Original Research

Spatial Non-Equilibrium and Its Solidification Effect of China's Per Capita Transportation Carbon Emissions

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Abstract

It is of great significance to understand the spatial non-equilibrium and the solidification degree of transportation carbon emissions, so that differentiated measures can be taken to reduce transportation carbon emissions. Based on China's provincial data from 2005 to 2015, this article uses the Dagum Gini coefficient to decompose the spatial non-equilibrium of per capita transportation carbon emissions from static viewpoint. The results indicate that the overall spatial non-equilibrium shows a significant downward trend; the intensity of transvariation has had an increased contribution rate year by year since 2008, and replaces the inter-regional differences as the main source of the overall spatial non-equilibrium. Next, Kernel density estimation is employed to analyze the evolution laws of spatial non-equilibrium from dynamic viewpoint. The results show that the per capita transportation carbon emissions in the eastern region are successively higher than those at the national level, and in other regions. Meanwhile, some provinces are concentrated at a low level, while others at a high level. Finally, Markov chains approach is applied to identify the solidification effect of the spatial non-equilibrium. The results indicate that the effect is obvious and the state transitions occur only between adjacent types. Moreover, the solidification effects of the provinces with higher per capita transportation carbon emissions are stronger than those provinces with a lower level.

Introduction

Carbon emissions and the resulting global warming problem have always been important topics of global concern [1-3]. To deal with global warming, some countries signed The Paris Agreement in 2015 [4]. The Agreement urges countries to control the increase in the global average temperature below 2ºC above "pre-industrial levels" and make great efforts to limit the temperature increase to 1.5ºC above "pre-industrial levels". In order to achieve this goal, the IPCC

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(Intergovernmental Panel on Climate Change) predicts that by 2030, CO_2 emissions as the main greenhouse gas should be at least 45% lower than in 2010 [5]. However, in recent years, the global CO_2 emissions have not shown an evident downward trend, even reaching 37 billion tons in 2018, the highest ever recorded.

The main drive of the rapid increase in carbon emissions is high energy consumption [6-8]. As shown by data, the carbon emissions from energy consumption account for about 80% of the global carbon emissions [9]. Transportation sector is highly dependent on fossil energy, and its energy consumption accounts for about one-third of the total energy consumption [9]. It has become the main carbon emitter after the power and heat industries [9]. According to the statistics from the International Energy Agency, in 2015, the carbon emissions from the transportation sector around the world reached 7.969 billion tons/person, and their total carbon emissions accounted for 24% of the global carbon emissions [9]. Therefore, transportation sector has been considered one of the most difficult sectors for carbon emission reduction [10].

The task of reducing carbon emissions in the transportation sector is equally arduous for the world's largest carbon emitter – China. As far as China is concerned, the transportation sector is one of its "three major carbon sources" [11]. The annual average growth rate of energy consumption in transportation sector has been close to 8% since 1985 [12]. The increase in transportation energy consumption resulted in transportation carbon emissions accounting for 5%-9% of the total carbon emissions generated by fuel combustion during 1985-2014 [9]. China is committed to controlling CO_2 emissions to peak in around 2030, and proposes the "13th Five-Year" energy conservation and emission reduction goal to reduce energy intensity by 15% and carbon intensity by 18% as of 2020 compared with 2015. But, the World Energy Outlook 2017 China Special Report shows that only the transportation sector among China's industries cannot reach its peak before 2040. Therefore, the transportation sector has become an important industry that restricts China's energy conservation and emission reduction.

China has 34 provincial level administrative regions. Their economic development and environment vary greatly, which results in significant differences in the levels and evolution characteristics of transportation carbon emissions. For example, in the period from 2005 to 2015, the eastern region had higher per capita transportation carbon emissions than the central and western regions, but had a lower average annual growth rate [13]. Therefore, the per capita transportation carbon emissions in various provinces could converge to the different clubs with different carbon emission levels [14]; moreover, different provinces are also in different positions and play different roles in the spatial association network of transportation carbon emissions [15]. In general, the spatial non-equilibrium implies that there

are significant differences of per capita transportation carbon emissions at the regional level in China. Given the overall regional differences unchanged, provinces with a higher level of transportation carbon emissions may transfer to another level. If the mobility among various levels is relatively low, regional differences will have little variations with time, which is considered as a solidification of spatial non-equilibrium [16]. In other words, the solidification of spatial non-equilibrium is roughly equivalent to having no evident change in regional differences of China's per capita transportation carbon emissions over time, which means regional differences are hard to change spontaneously. Hence, the central government should perform an intervention to guide provinces with higher transportation carbon emissions to transfer to lower level. In order to fit the potential transportation carbon emissions in different provinces, reduction policies should be made based on overall spatial non-equilibrium and its solidification effect. Through the above analyses, it is of great significance to explore the spatial non-equilibrium of China's transportation carbon emissions and its solidification effect, clarify the sources of the spatial non-equilibrium as well as understand their evolution rules [17]. Then, differentiated transportation carbon emission reduction measures can be taken to equalize efficiency and fairness.

To explore the evolution and the sources of spatial non-equilibrium of China's transportation carbon emissions from both static and dynamic perspectives, as well as to investigate the solidification effect of the spatial non-equilibrium, our work is as follows. First, the Dagum Gini coefficient is used to analyze the overall spatial non-equilibrium of per capita transportation carbon emissions in China from a static perspective, and then decompose the spatial non-equilibrium into the intra-regional difference, the inter-regional difference and the intensity of transvariation to investigate the sources of the spatial non-equilibrium and inequality in per capita transportation carbon emissions. Second, Kernel density estimation is employed to describe the dynamic evolution characteristics of per capita transportation carbon emissions at the national and regional levels, respectively. After studying the overall spatial non-equilibrium of China's per capita transportation carbon emissions from both static and dynamic perspectives, Markov chains approach is adopted to explore its solidification effect for the first time. Finally, the robustness of the solidification effect is analyzed. The above work can provide a basis for the national and local governments to develop differentiated carbon emission reduction policies.

Literature Review

There have been many studies regarding the regional differences of carbon emissions. Research methods gradually evolve from a single indicator to a

spatial-level decomposition. For example, Grunewald et al. [18] use the Gini coefficient to explore the evolution of inequality in CO_2 emissions in 90 countries around the world; Mussini and Grossi [19] link the relative CO_2 emission disparities, population size and country ranking through introducing a three-term decomposition of the Gini coefficient, so as to explain inequality state among European countries over 1991-2011; Wang and Zhou [20] adopt a new approach based on the Theil index and the index decomposition analysis (IDA) technique to find that the global emission inequality tends to decrease; based on the Theil index, Wang et al. [21] further apply spatial Markov chains and multi-level models to confirm that China's carbon emissions inequality has slowed down.

Compared with the studies on total carbon emissions, the works on the spatial differences of transportation carbon emissions have increased in recent years. Meanwhile, the methods used in the existing studies can be roughly divided into two types. The first type uses a single indicator such as standard deviation, coefficient of variation, Gini coefficient, etc. to test the spatial differences of transportation carbon emissions. The other type uses composite models to comprehensively measure the spatial non-equilibrium of transportation carbon emissions from different perspectives. For the two types, the former is convenient to calculate and makes the results succinctly and effectively. But it only reveals one aspect of spatial non-equilibrium, and cannot fully explain it. The latter helps to make up the deficiency of the former, and integrates these single indicators about transportation carbon emissions from more thorough perspectives as shown in Table 1.

The above studies explore the spatial non-equilibrium of China's transportation carbon emissions from multiple dimensions, serving as a good inspiration for understanding the spatial pattern and regional differences of transportation carbon emissions at present. However, there are still three shortcomings as follows. (1) In terms of research perspective, the existing studies lack independent description and in-depth discussion of the evolution of transportation carbon emissions. Even if a few of them have investigated the spatial non-equilibrium in transportation carbon emissions from the static perspective, the sources and evolution trends of the spatial non-equilibrium are not further

Table 1 Studies on the spatial non-equilibrium of transportation carbon emissions.

Type	Perspectives	Studies	Methods	Key findings
Single indicator		Liu et al. [22]	Logarithmic standard deviation	The differences of China's transportation carbon emissions raise during 1996-2000.
		Yang et al. [23]	Gini coefficients	The regional differences of China's per capita transportation carbon emissions begin to decrease after 2005.
Composite model	The perspective of spatial econometrics	Zhang and Nian [24]	A stochastic impact by regression on population, affluence, and technology (STIRPAT) model	Different impacts brought by passenger transport make the characteristics of China's transportation CO_2 emissions across regions different.
		Lim et al. [25]	Moran index and STIRPAT model	The national transportation CO_2 emissions in the spatially dispersed urbanized countries have a high probability of being higher than those in the spatially polarized urbanized countries.
	The spatial non-equilibrium of transportation carbon emission efficiency	Zhang et al. [11]	A non-radial Malmquist CO_2 emission performance index (NMCPI)	The original efficiency change index of NMCPI of China's provincial transportation CO_2 emission has shown different performance.
		Wang and He [26]	A non-radial directional distance function model	The transportation CO_2 emission efficiency shows significant regional differences.
		Zhang and Wei [27]	A metafrontier non-radial Luenberger carbon emission performance index (MNLCPI)	The carbon emission performance of the transportation industry exhibits significant differences across China's three main areas.
	The spatial non-equilibrium of city-level transportation carbon emissions	Ma et al. [28]	A static spatial microsimulation	Residents who inhabit in Beijing's inner suburban zone take higher carbon travel behavior, while others in the central urban zone emit lower carbon.
		Liu and Wang [6]	Moran index and a multiproxy allocation system	There is an obvious difference between the center and periphery of Wuhan from the total transport-related carbon emissions.

decomposed and explored from the dynamic perspective. (2) In terms of exploring dynamic evolution rules, although a few studies indicate the dynamic evolution of spatial non-equilibrium, they neglect the solidification effect of spatial non-equilibrium. Actually, a stronger solidification effect has more of a chance to widen the spatial non-equilibrium of transportation carbon emissions. Thus, studying the solidification effect plays a vital role in analyzing the dynamic changes of spatial non-equilibrium. (3) In terms of study methodology, the existing studies prefer a single indicator such as Gini coefficient, Theil index, Moran index, etc. to briefly describe the spatial non-equilibrium in transportation carbon emissions without decomposing and analyzing the sources of the global difference. So, it is difficult to explain the characteristics of the subsamples.

Different from the existing studies, this work focuses on the global static and dynamic evolution laws of the spatial non-equilibrium of transportation carbon emissions and its solidification effect. The research objects are specific to China's 30 provinces. The sample years are from 2005 to 2015. By using the Dagum Gini coefficient and Kernel density estimation, we decompose the sources of the spatial non-equilibrium as well as describe the subsample characteristics. After that, Markov chains approach is used to investigate the solidification effect of the spatial non-equilibrium for the first time. Compared with the existing study methodology, the definition of Gini coefficient by subgroup decomposition proposed by Dagum [29] is relatively straightforward. It is conducive to portraying the evolution trend of spatial non-equilibrium. Meanwhile, it can be used to decompose the sources of spatial non-equilibrium and measure the distribution of subgroups, having unique advantages in analyzing the spatial non-equilibrium among samples. And Kernel density estimation in the distributed dynamic model is flexible and robust, with no need for priori settings for data distribution [30], which can directly reflect the overall status and dynamic evolution of the sample distribution. Therefore, it is mostly employed to study the regional polarization phenomenon. However, there is only little information provided by Kernel density estimation about the solidification effect of spatial non-equilibrium. Thus, Markov chains approach proposed by Quah [31] is applied. This approach can compensate for the limitation of Kernel density estimation in describing the dynamic changes within samples; reveal the relative mobility among different status of the samples; and analyze the solidification effect of spatial non-equilibrium well [32].

Hence, this paper analyzes the spatial non-equilibrium of China's per capita transportation carbon emissions as a whole from a static perspective; decomposes the sources of the spatial non-equilibrium; and describes the dynamic evolution laws of the spatial non-equilibrium. Most importantly, we further investigate the solidification effect of the spatial non-equilibrium for the first time. In conclusion, this paper

determines the sources of spatial non-equilibrium and the internal evolution of China's per capita transportation carbon emissions from both the static and dynamic perspectives so as to provide a basis for the formulation of differentiated transportation carbon emission reduction policies for China and provinces, as well as present a new perspective for the study of transportation carbon emissions.

Material and Methods

Methods

Analysis of the Spatial Non-Equilibrium from a Static Perspective – Dagum Gini Coefficient

Compared with the Theil index and the traditional Gini coefficient, the Dagum Gini coefficient can be used to measure the distribution of subgroups, and effectively identify the sources of regional differences. It has unique advantages in analyzing the spatial non-equilibrium among samples from a static perspective. In this study, the Dagum decomposition of the Gini coefficient is employed to investigate the spatial non-equilibrium of per capita transportation carbon emissions in China, and to decompose the sources of the spatial non-equilibrium. The Dagum Gini coefficient is defined as follows [29]:

$$G = \sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_k}\left|y_{ji}-y_h\right| \Big/ 2\mu n^2 \tag{1}$$

$$\mu_h \leq \cdots \mu_j \leq \cdots \mu_k \tag{2}$$

...where, $y_{ij}(y_{hr})$ denotes the per capita transportation carbon emissions of the province $j(h)$; μ denotes the average per capita transportation carbon emissions at the national level; μ_h denotes the average per capita transportation carbon emissions in the region h; n is the number of provinces ($n = 30$ in this study); k is the number of regions; $n_j(n_h)$ is the number of provinces in the region $j(h)$.

According to sub-groups, the Dagum Gini coefficient is decomposed into the contribution of the intra-regional difference G_w, the contribution of the inter-regional difference G_{nb} and the contribution of the intensity of transvariation G_t. And the above three satisfy $G = G_w + G_{nb} + G_t$ [29]. Specifically, G_w represents the internal difference in the per capita transportation carbon emissions in the region $j(h)$; G_{nb} represents the net difference in the per capita transportation carbon emissions between the regions j and h; and G_t represents the residual term of the Gini coefficient of the cross-effect of the regional per capita transportation carbon emissions [33].

$$G_w = \sum_{j=1}^{k} G_j \, p_j s_j \tag{3}$$

$$G_{jj} = \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} \left| y_{ji} - y_{jr} \right| \bigg/ 2\overline{Y}_j \, n_j^2 \tag{4}$$

$$G_{jh} = \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} \left| y_{ji} - y_{jr} \right| \bigg/ n_j \, n_h (\overline{Y}_j + \overline{Y}_h) \tag{5}$$

$$G_t = \sum_{j=2}^{k} \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j)(1 - D_{jh}) \tag{6}$$

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \tag{7}$$

$$d_{jh} = \int_{0}^{\infty} dF_j(y) \int_{0}^{y} (y - x) dF_h(x) \tag{8}$$

$$p_{jh} = \int_{0}^{\infty} dF_h(y) \int_{0}^{y} (y - x) dF_j(x) \tag{9}$$

...where, G_{jj} denotes the Gini coefficient within the region j; G_{hj} denotes the Gini coefficient between the regions j and h ($p_j = n_j/n$, $s_j = n_j/\overline{Y}_j/n\overline{Y}$, $j = 1,2,3,...,k$); D_{jh} denotes the relative impact of the per capita transportation carbon emissions between the regions j and h. Define d_{jh} as the difference in the contribution rates of the per capita transportation carbon emissions between the regions j and h. Define p_{jh} as the one order moment of transvariation. $F_j(h)$ and $F_h(h)$ represent the cumulative density distribution functions of the regions j and h, respectively.

Analysis of the Spatial Non-Equilibrium from a Dynamic Perspective – Kernel Density Estimation

As an important non-parametric estimation method to estimate the unknown density function based on sample characteristics, Kernel density estimation can not only overcome the defects of parameter estimation but also reflect the overall status and the dynamic evolution of the sample distribution. Hence, it has been widely used in the study of spatial non-equilibrium distribution from a dynamic perspective [2]. The basic principle is as follows. Assume that the random variables X_1, X_2........X_n are the n sample points of independent and identical distribution $F(x)$, and its probability density function $f(x)$ is unknown. Therefore, $f(x)$ is estimated by the samples.

$$f(x) = \frac{\sum_{i=1}^{n} K_h(x_i - x)}{n} = \frac{1}{h} \sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) \tag{10}$$

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \tag{11}$$

Eq. (10), i.e. Kernel density, can be adopted to estimate the probability density at the point x, which indicates the probability that x appears in a given region. In the Eq. (10), h is the smoothing parameter or bandwidth; n is the number of observations; x is the average; $K(\cdot)$ is Kernel function, which is a weight function. Kernel functions commonly used include triangular Kernel function, quadrangle Kernel function, Epanechnikov Kernel function and Gaussian Kernel function. Among them, Gaussian Kernel function has a better performance in terms of data mapping than others [34]. Therefore, it is used in this study to estimate the distribution density of provincial per capita transportation carbon emissions. It is defined as shown in Eq. (11). And then, their dynamic distribution characteristics are determined according to the position, ductility and shape of the obtained Kernel density curves.

Analysis of the Solidification Effect of the Spatial Non-Equilibrium from a Dynamic Perspective – Markov Chains Approach

In this study, Markov chains approach proposed by Quah [31] is adopted to explore the internal evolution characteristics of provincial per capita transportation carbon emissions. Kernel density estimation cannot describe the solidification effect of the spatial non-equilibrium from a dynamic perspective, but Markov chains approach can. It is the state space of a stochastic process $\{X(t), t \in T\}$. For any n values at time t, if $X(t_i) = x_i$, then the state transition probability of the conditional distribution function $X(t_n)$ satisfies the following:

$$P\{X(t_n) \leq x_n | X(t_{n-1}) = x_{n-1}\}, x_n \in R \tag{12}$$

Assume that the transition probability of the provincial per capita transportation carbon emissions is only related to the states i and j. If it is not related to n, then the time homogeneous Markov chains are obtained; otherwise, the non-time homogeneous Markov chains are obtained. The time homogeneous Markov chains can represent the probability distribution of random variables transiting from one state space to another. This study only focuses on the time homogeneous Markov chains, so Eq. (12) can be transformed into as following:

$$P\{X_{n+1} = j | X_n = i\} \tag{13}$$

Provided that the provincial per capita transportation carbon emissions are classified into N types, a $N \times N$ state transition probability matrix P (as shown below)

can be obtained through the Markov chains. In that way, the internal dynamic evolution characteristics of the provincial per capita transportation carbon emissions can be determined.

$$P = p_{ij} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1j} & \cdots \\ p_{21} & p_{22} & \cdots & p_{2j} & \cdots \\ \cdots & \cdots & & \cdots & \\ p_{i1} & p_{i2} & \cdots & p_{ij} & \cdots \\ \cdots & \cdots & & \cdots & \end{bmatrix} \tag{14}$$

$$p_{ij} \geq 0, i、j \in R \tag{15}$$

$$\sum_{j \in N} p_{ij} = 1, i、j \in N \tag{16}$$

...where, p_{ij} represents the probability of a province transiting from the state i in year t to the state j in year $t + 1$. The bigger the value of p_{ii}, the stronger the solidification effect. It is often estimated using the maximum likelihood method. And $p_{ij} = n_{ij}/n_i$, where, n_{ij} is the number of times that the per capita transportation carbon emission level transits from the state i to the state j during the sample period; n_i is the total number of the state i.

Data Sources and Regional Division

Currently, China has no official organization to directly release the data on transportation carbon emissions. Therefore, scholars often employ the top-down and bottom-up approaches to calculate the transportation carbon emissions [35-36]. The bottom-up approach requires complete data. However, the data on the types, quantities, mileage, energy consumption per unit mileage, etc. of various vehicles are not all available in China. So, the top-down approach is used herein to calculate the transportation carbon emissions according to the final energy consumption of the transportation sector. Based on the major energy consumption types of the transportation sector and the IPCC Guidelines for National Greenhouse Gas Inventories [37], the carbon emissions from the transportation sector[1] are calculated via the following equation:

$$c = \sum_i^8 e_i \times v_i \times ce_i \times r \tag{17}$$

...where, c denotes the total carbon emissions from the transportation sector; e_i denotes the fuel consumption of the fuel i; v_i denotes the average low calorific value

of the fuel i; ce_i denotes the carbon emission coefficient of the fuel i; $i r$ denotes the carbon oxidation rate. The consumption and the average low calorific values of various fuels are sourced from the 2006-2016 China Energy Statistical Yearbooks [38]. The carbon emission coefficients of various fuels are sourced from the IPCC Guidelines for National Greenhouse Gas Inventories [37]. The carbon emission coefficients and the average low calorific values of various fuels are shown in Table 2. Additionally, following Wang et al. [39], the carbon oxidation rate is regarded as 100%, so $r = 1$ in the Eq. (17). The research object of this paper is the per capita transportation carbon emissions. Hence, the per capita transportation carbon emissions of each province are obtained by dividing the total transportation carbon emissions by the total population of each province. The population data of various provinces is derived from the 2006-2016 China Statistical Yearbook [40].

This study selects the per capita transportation carbon emissions of China's 30 provinces (excluding Tibet, Hong Kong, Macao and Taiwan due to the unavailability of their data) during 2005-2015 to analyze the spatial non-equilibrium and its solidification effect. Meanwhile, in order to demonstrate the spatial non-equilibrium, these provinces are divided into three regions: the eastern region, the central region and the western region according to the criteria defined by the National Bureau of Statistics of China[2].

Results and Discussion

The Spatial Non-Equilibrium and Decomposition of China's per Capita Transportation Carbon Emissions

General Description

Table 3 shows the average per capita transportation carbon emissions at the national level and in the eastern, central and western regions as well as their changes during 2005-2015. According to statistics proved by Table 3, the average per capita transportation carbon emissions present a significant upward trend on the whole. Taking 2005 as the base year, the annual average growth rates at the national level and in the eastern, central and western regions were 5.4128%, 3.1487%, 8.2865% and 7.4859%, respectively in 2015. Among them, the annual average growth rates of the central and western regions were higher than the national level, while the annual average growth rate of

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[1]　China's official statistical agency combines transportation, warehousing and postal services into one industry. Therefore, the transportation sector in this study consists of transportation, warehousing and postal services.

[2]　In this study, the eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan; the central region includes Shanxi, Heilongjiang, Jilin, Anhui, Jiangxi, Henan, Hubei and Hunan; the western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang.

Table 2. Relevant coefficients of various fuels.

Type of fuel	Raw coal	Coke	Crude oil	Fuel oil	Gaso-line	Kero-sene	Diesel oil	Natural gas
Carbon emission coefficient	25.8	29.2	20	21.1	18.9	19.6	20.2	15.3
Average low calorific value	20908	28435	41816	41816	43070	43070	42652	38931
Conversion coefficient of standard coal	0.714	0.971	1.429	1.429	1.471	1.470	1.457	1.214

Notes: the carbon emission coefficients of natural gas and other fuels are expressed in m^3/GJ and kg/GJ, respectively; the average low calorific values of natural gas and other fuels are expressed in KJ/m^3 and KJ/kg, respectively.

the eastern region was lower than the national level. At the same time, the average per capita transportation carbon emissions in the eastern region were much higher than those at the national level, as well as in the central and western regions, but the gap between them were narrowing. As far as the time is concerned, the increase in the average per capita transportation carbon emissions indicates that China's transportation carbon emission reduction is relatively urgent. From the cross-sectional data, the decrease in the difference between averages indicates that the spatial non-equilibrium was narrowing. The carbon emissions in various provinces possibly converge.

Spatial Non-Equilibrium and Sources

In this study, the Dagum Gini coefficient and its decomposition approach by subgroups are respectively used to calculate the overall Gini coefficient of China's per capita transportation carbon emissions from 2005 to 2015 from a static perspective and its decomposition results according to the three regions, as shown in Table 4. From Table 4, it can be seen that the overall difference, difference within regions and difference between regions of the Dagum Gini coefficient basically decline during the eleven years. Meanwhile, the contribution rate of difference between regions decreases, whereas the contribution rates of the other two increase.

(1) The spatial non-equilibrium and its evolution trend.

Fig. 1 depicts the Dagum Gini coefficient of China's per capita transportation carbon emissions and its evolution trend, which reflects the overall spatial non-equilibrium among provinces. It can be seen that the Dagum Gini coefficient shows a downward trend as a whole. Specifically, it declined from 0.3534 in 2005 to 0.2484 in 2015, with an annual average decline rate of 3.4641%, indicating that the overall spatial non-equilibrium of China's per capita transportation carbon emissions was gradually narrowing. The conclusion is also supported by the evidence from Li et al. [41]. They agree that China's per capita transportation carbon emissions at the city level show similar trends. This decline is bound up with the urbanization process, transportation structure, energy dependence, energy efficiency and other factors [42]. Obviously, rapid urbanization is accompanied by relatively frequent economic exchanges and high

Table 3. Average per capita transportation carbon emissions.

Year	National level	Eastern region	Central region	Western region
2005	0.0905	0.1383	0.0535	0.0697
2006	0.0993	0.1475	0.0583	0.0808
2007	0.1089	0.1588	0.0645	0.0913
2008	0.1191	0.1702	0.0739	0.1010
2009	0.1242	0.1750	0.0771	0.1075
2010	0.1318	0.1817	0.0809	0.1190
2011	0.1405	0.1871	0.0953	0.1268
2012	0.1481	0.1918	0.0989	0.1401
2013	0.1416	0.1791	0.1064	0.1297
2014	0.1474	0.1830	0.1128	0.1369
2015	0.1534	0.1886	0.1185	0.1436
Annual average growth rate	5.4128	3.1487	8.2865	7.4859

Note: the average per capita transportation carbon emissions are expressed in ton/person, and the annual average growth rate is expressed in %

Table 4. The Dagum Gini coefficient and its decomposition.

Year	Overall difference	Difference within regions			Difference between regions			Contribution rate (%)		
		Eastern region	Central region	Western region	Eastern-Central	Eastern-Western	Central-Western	Within regions	Between regions	Intensity of transvari-ation
2005	0.353	0.330	0.204	0.255	0.460	0.393	0.255	29.060	39.300	31.640
2006	0.358	0.350	0.208	0.273	0.455	0.387	0.276	30.300	37.350	32.350
2007	0.341	0.347	0.197	0.241	0.444	0.364	0.259	30.340	37.350	32.310
2008	0.330	0.322	0.253	0.224	0.430	0.346	0.276	29.850	31.770	38.380
2009	0.320	0.308	0.230	0.225	0.420	0.339	0.260	29.620	31.250	39.120
2010	0.304	0.293	0.201	0.219	0.407	0.317	0.255	29.500	31.510	38.990
2011	0.289	0.273	0.211	0.234	0.360	0.309	0.248	30.220	25.930	43.850
2012	0.282	0.264	0.186	0.241	0.350	0.297	0.249	30.350	24.930	44.730
2013	0.259	0.277	0.154	0.226	0.297	0.281	0.213	32.150	25.150	42.700
2014	0.243	0.275	0.152	0.191	0.288	0.263	0.191	32.080	23.280	44.640
2015	0.248	0.278	0.146	0.211	0.284	0.271	0.201	32.400	21.900	45.710

transportation demand [43]. During 2005-2015, China's urbanization process progressed rapidly, and the growth rate of urbanization in relatively underdeveloped provinces was generally faster than that in developed provinces, thereby narrowing the gap in transportation demand between provinces. Besides, the economically developed provinces with a high carbon emission level at the initial stage were gradually optimizing their transportation energy structure and have made a great progress, while the economically underdeveloped provinces still had an unreasonable transportation energy structure, and the consumption proportion of pollution fuels in some of these provinces also showed a certain upward trend. Specifically, using the energy consumption data of China's transportation sector [38] and the carbon emission coefficients of various fuels [37], we can obtain that the consumption proportions

of high-pollution fuels in the total fuel consumption in the four economically developed provinces (Beijing, Shanghai, Zhejiang and Jiangsu) showed a downward trend, with an annual average decline of 2.22%, 3.09%, 1.57% and 0.65%, respectively. Moreover, their transportation fuel efficiencies showed an upward trend [44]. Meanwhile, the calculation results also indicated the consumption proportion of high-pollution fuels in total fuel consumption in economically underdeveloped provinces showed an upward trend as a whole, with an annual average growth rate of 1.13%. Furthermore, the underdeveloped provinces had a lower energy efficiency than the developed provinces [44]. Therefore, relative to the initial stage, the increase of per capita transportation carbon emissions in underdeveloped provinces was growing faster than developed provinces, which implied the regions with lower transportation carbon emissions
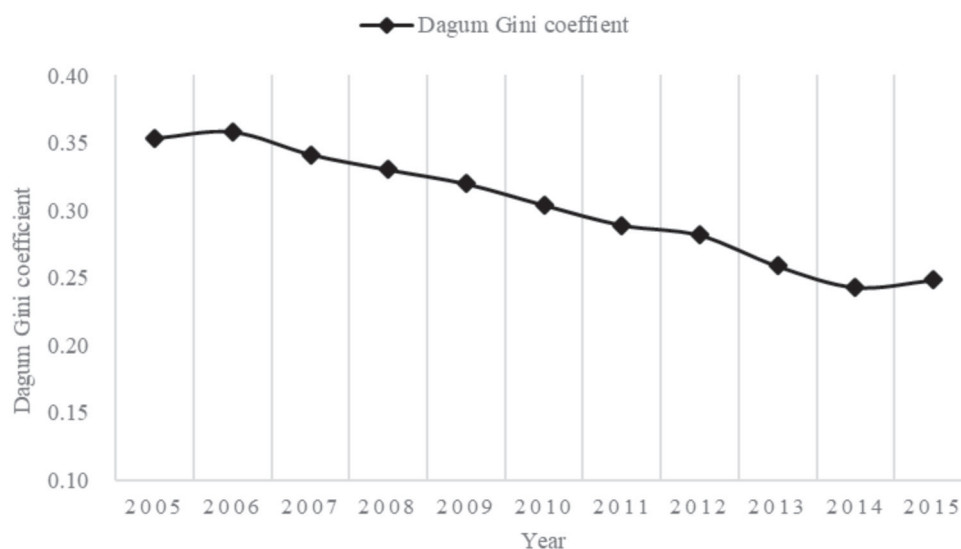

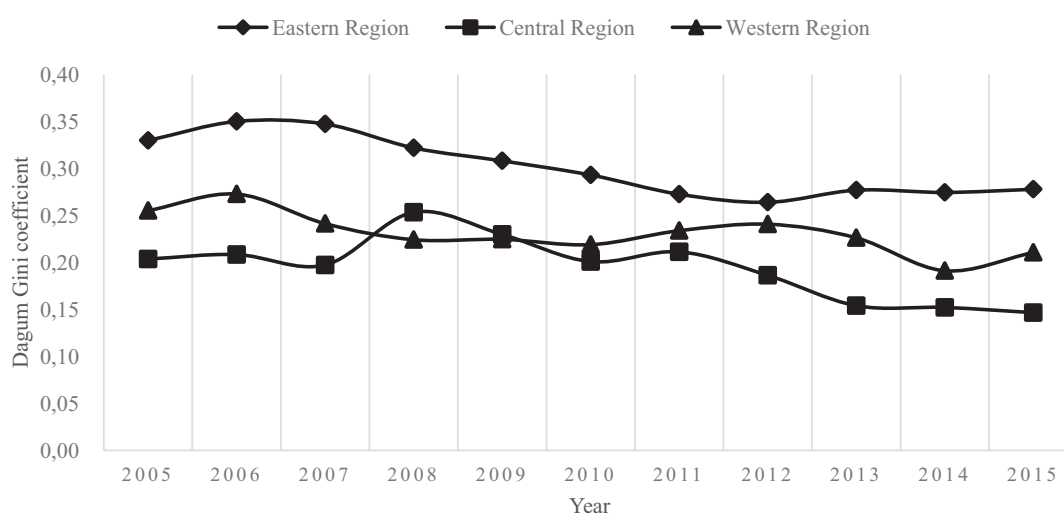Fig. 1. The Dagum Gini coefficient and its evolution trend.

Fig. 2. Evolution of the intraregional Gini coefficients in three regions.

was catching up with the higher. The above reasons eventually led to a narrowing of the overall spatial non-equilibrium among provinces in China.

(2) Intraregional differences and their dynamic evolution.

Fig. 2 depicts the evolution trends of the intraregional Gini coefficients of the per capita transportation carbon emissions. It can be seen that, in general, the difference within the eastern region is the largest, followed by the western and central regions. The reasons are as follows: (i) The eastern developed provinces (Beijing, Guangdong, Shanghai, Zhejiang and Jiangsu) have greater advantages in energy conservation, emission reduction as well as transportation energy structure adjustment. In addition, because of the relatively high population density, their per capita transportation carbon emissions have declined slightly. Meanwhile, with the advancement of urbanization, the eastern undeveloped provinces have an increased demand for transportation. However, subject to policy orientation, technology level, energy structure and other factors, their transportation energy intensity and the growth rate increase. Additionally, their population is also relatively small, resulting in relatively high per capita transportation carbon emissions. Finally, the per capita transportation carbon emissions show a significant polarization within the eastern region. According to the statistics, the annual average energy intensity of transportation in the eastern undeveloped provinces was 0.18% during 2005-2015, which was 3.6 times that of the eastern developed provinces [40]; (ii) some western provinces are rich in mineral resources and have a large resource transportation and cargo turnover, while the relatively harsh environment leads to a sparse population. So, they have relatively high per capita transportation carbon emissions. Moreover, some other provinces lack of natural resources and the terrain conditions are extremely complicated, resulting
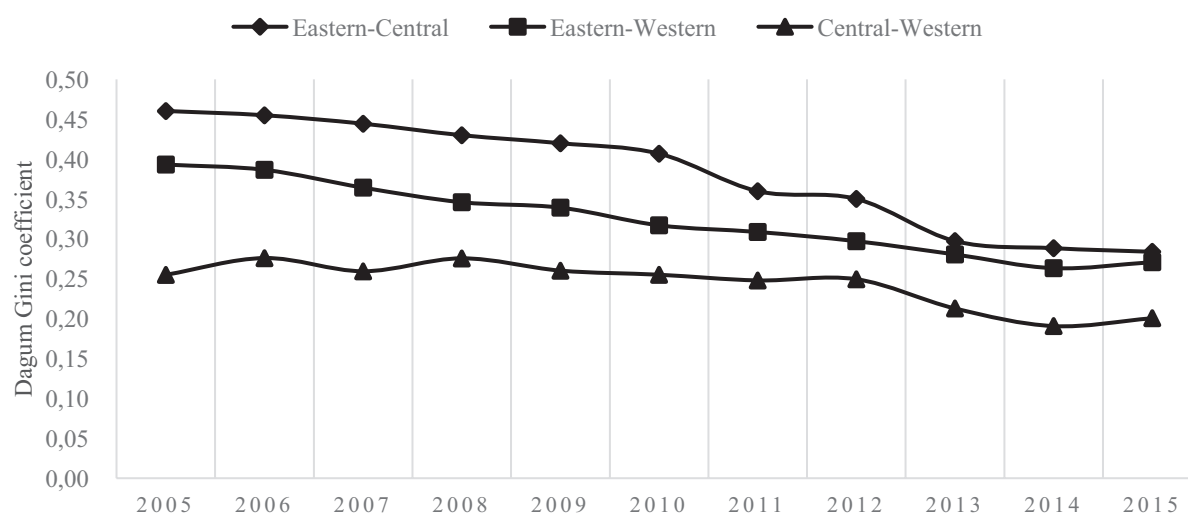

Fig. 3. Evolution of the interregional Gini coefficients.

in that their population growth and cargo transportation are restricted. Therefore, there is a certain difference in the per capita transportation carbon emissions within the western region; (iii) the differences in the natural resource endowments, transportation demand and technology level are relatively small between the central provinces, resulting in that the difference in the per capita transportation carbon emissions within the central region are not as prominent as those within the eastern and western regions. For instance, according to statistics, the difference rate of the extreme values of per capita R&D expenditures in the central region was only 2.40 from 2005 to 2015, which was 1/18 and 1/8 of that in the eastern and western regions, respectively [40]. On the other hand, from the evolution trend, the intraregional differences in the three regions show a downward trend as a whole, which is consistent with the trend of the overall spatial non-equilibrium among provinces. Taking 2005 as the base year, in 2015, the average annual decline rates of the differences within the eastern, central and western regions were 1.6990%, 3.2372% and 1.8994%, respectively.

(3) Interregional differences and evolution trends.

Fig. 3 depicts the differences in the per capita transportation carbon emissions between the three regions and their evolution trends. It can be seen that the three interregional differences were stratified clearly during the sample period. Specifically, the difference between the eastern and central regions was the largest, with an average Dagum Gini coefficient of 0.3814; the difference between the eastern and western regions was the second, with an average Dagum Gini coefficient of 0.3243; the difference between the central and western regions was the smallest, with an average Dagum Gini coefficient of 0.2438. The eastern region enjoys a superior geographical position and a high level of economic development with more frequent foreign trade activities and a large volume of passengers and freight. Its average annual road freight turnover during

2005-2015 reached 1582.779 billion ton-kilometers, accounting for 40.65% of the national average annual road freight turnover [40], thus resulting in higher per capita transportation carbon emissions in the eastern region. The western region is rich in resources, leading to a large freight volume. However, the freight volume is not as large as the eastern region, so that its per capita transportation carbon emissions are lower than those in the eastern region. The central region is an important passenger and cargo distribution center in China with a large inter-provincial transportation volume. However, most of provinces in this region have a large population. Meanwhile, energy-saving and emission-reduction technologies are also widely used, resulting in lowest per capita transportation carbon emissions. The above is clearly shown in Table 3. Therefore, the difference between the eastern and central regions is the largest, followed by the difference between the eastern and western regions, finally the difference between the central and western regions. Additionally, the differences between the three regions have gradually narrowed down, with annual declines of 4.7180%, 3.6602%, and 2.3651%, respectively.

Sources of the Spatial Non-Equilibrium and their Contribution Rates

Next, the overall spatial non-equilibrium of China's per capita transportation carbon emissions is decomposed into the intra-regional difference, the inter-regional difference and the intensity of transvariation. The percentage of their growth rates to the overall difference growth rate in each year is their respective contribution rate. Fig. 4 depicts the evolution trends of the contribution rates. It can be seen that the contribution rate of the inter-regional difference showed a downward trend during 2005-2015. Moreover, the contribution rate of the intra-regional difference remained basically
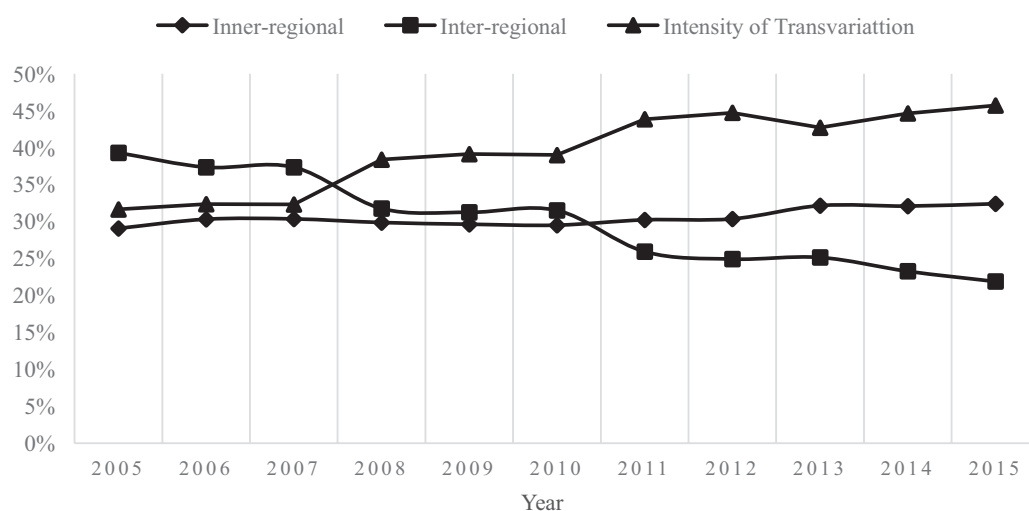

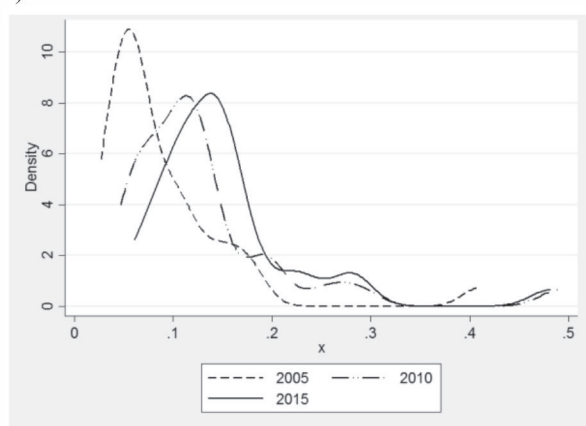Fig. 4. Contribution rates of various sources.

stable, while the contribution rate of the intensity of transvariation showed an overall upward trend, which has become the major contributor to the overall spatial non-equilibrium. This finding is also partly supported by Li and Jiang [45]. With the acceleration of urbanization in the undeveloped provinces in the central and western regions, the demands for transportation are gradually increasing, resulting in an increased energy consumption. Meanwhile, the underdeveloped provinces have a relatively backward technological level. In addition, the government prefers economic development rather than environmental protection, so their transportation carbon emissions have increased and failed to attract enough attention. While the eastern region has strong environmental improvement needs, thus gradually implementing energy-saving and emission-reduction technologies as well as environmental regulation policies. Its transportation carbon emissions are controlled to a certain extent [24]. Hence, the inter-regional difference is generally reduced. Due to the small change of differences in the urbanization process, population size, environmental regulation policies, etc. between the provinces within the three regions, the contribution rate of the intra-regional difference has remained basically stable.

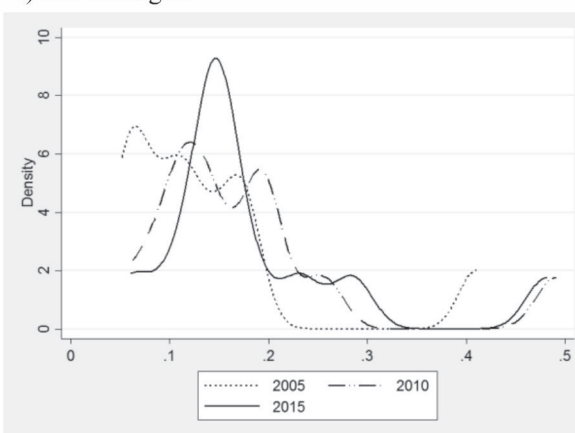## Dynamic Evolution of per Capita Transportation Carbon Emission

In order to more intuitively reflect the overall state and the dynamic evolution of China's per capita transportation carbon emissions, Gaussian Kernel density function is used from a dynamic perspective, and 2005, 2010 and 2015 are selected as the sample observation years. Fig. 5 depicts Kernel density curves of the per capita transportation carbon emissions at the national and regional levels. It can be seen that there are significant differences in Kernel density curves at the national and regional levels:

(1) Kernel density curves at the national level, and in the central and western regions showed a trend of moving to the right as a whole. The peak value showed a downward trend and the span became larger, indicating that the per capita transportation carbon emissions at the national level and in the central and western regions have shown a growth trend on the whole; the proportion of provinces with low transportation carbon emissions was decreasing; on the contrary, the proportion of provinces with high transportation carbon emissions was increasing. Meanwhile, the shapes of Kernel density curves at the national level, and in the central
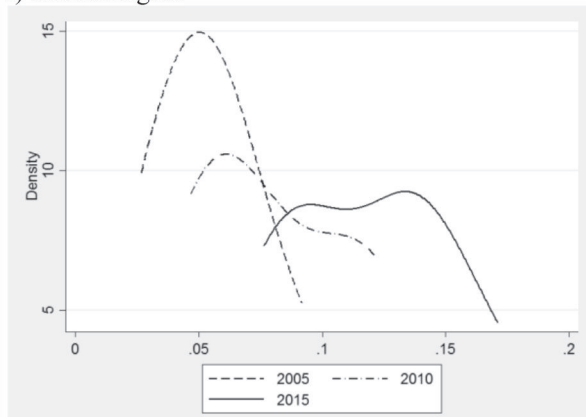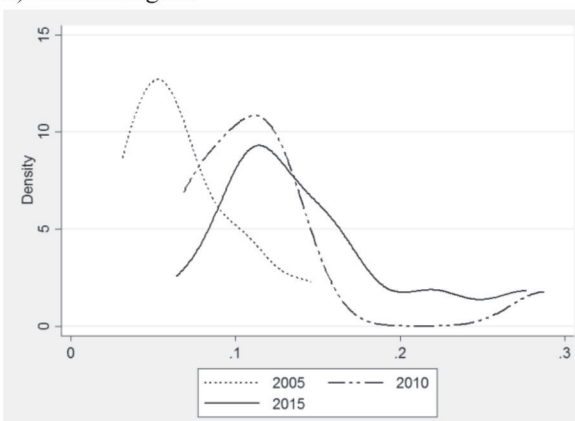

Fig. 5. Kernel density curves. a) National level, b) Eastern region, c) Central region, d) Western region.

region changed from a sharp peak to a broad peak, and the bimodal curves were more and more prominent, indicating that the per capita transportation carbon emissions at the national level and in the central region diverged obviously. There were different levels of club convergence, and the cluster shifted from a low level to a higher level. The right tail portion of Kernel density curve in the western region also moved to the right, with a tendency to cluster at a higher carbon emissions level, which is consistent with the carbon emission changing pattern that the low carbon concentration areas in western region were narrowing from 2005 to 2015 [41].

(2) Kernel density curve trend of the per capita transportation carbon emissions in the eastern region was different from the national level as well as the central and western regions. It shifted to the left on the whole, indicating that the per capita transportation carbon emissions were generally declining. The curve evolved from a broad peak to a sharp peak, and changed from a multimodal to a single peak, indicating that there was a convergence feature in the region. Meanwhile, the right tail part changed to the upper right side, indicating that the per capita transportation carbon emissions of some eastern provinces would be concentrated at a higher carbon emissions level.

Comparing Kernel density curves of the per capita transportation carbon emissions at the national level, and in the eastern, central and western regions, it can be found that the area of Kernel density curve distributed at a high level in the eastern region is successively larger than that at the national level, and in the western and central regions. At the same time, the tailing distribution of Kernel density curves at the national level, and in the eastern region was obvious followed by the western region. Kernel density curve in the central region did not have this characteristic, indicating that the central provinces didn't obviously cluster in high-carbon club. In general, these results not only indicate the concentration trend of the per capita transportation carbon emissions which is coincident to the analysis in Bai et al. [15], but also reveal the concentration law in different areas using the dynamic distribution of Kernel density curve.

The Solidification Effect of the Spatial Non-Equilibrium

Kernel density estimation cannot reflect the solidification effect of the spatial non-equilibrium of China's per capita transportation carbon emissions. Therefore, following the Markov chains approach proposed by Quah [31], this study classifies the per capita transportation carbon emissions of all provinces into four types to explore the transition probabilities of different types in detail and judges the solidification effect of the spatial non-equilibrium. Specifically, the provinces with the per capita transportation carbon emissions below 50% of the national average are type

I, called low level with an interval of (0, 0.0639]; the provinces with the per capita transportation carbon emissions between 50% and 100% of the national average are type II, called medium-low level with an interval of (0.0639, 0.1277]; the provinces with the per capita transportation carbon emissions between 100% and 150% of the national average are type III, called medium level with an interval of (0.1277, 0.1916]; the provinces with the per capita transportation carbon emissions above 150% of the national average are type IV, called high level with an interval of (0.1916, ∞). Then the Markov chains approach is used to further explore the solidification effect of the spatial non-equilibrium.

Table 5 shows the maximum likelihood estimates of Markov chains transition probabilities of China's per capita transportation carbon emissions. It can be seen that the transition probabilities on the main diagonal of the transition probability matrix was much higher than those on the non-main diagonal. This indicated that the mobility between various types was relatively low, and these types were relatively stable. In a sense, the solidification effect of the same types was significant especially in the types with higher per capita transportation carbon emission, which mean provinces with higher per capita transportation carbon emissions always maintain higher levels and drop in a high-carbon trap. At the same time, the different types often transferred in the adjacent interval, and the probability of transferring across the interval was small. This indicates that the state transition of transportation carbon emissions was a gradual process, and the possibility of dramatically transition was small. In other words, there was a certain degree of solidification between adjacent types, which is also consistent with the findings of Zhou et al. [46]. To be specific, for the low level type at the initial stage, 72.41% of the provinces remained unchanged at the end of the year, while 27.59% transferred to the medium-low level; for the medium-low level type at the initial stage, 85.29% of the provinces remained unchanged at the end of the year, while 2.21% fell to the low level and 12.50% rose to the medium level; for the medium level type, 84.06% of the provinces remained unchanged at the end of the year, while 7.25% fell to the medium-low level, and 8.70% rose to the high level; for the high level type, 94.59% of the provinces remained unchanged at the end of the year, while 5.41% fell to the medium level. In general, the provinces with medium and high levels were in a more stable status than the provinces with a low level, which implied the solidification effect with medium and high levels was stronger than low levels. Moreover, the provinces at the low and medium-low levels more likely transferred to the medium and high levels. This meant that the provinces with lower per capita transportation carbon emissions at the initial stage more likely grew into such provinces with medium- and high-carbon emissions, while the provinces with medium- and high-carbon emissions were unlikely to

significantly reduce their carbon emissions, resulting in a narrowing of the spatial non-equilibrium in per capita transportation carbon emissions between provinces in China. Meanwhile, China's provincial carbon emission transfer has spatial clustering characteristics [47]. The provinces at the high carbon cluster have environmental dumping and transfer effects on adjacent areas. The saturation of their traffic and environmental carrying capacity will squeeze out some of the transportation needs, which will have a negative external impact on the transportation carbon emissions in the surrounding provinces that undertake their carbon emission transfer [48]. It may form a "high carbon emissions trap" that will eventually limit China's transportation sector to achieve carbon emission reduction.

Additionally, the classification of types and intervals in Markov chains approach is somewhat random, and the changes of the two may affect Markov chains transition probability matrix, thus have an influence on the conclusion of the study to a certain degree. As a result, the robustness of the above Markov chains analysis results is tested by repeatedly changing the number of types and the interval range in this paper. (i) First, do not change the number of types. Still classify the per capita transportation carbon emissions of all provinces into four types, but change the interval range. Specifically, the provinces with the per capita transportation carbon emissions below 50% of the national average are type I, called low level with an interval of (0, 0.0639]; the provinces with the per capita transportation carbon emissions between 50% and 125% of the national average are type II, called medium-low level with an interval of (0.0639, 0.1596]; the provinces with the per capita transportation carbon emissions between 125% and 175% of the national average are type III, called medium level with an interval of (0.1596, 0.2235]; the provinces with the per capita transportation carbon emissions above 175% of the national average are type IV, called high level with an interval of (0.2235, ∞). On this basis, recalculate Markov chains transition probability matrix. The results are shown in Table 6. (ii) Change the number of types. Classify the per capita transportation carbon emissions of all provinces into three and five types, respectively, and also change the interval range. Specifically, when classifying them into three types, the provinces with the per capita transportation carbon emissions below 75% of the national average are type I, called low level with an interval of (0, 0.0958]; the provinces with the per capita transportation carbon emissions between 75% and 150% of the national average are type II, called medium level with an interval of (0.0958, 0.1916]; the provinces with the per capita transportation carbon emissions above 150% of the national average are type III, called high level with an interval of (0.1916, ∞); when classifying them into five types, the provinces with the per capita transportation carbon emissions below 50% of the national average are type I, called low level with an interval of (0, 0.0639]; the provinces

with the per capita transportation carbon emissions between 50% and 100% of the national average are type II, called medium-low level with an interval of (0.0639, 0.1277]; the provinces with the per capita transportation carbon emissions between 100% and 150% of the national average are type III, called medium level with an interval of (0.1277, 0.1916]; the provinces with the per capita transportation carbon emissions between 150% and 200% of the national average are type IV, called medium-high level with an interval of (0.1916, 0.2554]; the provinces with the per capita transportation carbon emissions above 200% of the national average are type V, called high level with an interval of (0.2554, ∞). Based on the above classification of three and five types, respectively recalculate Markov chains transition probability matrices. The results are shown in Table 7 and Table 8, respectively. It can be seen from the Tables 6-8 that after changing the number of types and the interval range, the recalculated Markov chains transition probability matrices are highly consistent with the previous research conclusions. In other words, (i) the transition probabilities on the main diagonal

Table 5. Markov chains transition probability matrix.

$t/t+1$	Sample observations	Type I	Type II	Type III	Type IV
Type I	58	0.7241	0.2759	0.0000	0.0000
Type II	136	0.0221	0.8529	0.1250	0.0000
Type III	69	0.0000	0.0725	0.8406	0.0870
Type IV	37	0.0000	0.0000	0.0541	0.9459

Table 6. Markov chains transition probability matrix based on four types of classification.

$t/t+1$	Sample observations	Type I	Type II	Type III	Type IV
Type I	58	0.7241	0.2759	0.0000	0.0000
Type II	184	0.0163	0.9457	0.0380	0.0000
Type III	33	0.0000	0.0606	0.8485	0.0909
Type IV	25	0.0000	0.0000	0.0000	1.0000

Table 7. Markov chains transition probability matrix based on three types of classification.

$t/t+1$	Sample observations	Type I	Type II	Type III
Type I	122	0.8607	0.1393	0.0000
Type II	141	0.0142	0.9433	0.0426
Type III	37	0.0000	0.0541	0.9459

Table 8. Markov chains transition probability matrix based on five types of classification.

$t/t+1$	Sample observations	Type I	Type II	Type III	Type IV	Type V
Type I	58	0.7241	0.2759	0.0000	0.0000	0.0000
Type II	136	0.0221	0.8529	0.1250	0.0000	0.0000
Type III	69	0.0000	0.0725	0.8406	0.0870	0.0000
Type IV	17	0.0000	0.0000	0.1176	0.7647	0.1176
Type V	20	0.0000	0.0000	0.0000	0.0000	1.0000

are much higher than those on the non-main diagonal, which means the amount of per capita transportation carbon emissions has a higher solidification degree in a certain province, and always maintains a same level for a long time; (ii) the solidification effect shows obvious difference for different types. The provinces with per capita transportation carbon emissions at the medium to high levels have a stronger solidification effect and a more stable state than the low-level provinces, which is reflected in that the transition probabilities of types III, IV, and V on the main diagonal are higher than that of type I; (iii) the provinces with per capita transportation carbon emissions at low and medium-low levels have a higher probability of transferring to the medium and high levels. The above results indicate that in the analysis of Markov chains, the change of the number of types and the interval range does not affect the conclusion of this paper, that is, the research results of Markov chains are highly robust.

Conclusions and Policy Implications

In this paper, the Dagum Gini coefficient and Kernel density estimation are used to analyze the spatial non-equilibrium of China's per capita transportation carbon emissions, which includes its sources and dynamic evolution over the 2005-2015 period. Most importantly, Markov chains approach is applied to investigates the solidification effect of the spatial non-equilibrium for the first time. The main results are as follows:

(1) According to the obtained Dagum Gini coefficients, the overall difference, intra-regional difference and inter-regional difference of China's per capita transportation carbon emissions showed a significant downward trend during the sample period, and the intensity of transvariation gradually became the main source of the spatial non-equilibrium.

(2) Kernel density estimation indicated that the per capita transportation carbon emissions in the whole China as well as the eastern, central and western regions have shown an overall growth trend. The per capita transportation carbon emissions at the national level obviously diverged on the whole; the eastern region had a tendency to cluster from low to high levels; the central region had a more obvious divergence characteristic; the western region generally clustered at a high level.

(3) Markov chains analysis showed that the state mobility of China's per capita transportation carbon emissions was low, which indicated the solidification effect among various types was relatively strong. Meanwhile, the provinces at the low and medium-low levels more likely transferred to the medium and high levels.

Based on the above conclusions, we propose the following policy recommendations:

According to the growth trend of the per capita transportation carbon emissions in the central and western regions, undeveloped provinces should pay more attention to the transportation carbon emissions and handle the relationship between the economic development and the ecological environment. They should reconstruct the transportation structure in the process of rapid urbanization and increase the investment in science and technology for traffic innovations. Meanwhile, the use of clean energies and energy-saving technologies also should be promoted to reduce the energy intensity and improve the energy efficiency [49-50], thus guiding the sustainable development of transportation sector.

Moreover, differentiated transportation carbon emission reduction policies should be formulated according to the initial carbon emission level, the economic development stage, as well as the scientific and technological innovation ability in the eastern, central and western regions. The eastern region with a high initial level should shoulder more responsibility for transportation carbon emission reduction. To be more specific, it should accelerate the transformation of economic structure with its first-mover advantage, strengthen regional environmental governance, use big data to monitor the transportation carbon emissions in real time and optimize transportation patterns. Meanwhile, it also should increase the investment in environmental protection technology, talents and R&D, promote the development of low-carbon transportation industry, form propagable experience and technologies and strive to reduce the growth rate of transportation carbon emissions. Considering that the provinces with a low initial level of transportation carbon emissions more likely grows into medium- and high-carbon provinces,

the central and western regions must curb the trend of increased carbon emissions. They should rationally plan the urban structure while vigorously developing the economy, gradually improve the transportation structure and the carrying capacity of the existing transportation system. Moreover, the provinces with a large population can moderately control the number of private cars. They can selectively learn from the experience and technologies of the eastern region. In order to harmoniously reduce the transportation carbon emissions, the eastern region should provide technology and talent support to form a regional experience sharing and joint mutual assistance mechanism.

Additionally, Markov chains analysis show that the solidification effect is relatively strong which can be equivalent to a small probability of transferring across the carbon emission types. Therefore, according to the characteristics of transportation carbon emissions in different provinces, the matching policies should be selected to implement more strict carbon reduction measures in such provinces with a low carbon level transferring to the medium carbon level. Meanwhile, the solidification effect of high-carbon provinces should be paid more attention, so as to reduce their impacts on neighboring provinces, and prevent the high-carbon cluster from expanding in the geospatial space.

Acknowledgements

Conflicts of Interest

The authors declare no conflict of interest.

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