The dynamic effect of smart transportation on the carbon emission of transportation industry based on PVAR model

Mingyu Liu
School of Civil Engineering, Tongji University, Shanghai, China
1505452359@qq.com

ABSTRACT

Smart transportation is of great significance to reduce regional carbon emissions and achieve the dual carbon goal. However, the current research does not deeply explore the long-term dynamic impact of intelligent transportation on transportation carbon emissions. Therefore, this paper selects 30 provinces in China, uses their fuel use data from 2005 to 2020 to calculate transportation carbon emissions, and divides different regions according to geographical location and national development strategy. The dynamic impact of intelligent transportation on transportation carbon emissions is analyzed based on the PVAR model. The results show that the size effect of the 30 provinces is much larger than the structure effect and the technology effect.The main impact indicators of transport carbon emissions are different in the different regions like Beijing-Tianjin-Hebei Urban Agglomeration, the Yangtze River basin and the central and western region.Based on the above research, this paper aims to provide policy recommendations on transportation carbon emission reduction for cities in different regions from the perspective of smart cities.

Keywords-PVAR, smart transportation, carbon emission of transportation industry

1. INTRODUCTION

Carbon emissions from transportation are an important part of China's carbon emissions. In 2018, the total carbon dioxide emissions from transportation in China were about 10.7%, which is one of the key industries of energy conservation and emission reduction [1]. Reducing carbon emissions from transportation is crucial to the realization of the dual carbon goal. As the concept of smart city realizing smart, efficient, dynamic and precise governance was put forward in 2008, by the beginning of 2020, the number of smart city pilot projects in China has reached more than 700 [2], and smart transportation, as an important part of smart city, is also booming. The new generation of information technology such as 5G and big data is realizing the interconnection of everything and integrating it into the construction of intelligent transportation[3], which plays an important role in improving traffic control and operation efficiency and reducing carbon emissions from transportation. At present, most of the research focuses on the impact of smart transportation on carbon emissions in the short term. However, factors such as technology may show an inverted U-shaped influence curve[4], that is, the effect will change. Therefore, tracking the long-term effect of influencing factors is of great significance for emission reduction. In addition, considering the differences in social and economic development and policy background in different regions, the effects of influencing factors often show different characteristics[5].The research results of all provinces in the country as the research object are not conducive to proposing targeted measures. Therefore, this study simulates the long-term impact of various factors of smart transportation on emission reduction, captures the difference characteristics of the impact effect in time, and divides China 's provinces into different regions according to economic development and geographical location to explore the emission reduction effect of smart transportation(Table 1,Table 2). The research results will provide a theoretical basis for the formulation of long-term and short-term intelligent transportation emission reduction schemes in different regions of China.Specifically,the measurement of intelligent transportation in this paper is composed of three dimensions : scale, technology and structure. Secondly, this paper uses the top-down method to calculate the traffic carbon emissions. Finally, the PVAR model is used to analyze the long-term dynamic impact of intelligent transportation on traffic carbon emissions, including granger causality test and impulse response analysis.

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Table 1.Provinces within dividing regions based on national development policies

Regions	Provinces
Beijing-Tianjin-Hebei Urban Agglomeration	Beijing,Tianjin,Hebei
Yangtze River Basin	Qinghai, Xizang, Sichuan, Yunnan, Chongqing, Hubei, Hunan, Jiangxi, Anhui, Jiangsu, Shanghai
Yellow River Basin	Qinghai, Sichuan, Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Henan, Shandong

Table 2.Provinces contained within dividing regions based on geographical location

Regions	Provinces
Eastern Region	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Western Region	Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet
Central Region	Shanxi, Anhui, Jiangxi, Henan, Hunan, Hubei
Northeastern Region	Liaoning, Jilin, Heilongjiang,

2. METHODOLOGY

2.1. Carbon emissions from transportation

In order to calculate the overall transportation CO_2 emissions of the thirty provinces from 2005 to 2020, decompose factors from a macro perspective, and propose emission reduction strategies from an overall perspective, this article adopts the "top-down" method for the transportation CO_2 emissions of each province in each year.The "top-down" method, which estimates carbon emissions by multiplying transportation fuel sales data within a country or region by the fuel carbon emission coefficient[6].

The models used for calculating the annual CO_2 emissions from transportation in thirty provinces from 2005 to 2020 are as follows

$$C = \sum_{i=1}^{n} E_i \times D_i \times F_i \times \frac{44}{12} \tag{1}$$

where C is the CO_2 emissions from transportation, i is the type of energy, E_i is the consumption of the i-th energy in the transportation industry, Di is the conversion coefficient of the i-th energy to standard coal, and F_i is the carbon emission coefficient of the i-th energy.

2.2. Influencing Factors

This article starts with the concept of intelligent transportation and measures its impact on carbon dioxide emissions from three aspects[7].Firstly,intelligent transportation can help promote the overall development of the transportation industry, expand transportation scale, and strengthen infrastructure construction. This expansion is defined as the "transportation scale effect".Secondly,changes in the investment ratio between the transportation industry and other industries may alter the overall economic structure, leading to changes in carbon dioxide emissions. This is defined as the 'structural effect'.Thirdly,intelligent transportation is also conducive to promoting innovation in transportation technology[8], which helps reduce carbon dioxide emissions (i.e. "technological effects").The specific evaluation indicators are as follows(Table 3) [9]:

Table 3. Smart Transportation Indicator Framework

Intelligent transportation indicators	Scale Effect	GDP of Transportation Sector(Ten thousand Yuan)	GDP
		Number of public transport vehicles per 10,000 people	NPT
		Vehicles per 100 households	VH
		Length of railway in operation	LRO
	Structure effect	Proportion of fixed assets investment in transportation sector and other investment sectors	PIT
		Proportion of the employed population in the transportation industry to the total employed population	PEP
	Technology Effect	Number of patents granted	NPG
		Number of traffic accidents	NTA

2.3. The impact on carbon emissions

To further explore the relationship between smart transportation and carbon emissions, we established a PVAR model[10]:

$$Y_{it} = \gamma_0 + \sum_{j=1}^{p} \gamma_j Y_{it-1} + \alpha_i + \beta_t + \varepsilon_{it} \tag{2}$$

where i represents the city; t represents the year; P represents the lag order of the endogenous variable ;$\gamma_j$is the coefficient matrix of the estimated lag term; α_iIs a fixed effect vector;β_tIs the time effect vector; ε_{it}Is a random interference term.

Considering that the use of PVAR model for empirical testing requires data to be stable, the logarithm of all variables is taken, and then the first-order difference is performed.”dlnA” is used to represent the processed A-index data.The llc stationarity check method is used. On the basis of passing the data stationarity test, this article uses three standards: AIC, BIC, and HQIC to select the lag order. The Granger causality test determines that variables have a mutual influence relationship. The direction and proportion of the mutual influence between variables still need to be further analyzed through impulse response analysis. In this paper, the investigation period is set as 10 periods.

3. DATA

The data on transportation energy consumption mainly comes from the "China Energy Statistical Yearbook". Among them, the conversion coefficients of fossil fuels to standard coal are based on the values specified in the China Energy Statistical Yearbook (2009), while the conversion coefficients of coal, oil, and electricity to standard coal are 0.7143, 1.4286, and 0.1229t standard coal/t, respectively. At present, the carbon emission coefficient values used by various countries are not entirely the same. In this article, the average values are used, and the carbon emission coefficients of coal, oil, and electricity [11] are 0.7329, 0.5574, and 2.2132t carbon/t standard coal, respectively.Data for various specific indicators of smart transportation were obtained from China Statistical Yearbook and statistical yearbooks of various provinces and cities[12]。

4. RESULT

4.1. Carbon emissions in transportation sector

As shown in Figure 1, the 30 provinces show an overall growth trend, which starts to remain stable or show a downward trend in 2020, but there is a large gap between the absolute values of each province. However, in some provinces, such as Shandong, there will be a steep drop in the middle and then an upward trend, which is relatively special.

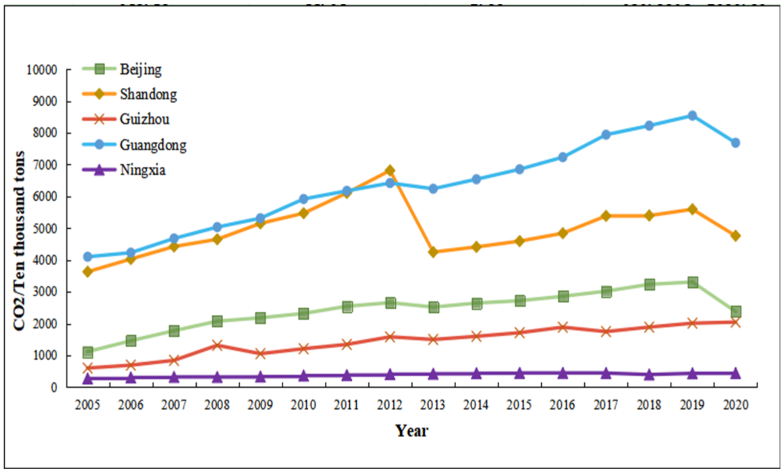


Figure 1. Transportation carbon emissions in typical provinces

4.2. Analysis results of 30 provinces

4.2.1. Unit root test

The panel unit root test results show that the variables are all stationary sequences, indicating that a PVAR model can be constructed(Table 4).

Table 4.Results of the unit root test for the panel data

	Coefficient	T-value	T-star	P>t
dlnNTA	-1.00524	-14.026	-4.68347	0.0000
dlnNPG	-0.72427	-12.107	-4.04980	0.0000
dlnGDP	-0.87539	-13.461	-4.19010	0.0000
dlnNPT	-1.15983	-17.638	-5.45716	0.0000
dlnVH	-0.64695	-16.251	-7.39881	0.0000
dlnLRO	-1.29054	-17.418	-8.45288	0.0000
dlnPIT	-0.94947	-14.193	-5.25689	0.0000
dlnPEP	-1.19362	-15.132	-6.61450	0.0000

4.2.2. Selection of the optimal lag order

The results are shown in Table 5, and all three standards should choose the lag order with a smaller exponential value. Table 5 shows that lagged first order should be selected for PVAR analysis.

Table 5.The optimal lag orders of the PVAR model

Lag	MBIC	MAIC	MQIC
1	-998.189	-187.061	-511.676
2	-609.056	-97.943	--302.486
3	-221.407	-6.588	-92.559

4.2.3. Granger causality test

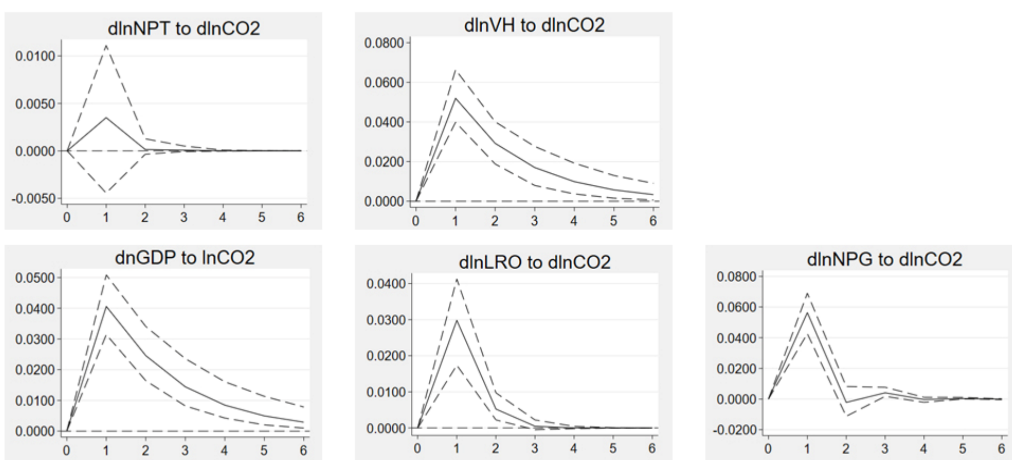
All indicators have passed the Granger causality test (Table 6).

Table 6.Results of the unit Granger causality test for the panel data

Equation	Chi2	Prob>chi2
dlnCO2		
dlnNTA	1.926	0.165
dlnNPG	40.147	0.000
dlnGDP	28.060	0.000
dlnNPT	4.152	0.042
dlnVH	36.659	0.000
dlnLRO	3.188	0.074
dlnPIT	0.404	0.525
dlnPEP	3.284	0.070

4.2.4. Impulse response analysis

Through pulse response analysis, we conclude that for 30 provinces across the country, the impact of scale effects is much greater than that of structural effects and technological effects in terms of the three effects of smart transportation.



(a)Scale Effect (b)NPG

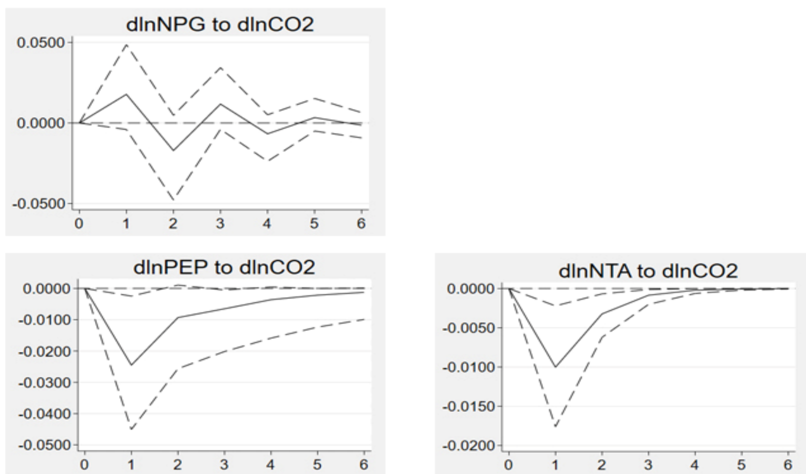
Figure 2. Impulse response diagram of thirty provinces

As shown in figure 2(a)，in the scale effect, the influence of VH and GDP is long-term and significant. This phenomenon is because the development of intelligent transportation promotes the construction and investment of transport infrastructure, increases the supply and demand of transportation, and thus increases the total traffic volume. With the increase of the total transportation scale, the supply and demand of transportation and logistics industry also increase, and people's demand for private cars also gradually increases, this increases carbon dioxide emissions. With the improvement of the effectiveness of smart transportation technology, it should have driven investment and construction in innovative transportation systems, as well as the continuous updates of related technologies in the transportation field, which should have a suppressive effect on transportation carbon emissions. However, according to the figure2(b) , with the increase of patents, carbon dioxide emissions increase. The reason for this phenomenon may be the increase in technological effects. Although it may lead to an increase in production efficiency and a reduction in carbon dioxide emissions from some cars, it also increases output and production scale, leading to more energy consumption and increased carbon dioxide production. The increase exceeds the reduction in carbon dioxide caused by technological optimization, and the overall trend of carbon dioxide emissions is on the rise.

4.3. Analysis results of provincial groups

4.3.1. Beijing-Tianjin-Hebei Urban Agglomeration:

Compared to 30 provinces across the country, as shown in figure 3(a)，the impact of PEP on carbon dioxide emissions in the Beijing-Tianjin-Hebei Urban Agglomeration is more significant and long-term in terms of traffic structure effects. This may because the continuous deepening of the integration and coordinated development of the Beijing-Tianjin-Hebei Urban Agglomeration since its official rise to national strategy in 2014[13] makes the Beijing-Tianjin-Hebei Urban Agglomeration be in an important stage of building a modern transportation network system and promoting industrial transformation and upgrading. The industrial structure has a significant impact on the development of the transportation industry, playing an important role in controlling transportation carbon emissions.



(a)Beijing-Tianjin-Hebei Urban Agglomeration (b)The Yellow River Basin

Figure 3. Partial area impulse response map

The pulse response graph of its NPG is initially positive and then negative, indicating that the impact of technological development on transportation carbon emissions in the Beijing Tianjin Hebei region is difficult to determine, but it is positive in the short term. This indicates that technological development has led to an increase in production and consumption scale, leading to an increase in carbon emissions. However, at this time, the positive impact of technology should not be too urgently denied, as the reduction in carbon dioxide emissions caused by technology in the later stage should also be taken into account. The government should adjust innovation policies reasonably and reduce carbon dioxide emissions with changes in industrial structure.

4.3.2. Yangtze River Basin and the Yellow River Basin:

The laws obtained from the analysis of the Yangtze River Basin and the Yellow River Basin are similar to those of provinces across the country, but as shown in figure 3(b) the fewer NTA in the Yellow River Basin, the more carbon dioxide emissions there are.

According to the previous analysis, the fewer traffic accidents, the better the technological effect has been demonstrated. The higher the emission and driving efficiency, the less carbon dioxide emissions should be. However, the higher the technological effect, the more likely the corresponding road scale will be expanded, resulting in an increase in traffic and an increase in total carbon emissions. Overall, this phenomenon is also the result of the combined effects of technology and scale.

4.3.3. Eastern Region,Western Region,Central Region and Northeastern Region:

Observing the pulse response maps of the eastern, western, central,and northeastern regions, it was found that their patterns were similar to those obtained by provinces across the country. The VH and GDP in the eastern, western, and northeastern regions had a significant impact on carbon dioxide emissions, with the Northeast region being particularly prominent. The VH impact on carbon dioxide emissions can reach a maximum of 2,while in other regions it does not exceed 1. The NPG value has varying degrees of impact on these four regions, with the Northeast region having a more significant impact.The impact of LRO and PEP on carbon dioxide emissions in the central region is also relatively high.

5. CONCLUSION

Using data on transportation carbon emissions and various indicators of smart transportation from 30 provinces in China from 2005 to 2020, different regions were divided from a socio-economic perspective and national strategy. The dynamic impact of smart transportation on transportation carbon emissions was analyzed based on the PVAR model.

In light of above findings,we propose the following policy implications. First of all, it is necessary to control the number of private cars in the family nationwide, rationally plan and optimize the transportation road network, and reduce the excessive and unscientific scale investment and construction in the development of smart transportation, so as to improve the emission reduction effect brought by technological innovation.

The Beijing-Tianjin-Hebei Urban Agglomeration should actively promote the transformation and upgrading of the industry, and promote the cooperation and exchange of the transportation industry in the three regions, and actively complete the adjustment and optimization of the industrial structure. At the same time, scientific and technological innovation should be encouraged to realize the coordinated development of scientific and technological innovation and industrial structure adjustment and optimization.

In the Yellow River basin, the scale of investment should be well controlled, and the scale should be steadily advanced instead of blindly expanding.

For the eastern, western and northeastern regions, we should pay attention to the control of family car ownership and adjust the scale of transportation construction investment. For the central region, it is necessary to control the scale of railway construction, optimize the railway network, adhere to the adjustment of industrial structure, and promote the coordinated development of transportation industry and other industries.

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