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Understanding the Driving Patterns of the Carbon Emissions in Transport Sector in China: A Panel Data Analysis and Zoning Effect

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Abstract: China's transportation industry has made rapid progress, which has led to a mass of carbon emissions. However, it is still unclear how the carbon emission from transport sector is punctuated by shifts in underlying drivers. This paper aims to examine the process of China's carbon emissions from transport sector as well as its major driving forces during the period of 2000 to 2015 at the provincial level. We firstly estimate the carbon emissions from transport sector at the provincial level based on the fuel and electricity consumption using a top-down method. We find that the carbon emission per capita is steadily increasing across the nation, especially in the provinces of Chongqing and Inner Mongolia. However, the carbon emission intensity is decreasing in most provinces of China, except in Yunnan, Qinghai, Chongqing, Zhejiang, Heilongjiang, Jilin, Inner Mongolia, Henan and Anhui. We then quantify the effect of socio-economic factors and their regional variations on the carbon emissions using panel data model. The results show that the development of secondary industry is the most significant variable in both the entire nation level and the regional level, while the effects of the other variables vary across regions. Among these factors, population density is the main motivator of the increasing carbon emissions per capita from transport sector for both the whole nation and the western region, whereas the consumption level per capita of residents and the development of tertiary industry are the primary drivers of per capita carbon emissions for the eastern and central region.

Keywords: Transportation, Carbon emission, Carbon intensity, Panel data analysis, China

1. Introduction

Transportation is essential to national economic development, because it provides carriers for product circulation. With prosperous economic development, the transportation industry has developed rapidly, with vast quantities of fossil fuel consumption and increasing negative influence on the environment. Transportation has become the second highest carbon emission industry and attributed approximately 23% of total carbon emission in 2013 in the world; these proportions will increase continuously due to higher levels of energy consumption and be projected to reach to 3206 million tons of standard oil equivalents in 2035 [1]. In rapidly developing China, transport sector has undergone dramatic development. For example, according to China's National Bureau of Statistics, China's freight turnover and passenger turnover increased by average annual rate of 19.7% and 6.8% over the past 16 years, respectively. The energy consumption and carbon emissions grew with the boom of transportation. The average annual growth of energy consumption in transport sector is 14.67%, which is more than the total energy consumption growth rate, 12.03%. Furthermore, the transport carbon emissions increased from 174.7 million metric tons in 2000 to 754.3 million metric tons in 2015. Based on the forecast of the International Energy Agency and the study of Auffhammer and Carson [2], China's transport sector will accounts for more than one-third of the world's transport carbon emissions in 2035.

China has been a pioneer on the path of reducing carbon emissions since the government announced that China will sharply reduce its carbon emissions before 2020 in the Intended Nationally Determined Contributions in 2015. China's government is turning this commitment into effective action. They presented plans which required that, compared to 2005, carbon intensity must decrease by 40%~45% in 2020 and 60%~65% in 2030 by effectively controlling industrial carbon emissions. As a matter of fact, decreasing the carbon emissions from transport sector is the requirement of China's sustainable development strategies, and it will accelerate the sustainable development of transport worldwide. In the literatures, it is commonly acknowledged that the carbon emissions from transport are likely to grow with socio-economic development. Wang and Liu [3] examines the features and driving factors of carbon emission from commuter traffic in Beijing from 2000 to 2012, and find the per capita disposable income, vehicle-use intensity, population and transport capacity effects are the main drivers that increase carbon emissions. Loo and Li [4] trace the historical evolution and spatial disparity of carbon emissions from passenger transport in China from 1949 to 2009, and the result shows that the income growth is the principal factor leading to the growth of passenger transport carbon emissions and the main factor contributed to carbon emission reduction is the lower emission intensity supported by policies, although the effect is weak. The impact of freight transportation on carbon emissions has also attracted attention. By exploring the impacts of factors on the carbon emissions from road freight transportation in China from 1985 to 2007, Li *et al* [5] found that the economic development is the primary driving factor of carbon emissions, whereas the ton-kilometer per value added of industry and the market concentration level contribute significantly to reduce carbon emissions. Effects of fossil fuel share, fossil fuel intensity, and road freight transport intensity are all found responsible for carbon emissions [6]. Researchers have examined the dynamic changes in total factor carbon emissions performance of China's transport sector [7], and used the co-integration method to examine the long-run relationship between carbon emissions and affecting factors, including urbanization rate, energy intensity, carbon emission intensity and economic activity in transport sector [8]. Understanding the main driving forces of carbon emissions of transportation is important since that the transportation is a major source of carbon emissions in China [9]. However, konwledges on the driving forces of carbon emissions in China's transport sector are insufficient for different regions. Particularly, due to China's imbalanced development, different regions are facing different challenges, which may lead to different carbon emissions patterns [10]. Therefore, it's necessary to conduct a study of driving factor at the region level so that some control policies considering local realities can be provided for policymakers.

This research distinguishes itself from previous studies in the following four aspects. First, although some studies used time-series data to examine the factors of carbon emissions from transport sector in China [8], the data used are stale, and many data for the 20th century are missing. Second, the previous studies [7] did not divide China into different regions when analyzing the carbon emissions from transport sector, which may result in bias in the driving patterns of the carbon emissions. The reason is that China has a wide geographical area, a large population, and a complex economy, with significant differences between regions. It may lead to a bias conclusion if we don't take the regional inequality into account. [11]. Third, many studies ignored the carbon emissions from transport sector generated by using electricity and instead considered it to be clean energy, but we must recognize that most electricity in China is produced by thermal power plants, which also emit carbon dioxide [12]. Fourth, the energy carbon emission intensity used in previous articles refers to the amount of CO_2 produced by complete combustion of a unit of fuel, which reflects energy efficiency. It is influenced by many factors and has gradually increased with the progress of automobile manufacturing technology. Therefore, the use of a fix value to calculate the carbon emission intensity of energy may lead to inaccurate results. To overcome these deficiencies, this study first calculates China's provincial transport carbon emissions generated by fossil fuel and the electricity consumed by the transport industry over the past fifteen years and then examines the main driving forces of the carbon emissions, as represented by transport carbon emissions per capita (*PCT*) and carbon emission intensity (*CI*) using panel data models. Moreover, the zoning effects of the driving pattern are explored by dividing the whole nation into the western (Ningxia, Chongqing, Guizhou, Shaanxi, Qinghai, Sichuan, Xinjiang, Gansu, Guangxi and Yunnan), central (Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan) and eastern (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan) regions to process the model.

Figure 1. Zoning of China's mainland

2. Methodology

2.1. Estimation of carbon emissions from transport sector

Accurately measuring carbon emissions is the basis for analyzing the characteristics of the carbon emission from transport sector. For a mobile emissions source, there are two main approaches to calculating the carbon emissions. One is "bottom-up" method, which is an agent-based model calculating carbon emissions based mainly on the vehicle kilometers traveled, and it is widely used in the road transport sector [13, 14]. Although the method based on vehicle kilometers traveled can distinguish carbon emissions sources from different motor types and help clarify the underlying reason for carbon emissions, it also shows considerable uncertainty, especially in road transportation, because vehicle types, vehicle mileage, fuel types and road conditions will affect fuel consumption in different ways. The other one is a top-down method that measures the carbon emissions according to the consumed fuel. It has a distinct advantage in calculating the carbon emissions from China's transport sector [15]. Because the production and supply of fuel in China are a state monopoly, the official data can be collected completely and conveniently. In conclusion, we use top-down method, which is a unified standard method published by the Intergovernmental Panel on Climate Change (I*PCC*) Guidelines [16-18], to estimate the carbon emissions from China's transport sector. This method involves three parameters: energy type, amount of energy consumed and carbon emissions factor. The average low-order calorific value, average carbon content on an energy basis and carbon oxidation rates are multiplied to obtain the carbon emission factors of fossil fuel. The formula for calculating the carbon emissions from fossil fuel is as follows:

$$CF = \sum_{i=1}^{9} CF_i = \sum_{i=1}^{9} FC_i \times F_i = \sum_{i=1}^{9} FC_i \times ALC_i \times C_i \times R_i \times \frac{44}{12} \qquad (1)$$

where *CF* (kg CO_2) denotes the carbon emissions from fossil energy consumption; i denotes the different types of fossil fuel (including coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied gas and natural gas); *FC* (kg) represents the consumption; and *F* (kg CO_2/kg) is the carbon emissions coefficient; *ALC* (KJ/kg) is the average low-order calorific value; *C* (t/TJ) is the carbon content; and *R* is the carbon oxidation rates.

Carbon emission from electricity is calculated using:

$$CE = EC \times EF \tag{2}$$

where CE (kg CO_2) represents the carbon emissions from electricity consumption; EC (kg) represents the consumption of electricity; and EF (kg CO_2/kg)is the carbon emissions factors of electricity.

The total carbon emission from transport sector is calculated as follows:

$$CT = CF + CE \tag{3}$$

where CT (kg) represents the total carbon emissions from transport sector in a province.

2.2 Panel data analysis

As an analysis method, the Kaya identical equation [19] is widely applied to investigate the factors that influence carbon emissions from transport sector by explaining the varying quality of carbon emissions. It is usually combined with decomposition methods, such as the logarithmic mean Divisia index (LMDI) methods [10] and the Fisher index method [20], to investigate the influencing factors. However, the Kaya identical equation is not suitable for explaining the existing quantity of emissions and instead ignores the historical factors. The Stochastic Impacts by Regression on Population Affluence and Technology (STIRPAT) model [21], an extension of the Impacts by Regression on Population Affluence and Technology (IPAT) model [22], is also a popular model for analyzing transport carbon emissions [10, 23] because it can adopt any variables influencing environment in the model. There are other methods for investigating the carbon emissions from transport sector, such as the dynamic Vector Auto Regression Model [9] and the Tobit regression model [24]. However, the multicollinearity of variables must be considered before using these regression models. Choosing an appropriate model is important because this choice can affect the interpretation of results. Panel data analysis is a method of investigating a regression relation in the spatial and temporal dimensions with many advantages. First, panel data model can reflect the individual heterogeneity in both dimension of space and time, this advantage prevent the biased results caused by time series data or cross-section data analysis. Second, panel data can provide more reliable estimation of parameter because it has more information, a wider range of variability and weaker multicollinearity. Third, panel data is more suitable for researching the process of dynamic regulation for it can associate experience and behavior at different times and locations. Fourth, the unit root test of panel data can solve the problem that nonstandard gradual distribution caused by the unit root test of time series. Researchers in many fields thus favor using panel data model to analyze the carbon emissions [25-27]. This study employs the panel data model to explore the factors that affect carbon emissions related to transport sector. It is difficult to judge the size of a population when choosing the model types of panel data. Hence, there are two perspectives on choosing a model type: one is based on the analytical goal. When the analytical goal is to estimate the parameter and the sample in the model is not very big, the fixed effects model is better. When the error components of the model are to be analyzed, we choose the random effects model to determine whether there is a relationship between some explanatory variables and the individual effect in the model. The other goal is to judge the precondition of the model. The fixed effects model assumes that the heterogeneity term and the independent variables are correlated. In contrast, the random effects model assumes that the heterogeneity term and the independent variables are not correlated. In this study, we choose the latter method. The procedures for setting up the panel data model in this method are as follows: first, conduct unit root tests to validate the stationarity of variables at the provincial level; second, perform cointegration tests to judge whether there is a long-term relationship between the variables; and finally, establish the panel data model.

The panel data models can be divided into three types: pooled, fixed effects and random effects regression models. The model type is confirmed by the F-test and Hausman test. The process of model selection is shown in Figure 2. Under a certain significance level, if $F<F_{0.05}(N-1,NT-N-k)$, then the pooled panel model is employed; otherwise, the Hausman test should be conducted to choose the random effect panel model or the fixed effect panel model. When the probability of the Hausman test is less than 10%, the fixed effects panel model should be selected; otherwise, we should choose the random effects regression model [28]. After confirming the model type, Seemingly Unrelated

Regression method is employed to set up the regression equations, which can eliminate the effect from the cross sections heteroscedasticity and the autocorrelation of time series [29].

The formula of the F-test is:

$$F = \frac{(SSE_r - SSE_u)/(N-1)}{SSE_u/(NT-N-k)} \sim F(N-1, NT-N-k) \quad (4)$$

where SSE_r and SSE_u represent the residual sum of squares of the pooled regression model and fixed effects regression model, respectively; k is the number of public parameters; and N is the constraint conditions. Under a certain significance level, if $F<F_{0.05}(N\text{-}1,NT\text{-}N\text{-}k)$, then it is better to choose the pooled regression model; otherwise, the fixed effects regression model should be chosen.

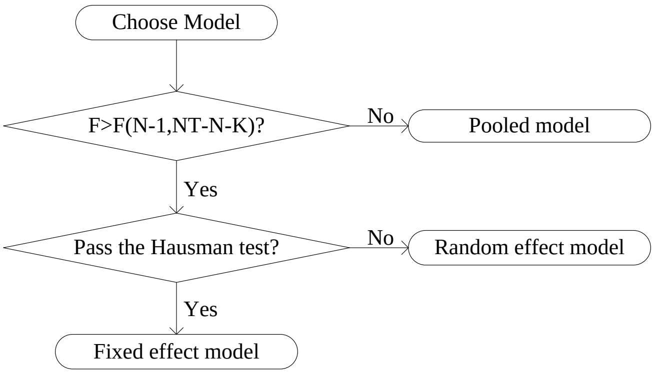

Figure 2. Flowchart of model decision

3. Data and data source

3.1 Data

Table 1 shows the variable of the models. *PCT* is an important index for precisely describing the carbon emissions. In addition, to investigate the energy efficiency of the transportation industry, *CI* is proposed as an index to describe carbon emission intensity. *CI* is an explicit value which means carbon emission in unit output value of transport sector. A smaller *PCT* or *CI* value indicates a greater environmental benefit from unit transportation activity. Thus, the *PCT* and *CI* indices are considered dependent variables for examining the driving patterns. Then, the proportion of secondary and tertiary industries added value to GDP (*SGDP* and *TGDP*), passenger turnover (*PT*), freight turnover (*FT*), road network density (*RD*), population density (*PD*), consumption level of residents per capita (*PCC*), motor vehicle population (*VP*) and energy consumption structure (*ES*) are selected as the explanatory variables in the panel data models. *ES* is the ratio of clean fuel consumption to the total energy consumption, which measures the rationality of energy use in transport sector [30, 31]; electricity, liquefied gas (LPG) and natural gas (CNG) are classified as clean fuels in this study. *CI* and *PCT* are the carbon emissions indexes; *SGDP* and *TGDP* are the industry structure indexes; *PT*, *FT* and *ES* represent the development of transport industry; *RD* and *PD* stand for the road facility and population concentration levels respectively; and *PCC* and *VP* show the social development levels. *PCT* and *CI* are calculated by formulas (5) and (6) respectively.

$$PCT = \frac{CT}{P} \quad (5)$$

$$CI = \frac{CT}{GDPT} \quad (6)$$

where *P* (10,000 people) and *GDPT* (billion RMB) donate the population and the GDP of transport industry in certain province, respectively.

Table 1. Variables

Categories	Variables	Abbreviation	Unit
Carbon emissions index	Carbon emissions from per capita transport sector	*PCT*	Ton/per person

	Carbon emission intensity	*CI*	Ton/ billion RMB
Industry structure	The proportion of secondary industries added value to GDP	*SGDP*	%
	The proportion of tertiary industries added value to GDP	*TGDP*	%
Transport structure	Passenger turnover	*PT*	Times/billion person
	Freight turnover	*FT*	km/ billion ton
	Energy consumption structure	*ES*	%
Road facilities level	Road network density	*RD*	km/m²
Population concentration level	Population density	*PD*	10000 people/km²
Social development level	Per capita consumption level of residents	*PCC*	RMB /person
	Motor vehicle population	*VP*	Million vehicles

3.2 Description of data

For better grasping the geographic distribution features of *CI* and *PCT* in different provinces and regions, all provinces are identified with different colors based on the total change rate in *CI* and *PCT* from 2000 to 2015, with the values of year 2000 as reference. The deeper the color is, the higher the change rate is. The overall trend is that the *CI* decrease with the time since the China's government decision was announced at the UN climate summit, i.e. to decrease *CI* by 2020, expect in some provinces, like Zhejiang, Chongqing, Yunnan, Qinghai, Heilongjiang, Jilin, Inner Mongolia, Henan and Anhui. In addition, we find that most of these provinces are concentrated in central regions (Figure 3). Across China, the *PCT* is steadily increasing due to the high rising transport energy consumption rate and the comparatively low population growth rate, especially in Qinghai, Chongqing, Inner Mongolia, Henan, Anhui and Jilin (Figure 4).

The trends of the explanatory variables of the three regions and the whole nation are shown in Figure 5. The figure indicates that the country shares the same trend in all three regions. From 2000 to 2015, the values of *VP*, *PCC*, *RD* and *PD* increase monotonically, *TGDP* and *FT* increase with fluctuations, and *SGDP* rises and then decreases in 2011. This resulted from the Chinese government implementing an industrial structure adjustment policy since the 1990s, and the intensity of this structure adjustment has increased gradually, especially since 2000, with the environment receiving more attention from the public. *PT* shows the same changed in trend with *SGDP*, and this change is caused by the policy allowing citizens to drive on the highway for free during holidays, as implemented in August 2012. This policy has decreased the number of people who travel by public transport and increased the number of self-driving tourists. *ES* has the opposite trend as *PT*: it decreases first and then increases because of the increasingly widespread use of new-energy automobiles and projects that aim to balance regional energy sources, such as the west-to-east gas transmission project.

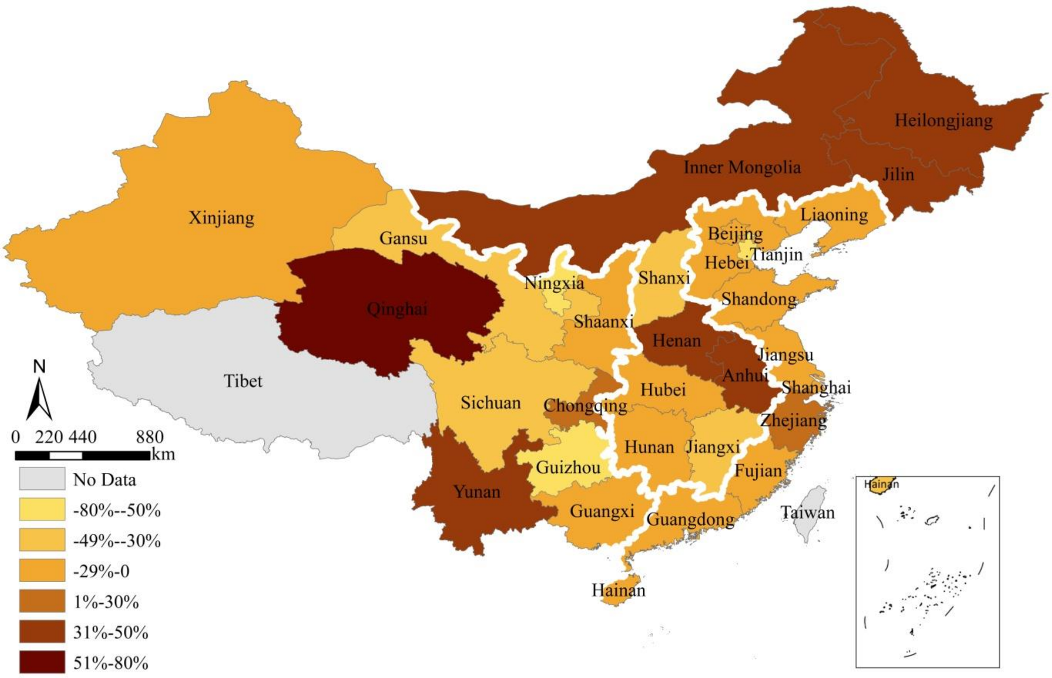

Figure 3. The distribution of the *CI* change rate from 2000 to 2015

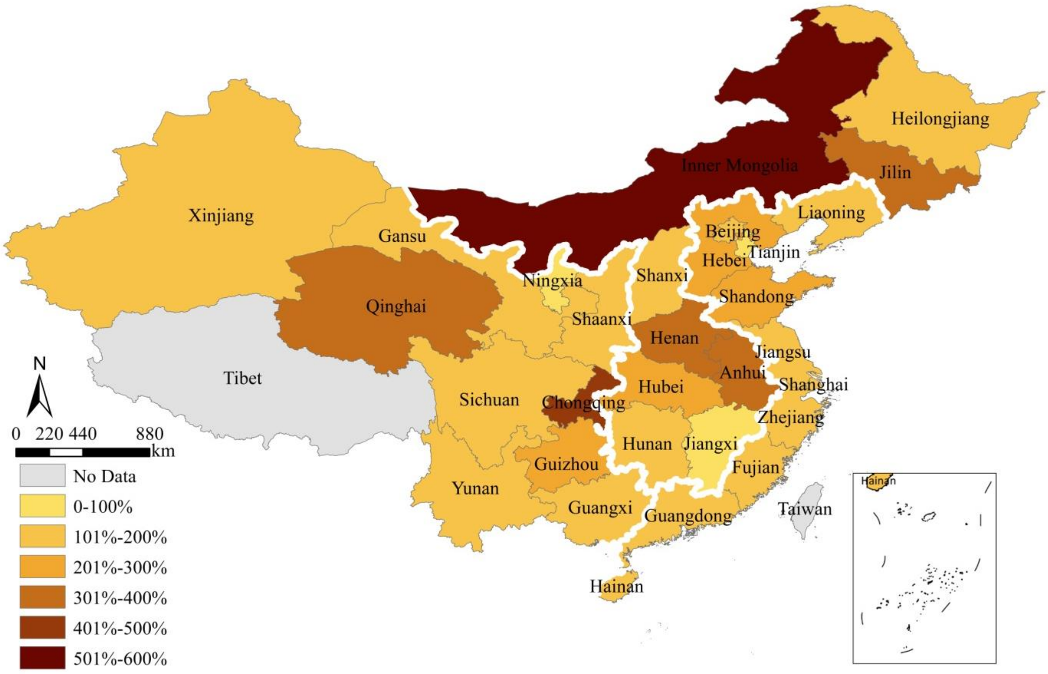

Figure 4. The distribution of the *PCT* change rate from 2000 to 2015

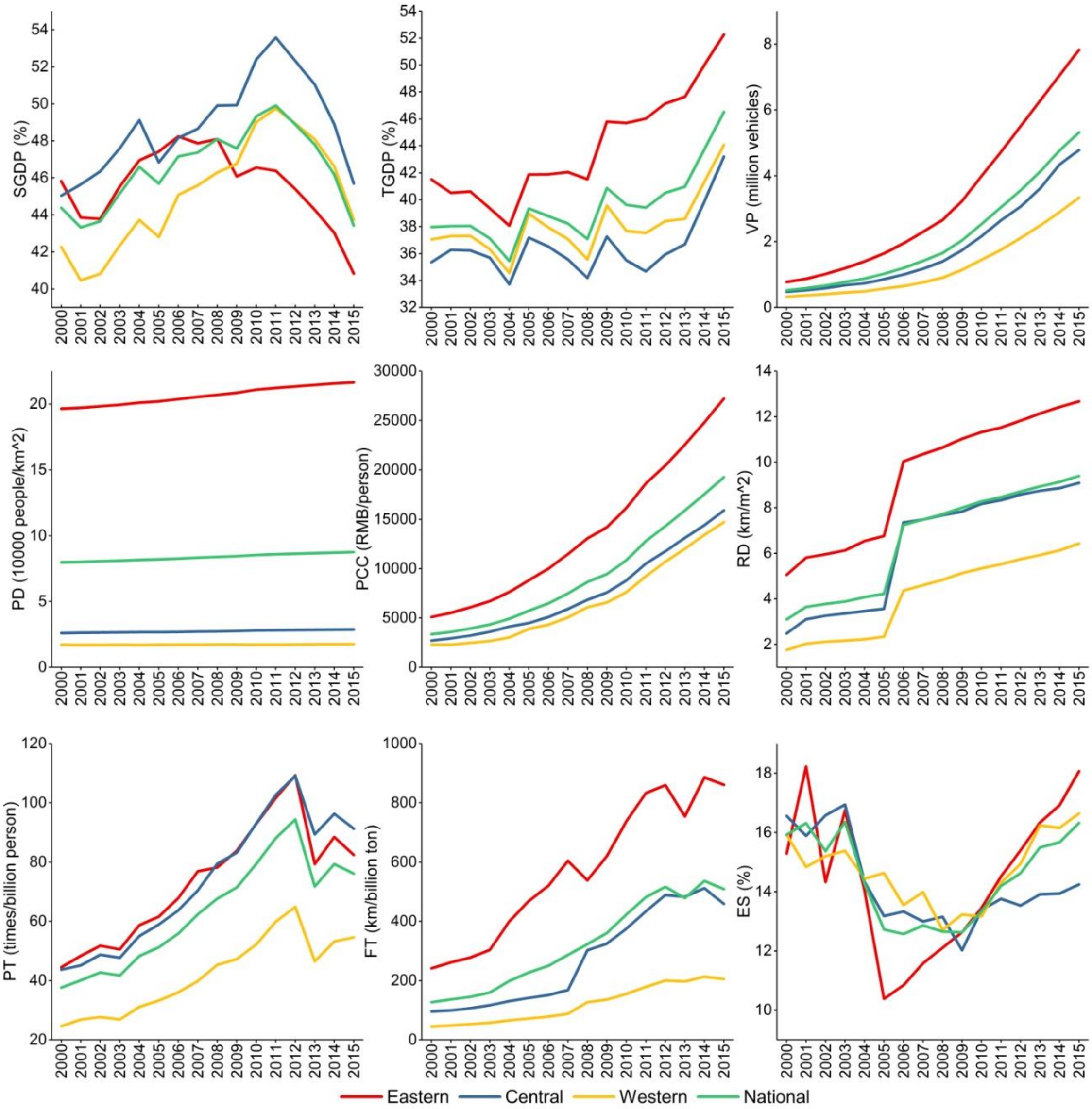

Figure 5. Trends of the explanatory variables

3.3 Data source

The carbon emission factor of electricity production and fuel consumption are affected by fuel quantity and consumption technology level, which is relatively stable in a shorter period of time (i.e., several years). Besides, the annual data of China's electricity production and fuel consumption carbon emissions factor is unavailable. For these reasons, the standard value of carbon emission factor is employed in this research. Thus, the carbon content of fossil fuel, carbon oxidation rates (Table 2) and electricity carbon emission factors (Table 3) are derived from the Guidance for Compiling Provincial Greenhouse Gas Emission Lists (Trial). Fossil fuel consumption data, electricity consumption data and average low-order calorific values are collected from Energy Statistical Yearbook of China. The data of population, GDP of the transport industry and explanatory variables can be accessed from the Statistical Yearbook of China.

Table 2. Parameters used to calculate the carbon emissions of fossil fuels

Fuel	The average low-order calorific value (ALC) KJ/kg	Carbon content (C) t/TJ	Carbon oxidation rates (R)
Coal	20908	26.37	0.94
Coke	28435	29.5	0.93
Crude oil	41816	20.1	0.98
Gasoline	43070	18.9	0.98
Kerosene	43070	19.6	0.98
Diesel	42652	20.2	0.98
Fuel oil	41816	21.1	0.98
Liquefied gas	44200	17.2	0.98
Natural gas	38931	15.9	0.99

Table 3. Carbon emission factors of electricity in different provinces

Province	Carbon emission factors ($kg\ CO_2 / kW \cdot h$)
Beijing, Tianjin, Hebei, Shanxi, Shandong, Inner Mongolia	1.246
Liaoning, Jilin, Heilongjiang,	1.096
Shanghai, Jiangsu, Zhejiang, Anhui, Fujian	0.928
Henan, Hubei, Hunan, Jiangxi, Sichuan, Chongqing	0.801
Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	0.977
Guangdong, Guangxi, Yunnan, Guizhou	0.714
Hainan	0.917

4. Empirical results

4.1 Unit root test

To avoid heteroskedasticity and non-stationarity phenomena, a natural logarithm transformation is conducted for some variables, including *PD*, *PCC*, *RD*, *VP*, *PT* and *FT*, before implementing the panel data analysis. Then, two different models are built. Model 1 depicts the relationship between transport carbon emissions and human activity, so we choose *PCT* as the dependent variable and *PD*, *PCC*, *RD*, *VP* and *TGDP* as independent variables. Model 2 is used to describe the effect on the carbon emissions from transport sector from the development of transport industry. Hence, *CI* is chosen as the dependent variable, and *TGDP*, *SGDP*, *PT*, *FT* and *ES* are chosen as independent variables.

Model 1:

$$\ln PCT_{i,t} = C_0 + \beta_1 \ln PD_{i,t} + \beta_2 \ln PCC_{i,t} + \beta_3 \ln RD_{i,t} + \beta_4 \ln VP_{i,t} + \beta_5 TGDP_{i,t} + \varepsilon_{i,t} \quad (7)$$

Model 2:

$$\ln CI_{i,t} = C_0 + \delta_1 TGDP_{i,t} + \delta_2 SGDP_{i,t} + \delta_3 \ln PT_{i,t} + \delta_4 \ln FT_{i,t} + \delta_5 ES_{i,t} + \varepsilon_{i,t} \quad (8)$$

where i=1,…, N for each province in the panel and t=1,…, 16 refers to the time period from 2000 to 2015. C_0 and $\varepsilon_{i,t}$ denote the constant terms and white noise respectively.

The prerequisite for Pedroni cointegration is that all variables in the models must be integrated of the order one. The IPS unit root test is conducted to confirm this state, and the results are reported in Table 4. The results show that except for the *ES* of the entire nation, all variables accept the null hypothesis of non-stationarity at a less than 10% level of significance at the original series. However, for the first-order differences, all variables are stationary at the 1% significance level. Based on this finding, we conclude that all variables are integrated with first-order differences, other than the *ES* of the entire nation.

Table 4. Results of the IPS unit root test

	Whole nation		Eastern region		Central region		Western region	
	Original series	First order differences	Original series	First order differences	Original series	First order differences	Original series	First order differences
ln(*PCT*)	4.279	-13.328***	1.533	-6.751***	4.232	-7.076***	1.815	-9.282***
ln(*CI*)	1.920	-13.909***	0.939	-8.903***	0.786	-7.458***	0.162	-8.888***
SGDP	-1.044	-7.954***	-0.421	-5.835***	-1.175	-2.657***	-0.242	-5.152***
TGDP	4.583	-11.040***	5.389	-6.213***	1.171	-5.470***	1.162	-7.410***
ln(*PD*)	1.371	-5.333***	-0.831	-3.864***	2.234	-2.222***	1.167	-3.074***
ln(*PCC*)	8.947	-10.001***	4.302	-4.300***	4.882	-5.860***	6.37	-7.249***
ln(*VP*)	7.375	-6.336***	0.688	-3.541***	5.309	-3.336***	6.891	-4.095***
ln(*PT*)	0.327	-12.910***	-0.314	-8.743***	0.215	-6.060***	0.695	-7.452***
ln(*FT*)	2.479	-9.273***	0.701	-5.081***	1.836	-5.610***	1.854	-5.424***
ln(*RD*)	-0.412	-15.085***	-0.102	-8.748***	-0.177	-7.376***	-0.439	-9.955***
ES	-2.709*	-	-0.982	-3.561***	0.192	-4.081***	0.04	-2.796***

[1] The unit root tests of each variable are carried out with individual intercept.
[2] ***, ** and ** denote significance at 1%, 5% and 10%, respectively.

4.2 Pedroni cointegration test

The Pedroni cointegration test is used to estimate the long-run relationship of the independent variables because all variables are stationary for the first-order difference. Table 5 shows the results of the seven test methods; of them, three accept the null hypothesis of no cointegration, and four reject it. In addition, the significance levels are different for these variables. According to the panel ADF-statistics, we further find that the independent variables of Model 1 and Model 2 all reject the null hypothesis of no cointegration at the 1% and 5% significance levels. The results of the Pedroni cointegration test obviously prove that regardless of the regions or models considered, the explanatory variables maintain a long-run relationship with the explained variable during the study period.

4.3 Driving patterns and zoning effects based on panel models

Model 1 and Model 2 are employed to estimate the driving patterns for both the entire nation and the three regions, respectively. The estimated results are given in Table 6 to Table 8. The null hypothesis of the F-test is that all models are based on pooled effects. As shown in Table 6, all of the F-values are higher than the critical value of the F-test at the 5% significance level, thus rejecting the null hypothesis of the pooled effects method. In addition, as indicated in Table 7, which shows the results of Hausman test, all of the P-values are less than the critical value at the 5% and 10% significance level, except for the western region in Model 2. This result indicates that the random effect model should be used for the western region in Model 2 and that the fixed effect model should be employed for the other Models.

Table 8 shows the regression results of Model 1, for which the fixed effect regression model is selected, and the R2 values are all greater than 0.9, which indicates good fitting. Further, it can be observed that the zoning effect of the carbon emissions from transport sector is prominent in China, which indicates that the factors have different effects on the carbon emissions from transport sector in different regions. Among the variables of Model 1, *PD*, *PCC* and *TGDP* have positive effects on *PCT* in all regions, but *VP* exerts a negative effect. In addition, the impacts of *RD* on *PCT* vary from region to region: it plays a driving role in the eastern region, plays a opposite role in the both entire nation and the western region, and has no significant influence in the central region.

Table 5. Results of Pedroni panel cointegration test

		Whole nation	Eastern region	Central region	Western region
Model 1	Within-dimension				
	Panel v-Statistic	-4.312	-0.566	-2.973	-1.724
	Panel rho-Statistic	4.635	2.773	2.931	2.25
	Panel PP-Statistic	-6.820***	-3.740***	-3.954***	-4.464***
	Panel ADF-Statistic	-4.441***	-3.237***	-2.698***	-4.486***
	Between-dimension				
	Group rho-Statistic	6.561	3.852	4.265	3.277
	Group PP-Statistic	-9.341***	-5.526***	-3.746***	-6.829***
	Group ADF-Statistic	-2.422***	-3.027***	-2.140**	-5.200***
Model 2	Within-dimension				
	Panel v-Statistic	-1.586	-1.365	-1.853	-1.622
	Panel rho-Statistic	2.276	2.621	2.003	2.592
	Panel PP-Statistic	-5.020***	-1.427*	-1.789**	-2.741***
	Panel ADF-Statistic	-4.870***	-3.817***	-2.105**	-3.976***
	Between-dimension				
	Group rho-Statistic	4.791	3.696	3.559	3.225
	Group PP-Statistic	-6.723***	-2.075**	-1.925**	-4.457***
	Group ADF-Statistic	-5.246***	-3.600***	-1.935**	-4.080***

[1] There are only four independent variables in Model 2 of the whole nation: *TGDP*, *SGDP*, *PT* and *FT*.

[2] ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 6. F-test result for Model 1 and Model 2

	Model 1	Model 2
Nationwide	$F_{0.05}(29,444)<46.708$	$F_{0.05}(29,445)<425.690$
Eastern	$F_{0.05}(10,160)<43.358$	$F_{0.05}(10,160)<2.973$
Central	$F_{0.05}(8,130)<18.663$	$F_{0.05}(8,130)<32.057$
Western	$F_{0.05}(9,145)<34.506$	$F_{0.05}(9,145)<267.057$

[1] There is only four independent variables in Model 2 of the whole nation: *TGDP*, *SGDP*, *PT* and *FT*.

Table 7. Hausman test result for Model 1 and Model 2

	Model 1		Model 2	
	Chi-Sq statistic	P values	Chi-Sq statistic	P values
Nationwide	89.766	0.000	11.605	0.021
Eastern	32.654	0.000	9.822	0.080
Central	19.929	0.001	18.204	0.003
Western	116.026	0.000	1.934	0.858

[1] There is only four independent variables in Model 2 of the whole nation: *TGDP*, *SGDP*, *PT* and *FT*.

As expected, *PD* exerts a significantly positive influence on *PCT*, especially in the western region, with a coefficient of 5.468. The *PD* has continuously increased over the past sixteen years in China, which has put substantial pressure on both transportation and the *PCT*. The study of Wang *et al* [32] showed that for an increase of one inhabitant, the number of day trips will increase 2.64 person-times. The western region is a vast territory with a sparse population which led to low transport intensity. Thus, the increasing demand of living material transportation and long-distance travel transportation with the expanded population scale will result in higher levels of carbon emissions. Therefore, it is unsurprising that growth in *PD* will lead to a corresponding increase in *PCT*.

PCC is found to have a positive influence on *PCT* in all three regions. Since 2000, with the overall increase of the consumption level in China, there has been an increasing tendency for high-end consumption, which represents choosing a high-energy-consumption trip mode, such as traveling by airplane, as the primary long distance trip mode. In developed regions, such as the eastern region, or in road- or railway-network-sparse regions, such as the western region, airplane travel is a superior choice. This explanation can be confirmed indirectly by data from the Statistical Bulletin for the Development of the civil aviation industry in 2016, which indicate that the handling capacity of airport passengers is highest (551 million people) in the eastern region, followed by the western region (301 million people).

TGDP is also found to contribute a positive effect on *PCT*. A booming tertiary industry leads to more demand on business and tourist transportation, particularly in road and air passenger transport. In terms of energy efficiency, rail and water transport are more efficient than road transport and air transport [4], thereby generating further growth in *PCT*. Furthermore, the central region has intensive road network while also having a less intensive high-speed railway than the eastern region, so travelers prefer road passenger transportation, which has led to higher carbon emissions due to the development of tertiary industry in the central region.

VP shows an inhibitory effect on *PCT*. With the rapid process of urbanization, more polycentric cities have appeared in China [33-35]. Such a smart growth mode with a higher degree of mixed land-use and an intensive road network would significantly shorten the commuting distance [36]. Furthermore, the vehicle oil consumption has been improved as the development of the technology. According to China's standard document named Fuel Consumption Limits for Heavy-duty Commercial Vehicle, the average fuel consumption of heavy-duty commercial vehicle produce in 2020 should decrease 15% than the same kind vehicle produced in 2015. As a result, an increasing *VP* contributes to some inhibitors in relation to *PCT*. A more stringent vehicle emission control policy and the polycentric urban development mode have caused the eastern region to have a superior ability to confront increasing *VP* compared with those of the other regions. Hence, the coefficient of the central region is the highest among the three regions.

RD influences *PCT* differently in various regions, but for the whole nation, it has an inhibitory action on *PCT*. The development of transportation infrastructure positively affects the carbon emissions in mega-cities, which are mainly concentrated in eastern China, but it has negative effects in medium-small cities [37]. Road construction plays a vital role in national economic as a kind of traffic infrastructure, and the economic significantly influences *PCT* [5]. The unbalanced development of transportation infrastructure ultimately results in different *PCT* in different regions.

Table 8 also shows the regression results of Model 2. There are only four independent variables in Model 2 for the whole nation: *TGDP*, *SGDP*, *PT* and *FT*, *ES* is not adopted because it rejects the null hypothesis of non-stationarity at 1% at the original series. Our result is in line with the studies of Guo *et al* [10]and Fan and Lei[20], which indicated that the *ES* has a great impact on the carbon emissions from transport sector. We also find that it is an important indicator for the carbon emissions from transport sector in both the eastern and central regions, with statistical significance at the 1% level. The individual fixed effects regression model is used for entire nation and for the central and eastern regions, but the random effects model is used for western region with an R2 value of the regression results of only 0.170. Nevertheless, some of the variables still have remarkable effects on the explained variable. In addition, the zoning effect also obviously exists. For example, except for the *SGDP* always significantly increasing the value of *CI*, the other variables affect *CI* differently in various regions.

Table 8. Estimation parameters of the panel data models

Variables	Model 1				Model 2			
	Whole nation	Eastern region	Central region	Western region	Whole nation	Eastern region	Central region	Western region
Constant	-1.919***	-2.146***	-1.628***	0.222	9.735***	7.182***	11.3885***	9.7763***
	(0.072)	(0.101)	(0.108)	(0.621)	(0.249)	(0.160)	(0.170)	(0.496)
ln(*PD*)	0.551***	0.657***	0.137*	5.468***				
	(0.092)	(0.067)	(0.072)	(0.313)				
ln(*PCC*)	0.411***	0.665***	0.382***	0.898***				
	(0.061)	(0.017)	(0.041)	(0.131)				
ln(*RD*)	-0.029	0.190***	-0.009	-0.498***				
	(0.019)	(0.013)	(0.013)	(0.066)				
ln(*VP*)	-0.114**	-0.369***	-0.122***	-0.279***				
	(0.037)	(0.016)	(0.030)	(0.092)				
TGDP	0.236**	0.375***	0.745***	0.443**	-0.635***	0.541***	-0.057	0.031
	(0.110)	(0.050)	(0.076)	(0.215)	(0.252)	(0.149)	(0.124)	(0.551)
SGDP					0.762**	4.576***	0.247***	1.338**
					(0.235)	(0.169)	(0.122)	(0.675)
ln(*PT*)					0.030	-0.394***	-0.433***	0.369***
					(0.051)	(0.022)	(0.046)	(0.103)
ln(*FT*)					-0.238***	0.028***	-0.127***	-0.375***
					(0.022)	(0.008)	(0.020)	(0.068)
ES					-	-0.291**	-2.766***	0.33
					-	(0.132)	(0.120)	(0.317)
Observations	480	176	144	160	480	176	144	160
Individuals	30	11	9	10	30	11	9	10
Model types	Fixed effects model	Fixed effects model	Fixed effects model	Fixed effects model	Fixed effects model	Fixed effects model	Fixed effects model	Random effects model
Adjusted R^2	0.909	0.994	0.962	0.961	0.988	0.984	0.965	0.17
F-statistic	142.149***	2044.865***	283.135***	282.770***	1162.886***	653.192***	300.736***	7.520***
DW statistic	0.439	1.796	1.695	1.536	0.74	1.817	1.632	0.743

[1] Numbers in the parentheses are standard errors.

[2] There are only four independent variables in Model 2 of the whole nation: *TGDP*, *SGDP*, *PT* and *FT*.

[3] ***, ** and * denote significance at 1%, 5% and 10% level of significance respectively.

From Table 8, we find that the impact of tertiary industries on the *CI* is positive only for the eastern region; it is negative for the whole nation and is statistically non-significant for the central and western regions. Tertiary industry, which provides services for production and consumption, exists on a larger scale in the eastern region of China than in other regions. The flourishing tourism, catering, culture and sport industries strongly stimulate passenger transportation demand, drive the development of transport industry and generate more carbon emissions. However, compared with the impact of secondary industry development on transport *CI*, tertiary industry development has much less influence in the eastern region and is even an inhibiting factor for the entire nation. Secondary industry development maintains a significant positive role in relation to *CI* across China. The eastern region is in the late industrial stage [38], so the transportation mode is also developing a more convenient and higher *CI*, with the transformation of the product from bulky and low value-added to light-weight, deep processing and high value-added. In contrast, the other two region are in the early-middle industrial stage, so the transportation mode is quite different from that of the eastern region. Hence, the coefficient of *SGDP* of the eastern region is much higher than those of the other regions.

As shown in the results, *PT* is found to have inhibitory action on *CI* in the central and eastern regions, but a galvanizing impact in the western region and the entire nation. The carbon emissions of China's passenger transportation is related to the level of regional economic development and natural geographic conditions [39]. Compared with the western region, the better developed central and eastern regions are more likely to get the support of advanced carbon- reduction technologies and policies, which are significant for decreasing *CI*. The complicated natural geography in the west also indirectly inhibits the implementation of carbon-reduction policies and extension of advanced technologies.

FT has small impact but is highly statistically significant on *CI* in the eastern region. In terms of freight transport structure, vessel transportation is the main transport form in the eastern region, but it should not be ignored that there has been a sharp increas in freight volume in both airfreight and road freight, which have lower energy intensities. Conversely, *FT* is an inhibitor of *CI* in the entire nation and the central and western region. With the implementation of policies, such as the western development campaign and the plan of rejuvenating old industrial bases in Northeast China, that aim to improve the level of industrial agglomeration, the freight demand of unit industrial added value has declined steadily and the empty-loading rate has also declined. Moreover, long-distance freight transport has increasingly relied on more economic transport modes, such as water carriage, rail transport and pipeline transport.

Due to the geographic heterogeneity, *ES* inhibits the *CI* of transport sector in the eastern and central regions, especially in the latter, with a coefficient of -2.766, but it shows statistical significance in the western region. The western region has a high proportion of clean energy sources, but it also has a complex natural geographical condition, which results in inefficient energy use [40]. Additionally, natural conditions limit the development of efficient transport modes and the expanded use of clean energy. Therefore, with this geographic environment in the western region, road transportation, which includes low-energy intensity transport modes, has the largest proportion. The west-east pipeline project and the west-east power transmission project are indeed effective programs for balancing the energy distribution in China and decreasing *CI* by promoting the use of new-energy automoblies. In contrast, the use of natural energy is less frequent in the central region than in it is the western regional, but it is more common than that in the eastern region. Hence, it is much easier to promote the use of new-energy autombolies to decrease *CI*.

5. Conclusions and suggestions

This study examines the dynamics of the carbon emissions from transport sector in China during the period of 2000 to 2015. In the period, the *PCT* increased across China, especially in Chongqing and Inner Mongolia. However, *CI* decreased in most provinces in China, other than Zhejiang, Chongqing, Yunnan, Qinghai, Heilongjiang, Jilin, Inner Mongolia, Henan and Anhui, most of which are concentrated in the central region. The econometric panel data model is employed to estimate the effects of driving factors on *PCT* and *CI* of transport sector in China and their zoning effects. The result indicates clear zoning effects. *PD* is the most significant influencing factor on *PCT* in the entire nation and the western region with coefficients of 0.551 and 5.468, respectively. *PCC* and *TGDP* have the most significant impact on *PCT* in the eastern and central regions, with coefficients of 0.665 and 0.745, respectively. The only inhibiting factor of the *PCT* in the entire nation and the central and eastern regions is *VP*, whereas *VP* and *RD* are the restraining factors of the *PCT* in the western region. In terms of *CI*, the development of secondary industry is the primary motivator in all regions of China. Moreover, *TGDP*, *PT*, *FT* and *ES* have significantly diverse effects on the growth of *CI* at both the national and regional levels.

Our study has a good implication for policy maker in terms of transport sector. Here we propose some suggestions based on the empirical results of this study. First, some relevant recommendations are given for the promotion of clean energy vehicles. It's a complex system project that widespread use of clean energy vehicles in the western region, because it not only need to consider the social economic factor, but also environmental factors. So the government should narrow the promotion of clean energy vehicle down to the short-distance passenger and freight vehicles. According to the result, we find the potential for clean energy vehicles to reduce carbon emissions in the central region is huge. Hence, we suggest that the government should focus on opening the clean energy vehicle market in the central region and promoting clean energy vehicles by transferring clean energy vehicle production enterprises to the central region. In some eastern cities, clean energy vehicle population is influenced by the policy which limits the total number of vehicles, e.g. Beijing and Shanghai. Hence, we advise government in the eastern region to introduce favorable policies to exchange fossil fuel vehicle to clean energy vehicle. Second, Chinese government should proactively facilitate the shift of the secondary industry from eastern region to central region. Because the secondary industry development pattern of the eastern region in China has been changed from the mode of fast development to the mode of efficient development, hence the secondary industry with high energy-consumption and labor-intensive is not suitable for eastern China. Besides, compared with the western region, the central region has a distinct advantage of geography, resource and industrial base, and this study find that developing the secondary industry in central region also shows the smallest increase of the carbon emissions from transport sector among three regions. Third, improving infrastructure and optimizing urban layout is highly recommended. Natural condition of the western region limits the development of high-speed railway which is high-efficiency and low carbon intensity transportation mode, so the passenger turnover is increasing mostly concern in road passenger transport and air passenger transport. Based on this situation, we recommend government to increase the road and railway network density by sufficiently considering of geographic and ecological factor in the western region. Additionally, in order to resist the carbon emissions from transport sector pressure caused by increasing population density, we propose government to promote the conversion of traditional city model from a single-core city into a multi-core city.

It should be noted that this study ignores the transboundary issues of estimated carbon emission produced in provincial transportation, we focused only on the carbon emission produced from fuel consumption when calculating the carbon emission of provincial and regional transportation departments. However, in the further research, we will try to take passenger, cargo volume, scheduled flight volume and some other influence factors into account to solve the problem. Additionally, the inaccessibility in the data brought by the electric power departments required us to use only the standard value of carbon emission factor produced from electricity to calculate carbon emissions. This study is not restricted by the above limitations, creatively uses *CI* as the index to measure the carbon emission of transportation departments, and includes the carbon emission of transportation departments into its calculation.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix

Panel unit root tests

Using non-stationary variables to establish regression will lead to spurious regression. Therefore, it is significant to assess the variables with unit root tests [26]. For panel data, there are several unit root test methods, including the Levin-Lin-Chu test (LLC) [41], Im-Pesaran-Shin test (IPS), ADF-Fisher test [42] and Fisher-PP test [43]. The former three tests are universally used in research [44-46]. The LLC test assumes that the variables have identical unit roots, so the autoregressive coefficient is the same across the cross sections, whereas the IPS test loosens the assumption of LLC test and allows variance across regions under the alternative hypothesis [47]. Therefore, the IPS test is used to examine the stationarity of variables in this study. If the probabilities for the IPS test are less than 10%, we can reject the null hypothesis and consider the variables to be stationary.

Panel cointegration tests

After confirming that the variables are integrated of order one, the next step is to employ panel cointegration to identity whether a long-term relationship exists between the variables. The Pedroni test [48], Kao test [49] and Johansen [50] test are generally used in panel cointegration analyses. Pedroni test constructs seven statistics to verify the cointegration relation among panel variables based on the regression residual of the cointegration equation, so it is applied in this study. Among these seven statistics, the Group rho-Statistic, Group PP-Statistic and Group ADF-Statistic pool the regression residuals using the between-dimension approach. Four others, i.e., the panel v-statistic, panel r-statistic, panel PP-statistic and panel ADF-statistic, pool the coefficients of autoregressive across different numbers by the within-dimension method [51]. In addition, the panel ADF-statistic is found to be more precise than the other six statistics [52]. Thus, the panel ADF-statistic is used to determine the goodness of fit. When the panel ADF-statistic is less than 10%, it can be determined that there exists a long-run relationship between variables.

References

1. International Energy Agency. *Key world energy statistics 2015*.
2. Auffhammer, M.; Carson, R. T., Forecasting the path of China's CO emissions using province-level information. *Journal of Environmental Economics & Management* **2008,** 55, (3), 229-247.
3. Wang, Z.; Chen, F.; Fujiyama, T., Carbon emission from urban passenger transportation in Beijing. *Transportation Research Part D: Transport and Environment* **2015,** 41, 217-227.
4. Loo, B. P. Y.; Li, L., Carbon dioxide emissions from passenger transport in China since 1949: Implications for developing sustainable transport. *Energy Policy* **2012,** 50, 464-476.
5. Li, H.; Lu, Y.; Zhang, J.; Wang, T., Trends in road freight transportation carbon dioxide emissions and policies in China. *Energy Policy* **2013,** 57, 99-106.
6. M'Raihi, R.; Mraihi, T.; Harizi, R.; Taoufik Bouzidi, M., Carbon emissions growth and road freight: Analysis of the influencing factors in Tunisia. *Transport Policy* **2015,** 42, 121-129.
7. Zhang, N.; Wei, X., Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. *Applied Energy* **2015,** 146, 409-420.
8. Lin, B.; Xie, C., Reduction potential of CO_2 emissions in China's transport industry. *Renewable and Sustainable Energy Reviews* **2014,** 33, 689-700.

9. Xu, B.; Lin, B., Carbon dioxide emissions reduction in China's transport sector: A dynamic VAR (vector autoregression) approach. *Energy* **2015,** 83, 486-495.
10. Guo, B.; Geng, Y.; Franke, B.; Hao, H.; Liu, Y.; Chiu, A., Uncovering China's transport CO_2 emission patterns at the regional level. *Energy Policy* **2014,** 74, 134-146.
11. Huang, Y.; Todd, D., The energy implications of Chinese regional disparities. *Energy Policy* **2010,** 38, (11), 7531-7538.
12. Wang, Y.; Xie, T.; Yang, S., Carbon emission and its decoupling research of transportation in Jiangsu Province. *Journal of Cleaner Production* **2017,** 142, 907-914.
13. Gately, C. K.; Hutyra, L. R.; Wing, I. S.; Brondfield, M. N., A bottom up approach to on-road CO_2 emissions estimates: improved spatial accuracy and applications for regional planning. *Environ Sci Technol* **2013,** 47, (5), 2423-30.
14. Liu, Y.; Wang, Y.; Huo, H., Temporal and spatial variations in on-road energy use and CO_2 emissions in China, 1978–2008. *Energy Policy* **2013,** 61, 544-550.
15. Cai, B.; Yang, W.; Cao, D.; Liu, L.; Zhou, Y.; Zhang, Z., Estimates of China's national and regional transport sector CO_2 emissions in 2007. *Energy Policy* **2012,** 41, 474-483.
16. Bi, J.; Zhang, R.; Wang, H.; Liu, M.; Yi, W., The benchmarks of carbon emissions and policy implications for China's cities: Case of Nanjing. *Energy Policy* **2011,** 39, (9), 4785-4794.
17. Aydin, G., Modeling of energy consumption based on economic and demographic factors: The case of Turkey with projections. *Renewable & Sustainable Energy Reviews* **2014,** 35, (35), 382-389.
18. Cheng, Y., Spatiotemporal dynamics of carbon intensity from energy consumption in China. *Acta geographic sinica* **2014,** 24, (4), 631-650.
19. Kaya, Y. *Impact of carbon dioxide emission control on GNP growth: interpretation of proposed scenarios*; IPCC energy and industry subgroup, response strategies working group: Paris, 1990.
20. Fan, F.; Lei, Y., Decomposition analysis of energy-related carbon emissions from the transportation sector in Beijing. *Transportation Research Part D: Transport and Environment* **2016,** 42, 135-145.
21. Dietz, T.; Rosa, E. A., Rethinking the environmental impacts of population, Affluence and technology. *Human ecology review* **1994,** 1, 277-300.
22. Ehrlich, P. R.; Holdren, J. P., Impact of population growth. *Science* **1971,** 171, (3977), 1212.
23. Dong, J.; Deng, C.; Li, R.; Huang, J., Moving Low-Carbon Transportation in Xinjiang: Evidence from STIRPAT and Rigid Regression Models. *Sustainability* **2016,** 9, (1), 24.
24. Liu, Z.; Qin, C.; Zhang, Y., The energy-environment efficiency of road and railway sectors in China: Evidence from the provincial level. *Ecological Indicators* **2016,** 69, 559-570.
25. Ozcan, B., The nexus between carbon emissions, energy consumption and economic growth in Middle East countries: A panel data analysis. *Energy Policy* **2013,** 62, 1138-1147.
26. Wang, S.; Fang, C.; Wang, Y.; Huang, Y.; Ma, H., Quantifying the relationship between urban development intensity and carbon dioxide emissions using a panel data analysis. *Ecological Indicators* **2015,** 49, 121-131.
27. Hao, Y.; Chen, H.; Wei, Y.; Li, Y., The influence of climate change on CO_2 (carbon dioxide) emissions: an empirical estimation based on Chinese provincial panel data. *Journal of Cleaner Production* **2016,** 131, 667-677.
28. Hausman, J., A Specification Test in Econometrics. *Econometrica* **1978,** 46, (185), 1251-1271.
29. Kontoghiorghes, E. J.; Clarke, M. R. B., An alternative approach for the numerical solution of seemingly unrelated regression equations models. *Computational Statistics & Data Analysis* **1995,** 19, (4), 369-377.

30. Holmberg, K.; Andersson, P.; Erdemir, A., Global energy consumption due to friction in passenger cars. *Tribology International* **2012,** 47, 221-234.
31. Wu, Y.; Yang, Z.; Lin, B.; Liu, H.; Wang, R.; Zhou, B.; Hao, J., Energy consumption and CO 2 emission impacts of vehicle electrification in three developed regions of China. *Energy Policy* **2012,** 48, (5), 537-550.
32. Wang, W. W.; Zhang, M.; Zhou, M., Using LMDI method to analyze transport sector CO 2 emissions in China. *Energy* **2011,** 36, (10), 5909-5915.
33. Jiang, L.; Wu, F., A Study on Guangzhou's Employment Subcentres and Polycentricity. *Urban Planning Forum* **2009**, (3), 75-81(in Chinese).
34. Zhang, L.; Gao, S., Analysis on Spatial Connection in Beijing-Tianjin-Hebei Metropolitan Region from the Perspective of Polycentricity. *Urban Development Studies* **2014,** 21, (5), 49-54(in Chinese).
35. Ma, R., The Identification of Creative Spaces in Shanghai:Based on the Space Relation of Creative Enterprise. *Progress in Geography* **2012,** 31, (8), 1013-1023.
36. Jiang, Y.; He, D.; Zegras, C., Impact of Neighborhood Land Use on Residents Travel Energy Consumption. *Urban Transport of China* **2011**, (4), 21-29 (in Chinese).
37. Xie, R.; Fang, J.; Liu, C., The effects of transportation infrastructure on urban carbon emissions. *Applied Energy* **2017,** 196, 199-207.
38. Wu, H. Analysis of energy consumption and energy-saving potential of regional transportation in China. Beijing Jiaotong University, 2017.
39. Neumayer, E., Can natural factors explain any cross-country differences in carbon dioxide emissions? *Energy Policy* **2002,** 30, (1), 7-12.
40. Hu, J.; Wu, Y.; Wang, Z.; Li, Z.; Zhou, Y.; Wang, H.; Bao, X.; Hao, J., Real-world fuel efficiency and exhaust emissions of light-duty diesel vehicles and their correlation with road conditions. *Journal of environmental scineces* **2012,** 24, (5), 865-874.
41. Levin, A.; Lin, C. F.; Chu, C. S. J., Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics* **2002,** 108, (1), 1-24.
42. Dickey, D. A.; Fuller, W. A., Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association* **1979,** 74, (366), 427-431.
43. Fisher, R. A., Statistical Methods for Research Workers. *Quarterly review of biology* **1939,** 21, (82), 340-341.
44. Zhang, C.; Zhao, W., Panel estimation for income inequality and CO 2 emissions: A regional analysis in China. *Applied Energy* **2014,** 136, (C), 382-392.
45. Gao, W.; Zhu, Z., The technological progress route alternative of carbon productivity promotion in China’s industrial sector. *Natural Hazards* **2016,** 82, (3), 1803-1815.
46. Xu, H.; Zhang, W., The causal relationship between carbon emissions and land urbanization quality: A panel data analysis for Chinese provinces. *Journal of Cleaner Production* **2016,** 137, 241-248.
47. Shuai, C.; Shen, L.; Jiao, L.; Wu, Y.; Tan, Y., Identifying key impact factors on carbon emission: Evidences from panel and time-series data of 125 countries from 1990 to 2011. *Applied Energy* **2017,** 187, 310-325.
48. Pedroni, P., Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory* **2004,** 20, (3), 597-625.
49. Kao, C., Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics* **1999,** 90, (1), 1-44.

50. Johansen, S., The Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics & Control* **1988,** 12, (2), 231-254.
51. Ou, J.; Liu, X.; Li, X.; Chen, Y., Quantifying the relationship between urban forms and carbon emissions using panel data analysis. *Landscape Ecology* **2013,** 28, (10), 1889-1907.
52. Örsal, D. D. K., Comparison of Panel Cointegration Tests. *Journal of Quantitative & Technical Economics* **2010,** 3, (6), 1-20.