighboring provinces, including $LH_t \rightarrow LH_{t+1}$, $LH_t \rightarrow HL_{t+1}$.
- Type 0 describes how the provincial unit and its neighboring provinces remain in the same quadrant without a transition, including $HH_t \rightarrow HH_{t+1}$, $HL_t \rightarrow HL_{t+1}$, $LH_t \rightarrow LH_{t+1}$, and $LL_t \rightarrow LL_{t+1}$.

According to the 4 types of classification, the spatial stability of Moran I scatter plots can be expressed as follows:

$$S_t = \frac{F_{0,t}}{n} \tag{7}$$

...where S_t refers to the spatial stability index, $F_{0,t}$ refers to the number of space-time transition of Type 0 during the period $t \rightarrow t + 1$, n refers to the number of all transitions during the period $t \rightarrow t + 1$. As $0 \leq S_t \leq 1$,

the value is closer to 1, the spatial stability of transport CO₂ emissions will be stronger.

Table 4 presents the space-time transition matrices of Moran's I plot of transport CO₂ emissions in 4 time periods. It can be seen that the space-time transition of provinces mainly occurred in Type I and Type II, and most of the provinces still remain in the previous state. Meanwhile, according to the calculation results of spatial stability index, the value of spatial stability of Moran's I scatter plots during the period 2001-2006, 2006-2011, 2011-2016 was 0.80, 0.90 and 0.80, respectively. Besides, throughout the research period, the value of spatial stability index in 2001-2016 was 0.90. These results indicate that the spatial distribution characteristics of transport CO₂ emissions in China are highly stable, and show the characteristics of certain path-dependence or the spatial lock-in effect during the study period.

Factors Influencing CO₂ Emissions in China's Transport Sector

Due to the characteristics of our panel data and the introduction of one-period lagged term of the interpreted variable in the extended STIRPAT model, this may lead to the correlation between the explanatory variables and random disturbances. Meanwhile, the explanatory variables may also have endogeneity, and the random effect estimators and the fixed effect estimators may be biased, so we use the instrumental variables to estimate the model [52]. In this paper, we employ the method of Sys-GMM (system-generalized method of moments) [53] to estimate the extended STIRPAT model. When using the Sys-GMM estimation method, we employ the Hansen test to check the reliability of the instrumental variables. If the value of the Hansen test is small (corresponding to a large p value), we accept the null hypothesis suitable for the instrumental variables. Meanwhile, the important premise of the consistency of Sys-GMM estimators is that there is no second-order sequence correlation for the random disturbances after the first-order difference, but the first-order sequence correlation is allowed. Therefore, we use the first-order

Table 4. Space-time transition matrices.

Type	2001-2006	2006-2011	2011-2016	2001-2016
Type I	$LH \rightarrow HH$: Shandong, Hebei $LL \rightarrow HL$: Inner Mongolia	$HH \rightarrow LH$: Hunan $LL \rightarrow HL$: Shaanxi $HL \rightarrow LL$: Sichuan	$HL \rightarrow LL$: Shanxi, Shaanxi, Inner Mongolia $LH \rightarrow HH$: Hunan $LL \rightarrow HL$: Sichuan	$LH \rightarrow HH$: Shandong, Hebei
Type II	$LL \rightarrow LH$: Shanxi $HL \rightarrow HH$: Henan $LH \rightarrow LL$: Chongqing	None	$LL \rightarrow LH$: Chongqing	$HL \rightarrow HH$: Henan
Type III	None	None	None	None
Type 0	The remaining 24 provinces	The remaining 24 provinces	The remaining 24 provinces	The remaining 24 provinces
S_t	0.80	0.90	0.80	0.90

Table 5. Results of Sys-GMM regression analysis for different models.

Explanatory variable	Model I	Model II	Model III	Model IV
I_{it-1}	0.1005908*** (0.0154021)	0.093592*** (0.0151754)	0.0890914*** (0.0151534)	0.0425376** (0.0263652)
$\ln PGDP$	0.5887155*** (0.0304105)	0.5652816*** (0.0349423)	0.5478433*** (0.0441239)	0.6166843*** (0.0601113)
$(\ln PGDP)^2$	0.0148425 (0.0188028)	0.0281959 (0.029436)	0.0149025 (0.0273373)	0.0131461 (0.0620558)
$(\ln PGDP)^3$	-0.0324697*** (0.008051)	-0.0340467*** (0.0109577)	-0.0245083*** (0.009508)	-0.0128936*** (0.0506497)
$\ln PO$	0.6344935*** (0.0477226)	0.640722*** (0.031972)	0.6340494*** (0.0320871)	0.618423*** (0.0639586)
$\ln EI$	0.6142654*** (0.0218544)	0.626373*** (0.0295703)	0.6258782*** (0.0283079)	0.4800601*** (0.0359693)
$\ln PT$		0.023816** (0.0110231)	0.052173 (0.0106865)	0.0445274** (0.0211572)
$\ln FT$			0.0300955** (0.0136662)	0.0273227** 0.0137298
$\ln EL$				-0.1777859*** (0.0244016)
_cons	6.522483*** (0.1086485)	6.432531*** (0.146279)	6.354772*** (0.1925563)	5.896155*** (0.244775)
AR(1)	-2.6768 (0.0074)	-2.6788 (0.0074)	-2.6662 (0.0077)	-1.1851 (0.0695)
AR(2)	1.8207 (0.0686)	1.775 (0.0759)	1.6291 (0.1033)	0.4141 (0.6788)
Hanse test (p)	28.0567 (0.9223)	27.6548 (0.9303)	28.1215 (0.9210)	25.67258 (0.9616)
Observations	450	450	450	450

Notes: The number in parentheses of factors represents the standard errors; the number in parentheses of AR and Hansen test represents the p value.

The symbol * denotes $P < 0.1$, ** denotes $P < 0.05$, *** denotes $P < 0.01$.

and second-order sequence correlation test (AR(1) and AR(2)) of the first-order difference conversion equation to check whether the sequence correlation existed among the random disturbances [54].

Moreover, in order to test whether the multi-collinearity exists among the explanatory variables in the extended STIRPAT model, we calculated the correlation coefficients between the explanatory variables. The results show that the correlation coefficients were mostly relatively small, with only the coefficient between the freight turnover and per capita GDP, and the coefficient between the passenger turnover and the scale of population being relatively large. Besides, we further calculated the value of the variance inflation factors (VIFs); the results indicated that the average value of VIFs was below 10. Based on the above analysis, we can conclude that the problem of multi-collinearity among the explanatory variables was not serious.

By using the Stata software, Sys-GMM regressions analysis was performed, and the relevant results are presented in Table 5. As shown in Table 5, model I only presented the Sys-GMM regression results of the one-

period lagged term of the interpreted variable, per capita GDP (and its quadratic and cubic terms), the scale of population, and energy intensity. In order to check the robustness of Model I, we added three control variables (passenger turnover, freight turnover, and the proportion of electricity consumption) sequentially based on Model I, and the corresponding regression results were presented in Model II-IV, respectively. Based on the test results of AR(1) and AR(2) (Table 5), we concluded that the sequence correlation did not exist among the random disturbances. Besides, the results of Hansen test further indicated that we could not reject the null hypothesis. In other words, the choice of the instrumental variables was reliable, and the results of Sys-GMM regressions analysis were effective.

The empirical results of Sys-GMM regressions analysis showed that the coefficient of one-period lagged term of transport CO₂ emissions was statistically significantly positive. In other words, the transport CO₂ emissions in the last period were significantly positively correlated with the transport CO₂ emissions in the current period, which verified the hypothesis that CO₂

emissions in China's transport sector were a continuous and dynamic adjustment process. Once we added the new control variable sequentially based on Model I, we found that the influence of the former combination of variables changed. This finding was consistent with the studies of Wang et al. [55] and Shi [56]. When we considered all the factors that affected transport CO₂ emissions (Model IV), we found that the most important influencing factor was the scale of population, followed by the per capita GDP (linear term). This result was consistent with the study of Zhang et al. [3]. The coefficients of passenger turnover and freight turnover were positive, and both passed the significance test at the 5% level. The coefficients of energy intensity and the proportion of electricity consumption were positive and negative, respectively, and both passed the significance test at the 1% level.

In addition to the above basic results, we still found some interesting and meaningful findings based on the results of Sys-GMM regressions analysis.

(1) The EKC hypothesis did not exist in China's transport sector. The coefficient of linear term $\ln PGDP$ and cubic terms $(\ln PGDP)^3$ of per capita GDP was found to be positive and negative, respectively, and passed the significance test at the 1% level. The coefficient of quadratic term $(\ln PGDP)^2$ of per capita GDP was found to be positive (not significantly). According to the judgment criteria for the relationship between transport CO₂ emissions and economic development, we did not find the traditional inverted U-shaped relationship or the N-shape (and the inverted N-shaped) relationship between per capita GDP and transport CO₂ emissions. In other words, we could not support the existence of the EKC hypothesis in China's transport sector during the period 2001-2016. This finding was consistent with the other relevant empirical studies. For example, Ben Abdallah et al. [57] found that the inverted U-shaped relationship between the transport CO₂ emissions and economic development did not exist in Tunisia. Aslan et al. [58] found that the inverted U-shaped EKC hypothesis was not valid for the U.S. transport sector. Alshehry et al. [59] also found that the EKC hypothesis did not exist in Saudi Arabia's transport sector. Specific to our study, the main reason

the EKC hypothesis did not exist in China's transport sector during the observation period may lie in the fact that China is still a developing country, and the average per capita income is still relatively low. In other words, China was still on the left of the turning point of the EKC. Moreover, the relationship between transport CO₂ emissions and per capita GDP was very likely to show a monotonic and positive relationship in China. As shown in Fig. 8, there was a close relationship between the total amount of transport CO₂ emissions and the average per capita GDP ($R^2 = 0.9431$). The transport CO₂ emission was positively proportional to the per capita GDP. Objectively, the relationship between the environmental pressure and economic development is complex. In different research regions and observation periods, according to the different measurement indicators (especially for the control variables), the relationship between environmental pressure and economic development may be different [43, 55]. However, in this study, we did not find enough evidence to support the existence of EKC hypothesis in China's transport sector.

(2) The improvement of energy efficiency played a dominant role in transport CO₂ emissions reduction. The energy intensity reflects the efficiency of energy utilization, a decrease in transport energy intensity indicates an improvement in the efficiency of energy utilization and the technological progress level in the transport sector [60]. As shown in Table 5 (Model IV), a 1% decrease of energy intensity would lead to a 0.480% decrease in transport CO₂ emissions when other variables remained unchanged. Meanwhile, the impact of energy intensity on transport CO₂ emissions was only lower than the factors of scale of population and per capita GDP. However, during the period 2001-2016, the energy intensity generally showed an upward trend in China's transport sector. That is, the efficiency of energy utilization in the transport sector had a downward trend during the observation period. This result may be due to the low level of low-carbon technology in China's transport sector [48]. In the short and medium terms, the level of per capita income and the total scale of the population are expected to continue to grow in China. Therefore, the energy efficiency improvement will become more and more critical in transport CO₂

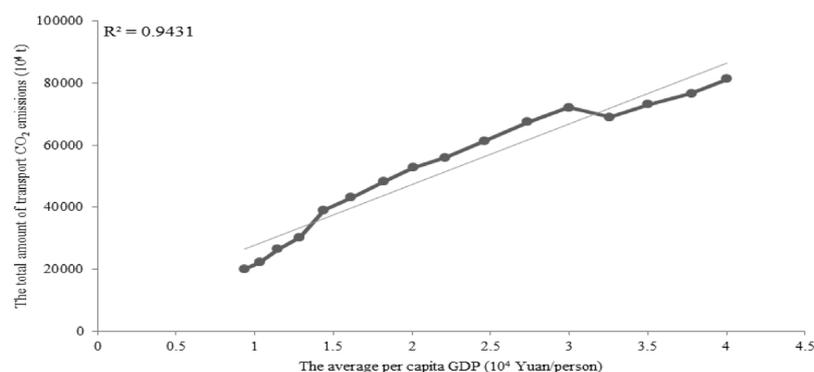


Fig. 8. Relationship between transport CO₂ emissions and per capita GDP.

emissions reduction.

(3) Compared to freight transportation, passenger transportation played a more important role in transport CO₂ emissions reduction. This finding was consistent with the studies of Zhang et al. [3], Wang et al. [61], and Wu et al. [32]. The main reasons may include two aspects. On the one hand, during the observation period, approximately an average of 91.52% passengers were transported by highway and civil aviation transportation; and approximately an average of 74.93% of freight turnover was transported by railway and waterway transportation. In other words, passenger transport mainly relies on highway and civil aviation transportation, while freight transport mainly relies on railway and waterway transportation. However, compared to railway and waterway transportation, highway and civil aviation transportation have lower carbon emission efficiency [62] and fuel economy [29]. On the other hand, with the further development of China's economy and urbanization, energy consumption and CO₂ emissions in the transport sector are expected to continue to rise [3]. However, compared to freight transportation, passenger transportation is more affected by economic-social development and urbanization in China [32].

(4) The improvement of the energy consumption structure had an important inhibitory effect on transport CO₂ emissions in China. As shown in Fig. 2, the proportion of low-carbon content energy or clean energy, including natural gas and electricity, was gradually increasing during the period 2001-2016. Namely, energy consumption in China's transport sector was constantly replacing high-carbon content energy with low-carbon content energy. As shown in Table 5 (Model IV), electrification had a significant effect on reducing transport CO₂ emissions, a 1% increase of electricity consumption to total energy consumption would decrease transport CO₂ emissions by 0.178% when other variables remained unchanged. This finding was consistent with the study of [63]. The main reasons may include two aspects. Firstly, as pointed by Holmberg et al. [64], electric vehicles have a higher fuel efficiency compared to internal combustion vehicles. Under the same amount of energy consumption, the electric vehicles would emit fewer CO₂ emissions. Secondly, as pointed by Ou et al. [63], even though the current power generation technologies remain unchanged, a 3-36% reduction of CO₂ emissions in different scenarios for electric vehicles could be achieved. When the technology of clean electricity production has great improvement, the space for CO₂ emissions reduction will be further expanded [65].

Conclusions and Policy Implications

This paper investigated the spatial distribution characteristics and influencing factors of transport CO₂ emissions from energy consumption in China by using

panel data covering the 30 provincial regions during the period 2001-2016. The empirical results are shown as follows.

The results indicated that the amount of transport CO₂ emissions in China has increased steadily during the observation period, from 200.42 million tons in 2001 to 814.10 million tons in 2016, for an average annual growth of 8.37%. Similarly, the amount of transport CO₂ emissions for each province also was found to increase steadily from 2001 to 2016. The level of economic development and geographical characteristics for different provinces generated us to pay attention to the issue of the inequality in growth of transport CO₂ emissions. By using the coefficient of variation, we found that transport CO₂ emissions existed in great heterogeneity among provinces and regions. However, the simple descriptive statistical analysis and the method of CV index are difficult to fully extract the different characteristics of CO₂ emissions data, so we further employed the ESDA method to mine the distribution characteristics of transport CO₂ emissions from the perspective of spatial dimension. The global Moran's I index indicated that transport CO₂ emissions in China presented a significant positive spatial dependence, and the spatial clustering degree had an increasing tendency during the observation period. The local Moran's I index further indicated that approximately half of the provinces belonged to the HH agglomeration area and LL agglomeration area. Combined with the space-time transition matrices, the results indicated that the spatial distribution of CO₂ emissions in China's transport sector presented the characteristics of path-dependence effect to some extent.

The application of the extended STIRPAT model enabled us to better understand the influencing factors of the transport CO₂ emissions. Based on the Sys-GMM regressions analysis, we found some interesting and meaningful findings. The scale of population was the most important influencing factor and followed by the per capita GDP. Furthermore, under the conditions that the economic development and the scale of population are expect to continue to grow in China; improvement of energy efficiency would play a dominant role in transport CO₂ emissions reduction. Compared to freight transportation, passenger transportation was more important in CO₂ emissions reduction due to its low efficiency of energy utilization and rapid growth. Meanwhile, electrification played an important inhibitory effect on transport CO₂ emissions because of its high fuel efficiency and less pollution. Importantly, we could not support the existence of the EKC hypothesis in China's transport sector. Moreover, the relationship between transport CO₂ emissions and per capita GDP was very likely to show a monotonic and positive relationship in China during the period 2001-2016.

These findings not only contribute to the existing literature, but also contain some important and meaningful policy implications. Firstly, it is necessary

to confirm the priority transport CO₂ emissions reduction areas. The spatial autocorrelation and agglomeration characteristics of province-level transport CO₂ emissions presented a high degree of stability and tended to be strengthened. The distribution characteristics reflect the fact that it is difficult for most provinces to break away from the original agglomeration area. Therefore, there are some differences in the pressure of CO₂ emissions reduction faced by China's provincial transport sector. According to a study of Chen et al. [66], the quadrant I-IV in Moran's I scatter plots belong to the "priority emission reduction area", "emission reduction observation area", "emission reduction buffer area", and "key emission reduction area", respectively. Therefore, it is necessary to set the priority CO₂ emissions reduction areas in accordance with the situation of spatial agglomeration. Secondly, it is necessary to improve transport energy efficiency. As pointed out by Adom [67], the lower energy efficiency is inclined to increase CO₂ emissions. The key to improving energy efficiency in China's transport sector is to strengthen the development and application of low-carbon technologies in the transportation field [48]. Thirdly, it is necessary to strengthen passenger transportation decarbonization policy. Owing to the great potential of market demand and the high pollutant intensity, passenger transport plays a more important role than freight transport in China's transport sector. Finally, it is necessary to highlight the model shift of fuel consumption. Different fuels have different carbon content, which leads to a significant difference in the contribution of carbon emissions. Some related policies are important to further reduce petroleum consumption in the transport sector, such as developing low-displacement and electric vehicles.

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Conflict of Interest

The authors declare no conflict of interest.

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