Forest Chemicals Review
www.forestchemicalsreview.com
ISSN: 1520-0191
July-August 2022 Page No. 139-151
Article History: Received: 30 March 2022, Revised: 8 April 2022, Accepted: 15 April 2022, Publication: 30 April 2022

Study on Influencing Factors of Transportation Carbon Emission: A Case Study of Beijing

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Abstract:

With the economic development, transport carbon emissions has become a major source of urban carbon emissions. A large number of literatures mainly focus on the national level, and there are few comprehensive studies on the urban level. To find the factors of influencing transport carbon emissions on city level and alleviate environmental pressure, the research examine the influencing factors on transport carbon emissions in Beijing from 2001 to 2019 with STIRPAT model incorporating PLS regression method. Results show that the expansion of economic development and population growth are the paramount driver. Higher energy prices is a major inhibited factor. Urbanization level has a significant positive effect on transport carbon emissions, followed by passenger turnover and freight turnover. Energy intensity has negative effect, but not significant. Combined with the above conclusions, Beijing should take measures to reduce carbon emissions from transportation.

Keywords: *Beijing; transport carbon emissions; factor; STIRPAT; PLS*

I. INTRODUCTION

With the development of urban economy, the harmonious development of human and environment has also been paid more and more attention. In the 20th century, the emergence of the term "temperature chamber effect" aroused people's intense attention to the degradation of ecological environment caused by greenhouse gases, especially CO_2 emissions. Global warming and other climate problems have brought great challenges to human survival and development. China accounted for 29% of global greenhouse gas emissions in 2013. [1] Total energy consumption in 2019 was 4.87 billion tons of standard coal equivalent (TCE). In order to deal with these problems, the government has taken measures on overall carbon emission reduction at the national level, including formulating corresponding policies, adjusting industrial structure and improving energy efficiency.

The carbon emission reduction of transportation industry has become the focus of research. Transportation, Energy and CARBON Dioxide: Towards Sustainable Development, a research report published by the International Energy Agency in 2009, pointed out that transportation has become the world's second largest emitter of greenhouse gas emissions and the industry with the fastest increase in CO_2 emissions.[2] According to the World Energy Organization, carbon emissions from urban transportation will grow at an annual rate of 1.7% by 2030, and the growth rate of developing countries

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and countries with economic transition will be higher, reaching 3.4% and 2.2% respectively. Energy consumption in the transport sector totaled 440 million tons of standard coal in 2019. Since 2000, passenger and freight turnover has grown at an annual rate of 9.07% and 18.43%, reaching 3.53 trillion person-km and 19.94trillion ton-km by 2019, respectively. Transportation industry, as one of the basic industries of economic development, acts as a link between people and logistics. With continuous development, it also faces severe risks such as energy consumption and environmental pollution.

A developed economy attracts people and promotes the development of industries, especially transportation. China is at a critical stage of development. Technological progress, population scale and urbanization level have a certain degree of impact on the development of transportation industry. How to balance low-carbon and high-quality development is an urgent problem for transportation industry. Due to different levels of urbanization and technological progress, transportation carbon emissions will be affected at the urban level. As the hub of China, Beijing undertakes important economic and political functions and has a perfect transportation network system. With the acceleration of economic development and urbanization, a large number of people are pouring into Beijing, and passenger turnover and freight turnover also show a rising trend. Carbon emission from transportation industry has become an important factor affecting the total carbon emission of Beijing.

How to coordinate the relationship between transportation carbon emission and economic growth, population scale and technological progress, explore the path of carbon emission reduction, and build low-carbon environmental protection transportation system has become one of the key issues of sustainable development. Existing studies are largely focused on carbon emissions at the national level, while there are relatively few studies on carbon emissions from transportation in specific cities. In this paper, the contribution of economic variables, population size, transportation micro factors, energy prices and other factors are incorporated into the econometric model to discuss the influencing factors and emission reduction direction of Beijing's transportation carbon emissions. The remaining chapters are described as follows: The second part is the literature review, which summarizes the research methods, influencing factors and specific transportation industry of carbon emissions. The third part is an empirical study on the carbon emissions in the transportation field of Beijing and the construction of an econometric model. Based on the empirical results, the fourth part explores the contribution degree of each factor to Beijing's traffic carbon emissions. The fifth part puts forward specific measures and policy suggestions for energy saving and emission reduction in Beijing transportation field.

II. LITERATURE REVIEW

The existing studies focus on transportation industry carbon emissions from different perspectives and approaches. Research on this issue has focused on two perspectives: previous studies have focused on specific modes of transport. González and Marrero(2012)[3] examined the impact of road transport carbon emissions in different countries from different factors, including network expansion, price and elderly population. Ruiling Han et al.(2022)[4] applied the influential factors of aviation carbon emissions with LMDI and STIRPAT. The results showed that aviation income and route structure had positive effects,

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while transportation and energy intensity had negative effects. Liao et al.(2011)[5] used time-series data to detect emissions from inland container transport. Other studies have shown carbon dioxide emissions across the industry. Mazzarino(2000)[6] evaluated the impact of the Italian transport sector on climate change.

There are generally three categories. The first is exponential decomposition. Transport emissions are broken down into several common elements that represent economic, demographic, and energy efficiency. Mazzarino(2000)[6] extended the transport intensity for five transport types of Italy and to decompose CO_2 emissions. Md. Afzal Hossain(2021)[7] used LMDI method to study Bangladesh's transport carbon emissions, which were decomposed into five factors: economy, population, energy intensity, economy and energy structure. Lian Lian et al. (2020)[8] studied the contribution of different industries to carbon emissions from transportation by using the structural decomposition method. Another kind of research method is econometrics. Using panel metrology techniques, Graham et al.(2009)[9] conducted a study on urban subway demand, Rentziou et al.(2012)[10] estimated the cumulative number of vehicles in 48 regions of the United States. Yong Jiang et al.(2019)[11] obtained the heterogeneity of the impact of public transport scale on carbon emissions in Various provinces of China through panel quantile regression, presenting an inverted U-shaped relationship. Xu Wang et al.(2022)[12] used data envelopment analysis to study carbon emission allocation of regional highway systems in China. Some studies use a combination of methods. Ruiling Han et al.(2022)[4] applied the methods of LMDI and STIRPAT. Yanmei Li et al.(2021)[13] based on the data of the first 15 years of 2010, used the combined model to predict the carbon emissions from 2011 urban transportation in 2017, and then analyzed and classified the influencing factors. Tangyang Jiang et al.(2022)[14] made a comparative analysis of carbon emission reduction of China's transportation before and after the economic "new normal" with three measurement methods, and found out the main driving factors in different periods.

There are many studies on the driving factors of transportation carbon emissions. Liddle(2012)[15] studied the interrelationships between OECD countries' gasoline consumption, income levels, energy prices and vehicle ownership. Lu et al.(2007)[16] suggest that rapid economic and vehicle ownership growth is the most critical factor in increasing CO_2 emissions, while population intensity contributes significantly to reducing emissions. Andreoni and Galmarini(2012)[17] analysed the main factors affecting CO_2 emissions from the European water and air transport sector from 2001 to 2008. Studies have shown that higher economic levels are a key factor in promoting CO_2 emissions. Kwon(2005)[18] used the IPAT equation to investigate the key factors in the evolution of carbon dioxide emissions from motor vehicle travel in the UK over the past 30 years. The results show that distance driven per capita was the main driver of emissions growth, with technological factors such as fuel efficiency and diesel replacement holding back growth to a certain extent and other factors contributing relatively little. The results show that the industrial scale factor has a significant effect on the carbon emission growth of transportation industry. Huaping Sun et al. (2020)[19] studied carbon emissions in the Yangtze River Delta region and showed that demographic and economic factors, stock of civilian vehicles, energy intensity, passenger and freight turnover rate and output value of transportation industry were significantly correlated with carbon emissions, while the energy structure and the people employed in the transportation industry are the main

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constraints on carbon emissions.

By studying previous studies, it is found that although there are many studies on the carbon emissions of transportation, the research directions are different and the conclusions are different. At the same time, most of the studies use the factorization method, but less for the more measurable methods, In addition, the study focused on the overall level of the country on a specific type of traffic on the study, the city for the study alone less. Therefore, this paper uses time series based on STIRPAT measurement model to study the influence factors of traffic carbon emissions in single city Beijing, compares the relative impact of passenger freight transportation, and introduces the energy price factor to focus on the sectoral perspective.

III. METHODOLOGY

3.1. The STIRPAT model

Environmental degradation is often affected by demographic factors, economic development, and technological development. In the 1970s, Enrlich and Holden proposed the IPAT equation to study the mechanism of action between population development (P), wealth (A), technological progress (T) and environmental issues. According to the I = PAT equation, the environment is constrained by three factors: population, wealth and technology. The equation assumes that the three factors have the same effect on the environment, and assume that when the influencing factors change by one percentage point, the environment will change percentage point. Although the IPAT equation is simple and practical, there are still limitations in the research process. It can not judge the importance of each driving factor, and the assumption that the environment is proportional to each factor is unreasonable. To overcome the shortcomings of the IPAT equation, Dietz et al.(1994)[20] established a Stochastic Impacts by Regression on Population Affluence and Technology model. The general expression is:

$$I_i = \mathrm{a}P_i^b A_i^c T_i^d u_i \tag{1}$$

Where I is for environmental impact, P is for population factors, A represents economic factor, and T represents technical factors. a is the model coefficient, b, c, and d are independent variable indices, u is the residual term, and i is the research sample unit. Taking the natural logarithm of both sides of equation (1) to obtain the equation:

$$\ln I_i = a + b(\ln P_i) + c(\ln A_i) + d(\ln T_i) + u_i \tag{2}$$

According to the concept of elasticity coefficient, the regression coefficient reaction of the equation is the elastic relationship between the dependent variable and the independent variable, that is, the degree of change of the dependent variable caused by the change of 1% of one of the independent variables when the other independent variables are unchanged.

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The STIRPAT model still maintains the original product structure of the IPAT equation, and still regards population, wealth and technology as the decisive factors affecting the environment. At the same time, the STIRPAT model accepts unit root tests and allows for the decomposition of environmental and technical factors. Given the flexibility of the STIRPAT model, relevant variables can be added to the original model for research purposes. According to the characteristics of Beijing's development and the pressure faced by Beijing traffic at the present stage, the study incorporates relevant factors into the STIRPAT model, and analyzes the impact on carbon emissions of economic level, population size, energy intensity, passenger turnover, freight turnover, energy prices and urbanization levels. The extended STIRPAT model is expressed as:

$$\ln C_i = a + b_1(\ln A_i) + b_2 (\ln P_i) + b_3 (\ln EI_i) + b_4(\ln PAS_i) + b_5(\ln FRE_i) + b_6(\ln EP_i) + c(\ln U_i) + +u_i \tag{3}$$

Where C represents environmental impact, expressed in Beijing traffic carbon emissions, A represents per capita GDPl, P is the population size; EI is the energy intensity; PAS is the passenger turnover; FRE is the freight turnover volume; EP is the energy price; U indicates urbanization levels.

3.2. Partial least square regression

There are usually multiple collinearity problems among various research elements. In order to obtain effective regression results, the study uses partial least squares regression (PLS).

Assume that n independent observation data (xi, ..., xip, yi), i = 1, ... n are collected from the p independent variables x1, ..., xp of the variable y

$$Y=\begin{bmatrix} \boldsymbol{y_1} \\ \cdots \\ \boldsymbol{y_n} \end{bmatrix},\ X=(x_1,\ \cdots\cdots,\ x_p)_{n\times p}=\begin{bmatrix} \boldsymbol{x_{11}} & \cdots & \boldsymbol{x_{1p}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x_{n1}} & \cdots & \boldsymbol{x_{np}} \end{bmatrix}$$

PLS steps are as follows:

Firstly, extract the first component t_1 and u_1 from the independent and dependent variable set respectively, represented as X and Y. The requirements for t_1 and u_1 are as follows:

(1) t_1 and u_1 are the linear combination of $\begin{bmatrix} \boldsymbol{x_{11}} & \cdots & \boldsymbol{x_{1p}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x_{n1}} & \cdots & \boldsymbol{x_{np}} \end{bmatrix}$ and $y_1, y_2, y_3, \dots, y_p$, respectively.

(2) t_1 and u_1 an get as many raw variables as possible.

(3) The correlation between t_1 and u_1 should be maximized to ensure that t_1 has the most explanatory power for u_1.

After the above conditions are satisfied, the regression equations of T1 and U1 are established. The algorithm terminates after extracting principal components to satisfactory accuracy.

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3.3. Variable importance analysis

To analyze the variable importance deeply, the VIPS (Variable Importance in Projection) of each variable have been calculated in the PLS regression. The value of VIP represents the explanatory power of each variable, expressing as:

$$VIP_j = \sqrt{\frac{p}{Rd\left(y;t_1,\ldots,t_m\right)}\sum_{h=1}^{m} Rd\left(y;t_h\right)w_{hj}^2}$$

In the equation, VIP_j stands for the VIP of x_j, p is the number of independent variables, and $VIP_1^2+\ldots+VIP_P^2=k$, $t_1,\ldots,t_m$ are the main components extracted from the variable X, $Rd\left(y;t_1,\ldots,t_m\right)=\sum_{h=1}^{m} Rd\left(Y;t_h\right)$ means the cumulative explanatory power of the primary components to Y. w_{hj} is the first j component of w_h-axis, which can be calculated as the projection on w_h-axis of the normalized variable x_j. It is used to measure the contributions of x_j for the construction of primary component t_h, and for any $h=1,2,\ldots m$, $\sum_j^p w_{hj}^2 = w_h^{'} w_h = 1$.

3.4. Data source

The data of Beijing from 2001 to 2019 are used to calculate the energy and energy intensity. The data are from the China Energy Statistical Yearbook 2002 to 2020(NBSC, 2002-2020). The data of population, passenger turnover, freight turnover and urbanization level are derived from the Beijing Bureau of Statistics (2002-2020). Energy price data from the "Yearbook of Price" (Price Yearbook of China, 2002-2020).

IV. RESULTS AND DISCUSSIONS

4.1. Ordinary least square regression of the model

In general, population change, socio-economic development, and technological innovation are interrelated, mutually influential, and mutually constrained, that is, multi-collinearity problems often exist in time-series data including three types of factors. Multicollinearity increases the variance of the parameter estimates and may also exclude important explanatory variables from the model, rendering the significance test of the variables meaningless. In the multiple regression model, it is necessary to judge whether the model has multi-collinearity problem based on the variable VIF value (variance expansion factor) through OLS regression. In general, a VIF value greater than 10 indicates severe multicollinearity between variables. The correlation between the variables in Table 1 is significant at the level of 1%, and the VIF values of the variables in Table 2 are all greater than 10. From the above two aspects, it can be judged that there is a serious collinearity problem in the time series data adopted by the research.

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Table I. Matrix of correlation among variables.

Variables	lnC	lnA	lnP	lnEI	lnPAS	lnFRE	lnEP	lnVEH
lnC	1							
lnA	.961**	1						
lnP	.948**	.968**	1					
lnEI	-.541	-.524	-.476	1				
lnPAS	.896**	.923**	.963**	-.485	1			
lnFRE	.870**	.886**	.891**	-.742*	.895**	1		
lnEP	-.921**	-.983*	-.964**	.402	-.953**	-.827**	1	
lnU	.923**	.954**	.996**	-.442	.979**	.864**	-.967*	1

** Significant at the 1% level

Table II. Analyzing results by OLS

Variable	Prob.	VIF
C		
lnA	.006	174.153
lnP	.001	764.721
lnEI	.096	10.304
lnPAS	.013	82.893
lnFRE	.048	20.596
lnEP	.008	118.673
lnU	.002	610.024

4.2. Partial least square regression of the model

First, the STIRPAT model was established, and then PLS regression was used to reduce the reduce the harm of multicollinearity, resulting in reliable regression results.

As shown in Figure 1, all sample data falls within the ellipse, indicating that the sample data is heterogeneous, the sample data is feasible, and the PLS regression results are acceptable. In Figure 2, t_1/u_2 is linear in the sample data, and the PLS regression model is suitable for solving the problem studied. [21]

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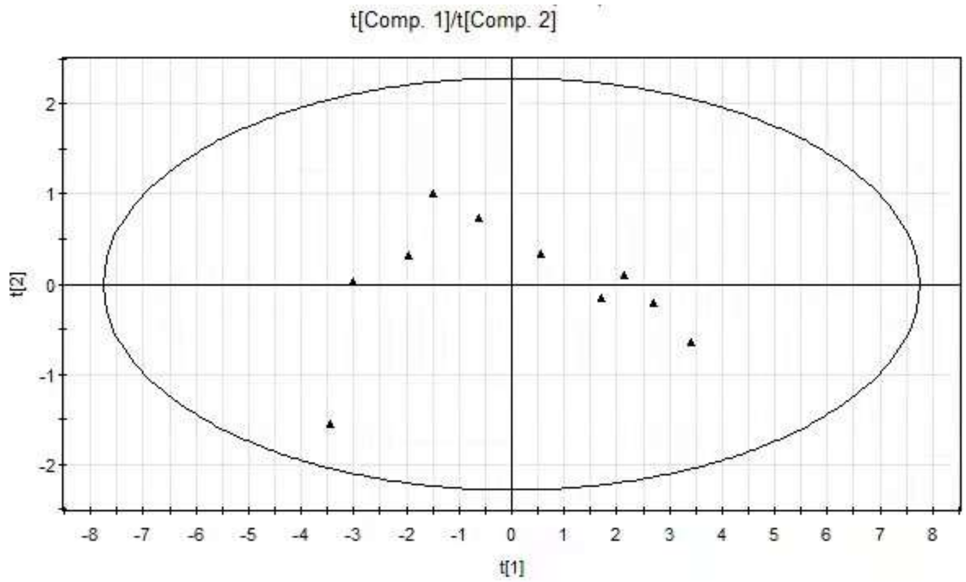

Fig 1. t_1/t_2 oval plot

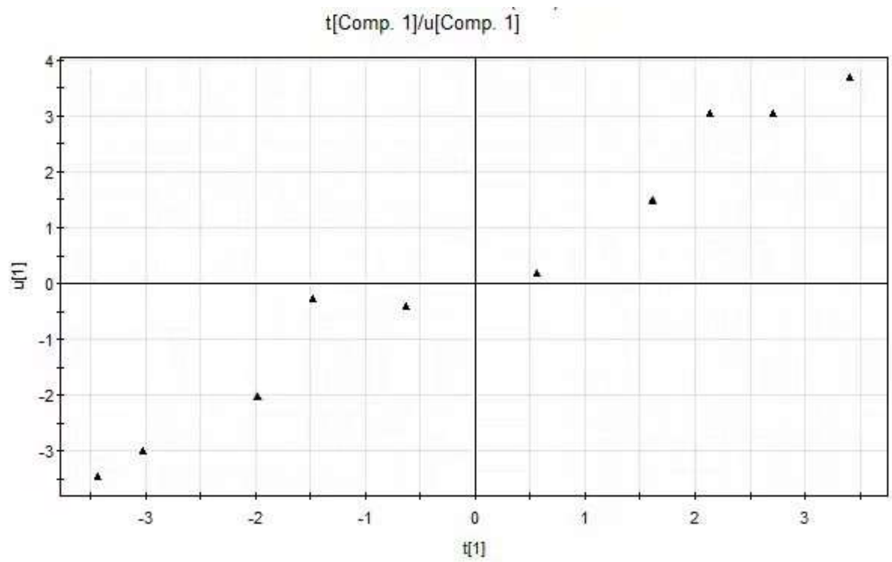

Fig 2. t_1/u_2 scatter plot

The study used SIMCA-P 11.5 (DEMO) to calculate PLS regression results. R^2X (cum), R^2Y (cum) and Q^2 (cum) are indicators of the degree of fitting of the extracted principal components. In general, the values of these three indicators are greater than 0.8, indicating that the regression results are ideal. As shown in Table 3, R^2X (cum) = 0.891, R^2Y (cum) = 0.956, and Q^2 (cum) = 0.959, indicating that the regression results are ideal. According to the direction of the elastic coefficient of the PLS variables in Table 3, the following conclusions can be drawn: per capita GDP growth, population size expansion, passenger turnover, freight turnover and Rapid urbanization have contributed to Beijing's carbon emissions. effect. The increase in energy intensity and energy prices will have an inhibitory effect on Beijing's carbon

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emissions.

Table III. PLS regression results overview

Variable	Unstandardized coefficients	Standardized coefficients
C	-35.7653	-5.17682
lnA	1.79542	0.199832
lnP	2.263312	0.182411
lnEI	-0.3238653	-0.0189472
lnPAS	0.665812	0.120314
lnFRE	0.9296372	0.120156
lnEP	-2.895241	-0.1768324
lnU	0.6503241	0.1496253
Number of principal component		2
R^2X(cum)	0.891	
R^2Y(cum)	0.956	
Q^2(cum)	0.959	

The VIP values of each variable are shown in Table 4. The greater the VIP value, the greater the importance of this factor for carbon emissions. According to the size of the VIP value, the importance of each driving factor to carbon emissions is ranked from high to low: per capita GDP, population size, energy price, urbanization level, passenger turnover, freight turnover, and energy intensity. Except for energy intensity, the VIP values of other variables are greater than 0.9, revealing that these factors have significant impact on Beijing's transportation carbon emissions from 2001 to 2019, and the impact of energy intensity is small.

Table IV. VIP values of factors

Variable	VIP
lnA	1.09057
lnP	1.07662
lnEP	1.06523
lnU	1.06212
lnPAS	1.03602
lnFRE	0．994021
lnEI	0.61201

4.3. Empirical analysis

From the regression results, economic factors are the most important factors affecting Beijing's traffic carbon emissions. The improvement of economic level can promote the increase of Beijing's traffic carbon emissions. For every 1% increase in per capita GDP, Beijing's traffic carbon emissions increased by 1.795%. The economic growth has led to an increase in the income of residents, which in turn has promoted the improvement of consumption levels and the changes in the way of life and travel. The

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products consumed by residents will generate a lot of CO_2 emissions in the transportation process. In the future, Beijing's economy will continue to grow steadily, which will largely lead to an increase in traffic carbon emissions.

The expansion of population size has also greatly contributed to an increase in carbon emissions. The expansion of population size will directly lead to an increase in energy demand, an increase in urban traffic pressure and an increase in population mobility, which will further increase traffic CO_2 emissions. Based on national and regional studies, population growth contributes greatly to the growth of carbon emissions from transportation. Wang et al.(2011) [22] pointed out that, by adding a resident population, the number of day trips to Beijing would increase by 2.64. With the acceleration of urbanization, the increase of Beijing's permanent population has put great pressure on the city's traffic and contributed to the increase of carbon emissions.

The impact of energy prices on transportation carbon emissions is second only to per capita GDP and population size. For every 1% increase in energy prices, Beijing's transportation carbon emissions will be reduced by 2.895%, which has a significant inhibitory effect. If the energy price changes, it means that the price of the factors invested in production will also change. The rise in energy prices will lead to an increase in the production cost per unit of production, and some of the increased costs will be passed on to consumers, thereby curbing demand and reducing the total energy consumption to achieve less carbon emissions; It will be reflected in energy consumers, affecting consumer demand to a certain extent, and then promoting energy-intensive enterprises to accelerate technological innovation. In the transportation field, it can stimulate the use of new energy and reduce energy by means of electricity instead of oil. The consumption has thus reached the goal of reducing emissions.

The empirical results show that there is a positive correlation between urbanization level and total carbon emissions. When the urbanization level increases by 1%, the traffic carbon emission of Beijing increases by 0.65%, and the VIP value is 1.062. The importance of all research factors ranks fourth, second only to economic, demographic and price factors. With the acceleration of urbanization, Beijing's population is highly concentrated, and people's pursuit of quality of life is gradually increasing. Private car ownership has increased year by year, leading to a decline in the proportion of people taking public green transport. Longer travel distances lead to an increase in energy consumption, which further contributes to the increase in carbon emissions from transport.

The increase in passenger and freight turnover will contribute the increase of traffic carbon emissions. When the passenger turnover increases by 1%, the corresponding Beijing traffic carbon emissions increase by 0.67%. When the freight turnover increases by 1%, the corresponding the carbon emissions of transportation increased by 0.93%, both of which are related to the level of economic development. From the perspective of the variance expansion factor of the two, the VIP value of the passenger turnover is 1.04, which is greater than the freight turnover of 0.99. Therefore, the effect of passenger turnover is more obvious than the impact of freight turnover. For one thing, passenger transport mainly relies on road, air and rail transport, while freight transport is more dependent on rail and water transport, which are more

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energy efficient than road and air transport. On the other hand, urbanization and accelerated economic development have resulted in a significant increase in passenger traffic in Beijing.

Beijing's energy intensity has a VIP value of 0.61, which has less impact on the factors studied, but the results show that its reduction will lead to an increase in traffic carbon emissions. When energy intensity drops by 1%, Beijing's traffic carbon emissions will increase. 0.32%, this conclusion is inconsistent with the improvement of technology will promote the efficiency of energy use. The increase in carbon emissions for an industry in a city is not caused by a single factor. First, both economic and demographic changes have an impact on them and play a key role in counteracting the positive effects of technological development. Secondly, we use the entire energy intensity of Beijing instead of the simple energy intensity of transportation, which may have a certain impact on the results. Finally, because of the rebound effect, technological development and innovation reduce energy consumption due to its efficiency, but it will increase the development and utilization of new energy. The two are used together for carbon emissions, and finally present technological development and innovation for Beijing traffic. Carbon emissions have had a positive effect. However, in any case, the reduction of energy intensity has always been an important means of saving energy and reducing carbon emissions. With the development and progress of society, there is still great potential for technological innovation.

V. CONCLUSIONS AND POLICY IMPLICATIONS

The article mainly studies the influencing factors of Beijing's traffic carbon emissions. Through analysis, economic development, population expansion, urbanization level, and passenger and freight turnover increase have all contributed to the increase of traffic carbon emissions. The increase in energy prices has significantly inhibited CO_2 emissions, and the increase in energy intensity has a negative impact on carbon emissions, but the impact is small.

Accordingly, in order to reduce carbon emissions and build a low-carbon city, Beijing should vigorously develop low-carbon transportation, optimize its industrial structure, and promote the development of high-tech industries and high-end services. In addition, in the process of economic development, we should control the size of the population and give consideration to the quality and quality of the population. Secondly, fuel and energy prices can be appropriately raised to improve energy efficiency, promote new energy vehicles, and advocate green travel for residents. Finally, improve the level of urban infrastructure, optimize the structure of urban transportation network, speed up the development of rail transit, expand the carrying capacity of existing public facilities, improve the network of medium and long distance and suburban lines, and reduce the turnover rate of passenger and cargo transportation. At the same time, through accurate information services, promote the development of intelligent transportation, so as to reduce Beijing's traffic carbon emissions.

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ACKNOWLEDGEMENTS

The research was supported by Tianjin Philosophy and Social Science Planning Project (Project No.: TJGL17-007).

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Forest Chemicals Review
www.forestchemicalsreview.com
ISSN: 1520-0191
July-August 2022 Page No. 139-151
Article History: Received: 30 March 2022, Revised: 8 April 2022, Accepted: 15 April 2022, Publication: 30 April 2022

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