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Study on Environmental Impact Factors of Carbon Emissions and Air Pollution Control in Transportation Industry

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Abstract. Since the industrial revolution, global warming has become more and more serious. Existing research shows that the significant increase in greenhouse gas emissions such as CO₂ is the most important cause of global warming. Therefore, all countries have begun to formulate practical and feasible carbon emission reduction policies and measures. China is the largest developing country in the world and the largest energy consumer, facing many pressures to reduce emissions. This paper takes the carbon emissions of China's transportation industry as the research object, based on the carbon emissions of China's transportation industry from 2003 to 2017. Through the analysis of data, transportation industry added value, transportation intensity, transportation energy intensity and transportation energy structure were introduced to study the environmental impact factors and air pollution control of China's transportation industry carbon emissions. Through the expanded STIRPAT model, the order of influence of various factors is ranked from the largest to the smallest: population size, transportation energy structure, transportation intensity, transportation energy intensity, transportation industry added value. This paper conducts a comprehensive and in-depth study on the influencing factors of China's transportation industry carbon emissions, identifies the main influencing factors, and lays an important theoretical foundation for China to develop emission reduction targets and measures that meet environmental requirements and self-development.

1. Introduction

Since the industrial revolution of the 19th century, large-scale industrial production activities have greatly satisfied the growing material needs of mankind and improved the living standards of people all over the world. Foreign studies on the environmental impacts of carbon emissions in the transportation industry started earlier. Banister et al. [1] divided the influencing factors of transportation carbon emissions into travel mode, vehicle full load rate and residential type. It is considered that the vehicle full load rate is the most important factor affecting transportation energy consumption. Darido et al. [2] analyzed the population size, population density, per capita GDP and other influencing factors of 17 cities in China, pointing out that population size intensive, income increase and urban expansion have promoted the carbon emissions of energy consumption in the transportation industry. Mazzarino [3] divided the factors affecting the carbon emissions of the Italian transportation sector into energy structure, energy intensity, transportation energy structure, transportation intensity and economic growth. The final research results show that economic growth is the main factor affecting the carbon emissions



of the transportation sector. Mendiluce et al. [4] used the LMDI method to decompose the energy consumption carbon emissions of passenger and cargo transportation in Spain from 1990 to 2008. The decomposition results show that the transportation turnover and transportation structure of passenger and freight transportation are the driving force for the growth of carbon emissions in the transportation industry. Factors, while energy intensity is a contributing factor to the increase in carbon emissions in the transportation industry. The results of Loo et al. [5] indicate that household income growth is the main factor leading to the growth of passenger transportation carbon emissions.

With the active development of energy-saving and emission-reduction work in China's transportation industry and the promotion of low-carbonization in the transportation industry, many scholars have paid attention to and studied the carbon emission problems of the transportation industry, and the research results on the factors affecting the carbon emissions of the transportation industry. It is also gradually increasing. Gao Biao et al. [6] used the STIRPAT model to decompose the carbon emissions of the transportation industry in Jilin Province from 1999 to 2011 into six factors: total population, per capita GDP, energy consumption per unit of GDP, transportation investment, urbanization rate, and number of private cars. Factors and comprehensive analysis of these influencing factors. The research results of Ding Xuejin [7] show that the improvement of traffic development level will cause a rapid increase in carbon emissions in China's transportation sector. At the same time, transportation energy efficiency and transportation structure will also have different effects on the increase of carbon emissions in the transportation sector. Lu Jianfeng et al. [8] believe that economic output and transportation structure have a significant pulling effect on the increase of carbon emissions in the regional transportation industry, and the change in transportation intensity does have a certain inhibitory effect on the increase of carbon emissions in the transportation industry.

2. Model establishment

The American ecologists Ehrlich and Holdren [9] first proposed the IPAT model, the environmental stress model, in 1971 to study the environmental impact of human social activities. The expression for this model is $I = PAT$, where I is the degree of environmental stress, P is the population size, A is the wealth level, and T is the technical level. The IPAT expression is an identity that reveals the mechanism of action between human social activities and environmental stress. It assumes that the influence of different influencing factors on the environment is elastic, but the actual research is contrary to it, so the model cannot reveal a single well. Changes in the impact of influencing factors on the environment.

In order to overcome this limitation, later scholars introduced an index to expand and supplement on the basis of the classic IPAT model, so that the model can better analyze the non-equalized impact of various influencing factors on the environment, that is, to propose an extensible STIRPAT model for random items. The model is used to measure the impact of human factors such as population size, wealth and technical level on the environment. The general expression is as follows:

$$I = aP^bA^cT^de \quad (1)$$

In formula (1): I , P , A , and T represent the degree of environmental impact, population size, wealth, and skill level; a is the model coefficient; b , c and d are the elastic coefficients of P , A , and T , respectively; The error term for the model. It can be seen from the above expression that when $a = b = c = d = e = 1$, the STIRPAT model is the IPAT model.

The STIRPAT model is a multivariable nonlinear equation. In order to facilitate the regression analysis, the logarithm of the two sides of the equation (1) is generally obtained, and the following equation is obtained:

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \quad (2)$$

In formula (2): $\ln I$ is the dependent variable, $\ln P$, $\ln A$, $\ln T$ are independent variables, $\ln a$ is a constant term, $\ln e$ is an error term, and b , c and d are the population size and wealth. Each change of

1% with the technical level causes changes in b%, c%, and d% of the degree of environmental impact, respectively.

Ordinary Least Square (OLS) is a mathematical optimization method based on the principle of least squares, in order to find the best function of the data by minimizing the sum of the squares of the errors. Regression analysis of the above equation (2) is usually performed using the OLS model parameters. An inevitable problem arises—multiple collinearity, which exhibits more or less correlation between independent variables. There is a certain dependency between them, which will have many adverse effects on the analysis results. Therefore, for models with multiple independent variables, scholars usually use the comprehensive statistical test to perform multi-collinearity test on the relevant independent variables.

According to the influencing factors mentioned above, in order to better study the carbon emissions of China's transportation industry, the indicator system of the STIRPAT model also includes the carbon emission factor of transportation energy, which is also convenient for the following factors to affect the carbon of China's transportation industry. Research on the contribution status of emissions. The specific model is as follows:

$$C = \alpha P^{\beta_1} A^{\beta_2} T^{\beta_3} S^{\beta_4} H^{\beta_5} M_1^{\beta_6} M_2^{\beta_7} M_3^{\beta_8} F^{\beta_9} \varepsilon \quad (3)$$

In Equation 3: C is the total carbon emissions (10,000 tons) of energy consumption in China's transportation industry; P is the total population at the end of the year (10,000 people); A is the level of economic development, expressed in terms of per capita GDP (10,000 yuan/person); T is the added value of the transportation industry (100 million yuan), which is the development status of the transportation industry; S is the transportation intensity, expressed as the ratio of the transportation turnover to the added value of the transportation industry (ton-km/million); H For the energy intensity of transportation, it is expressed by the energy consumption per unit of transportation turnover (ton/100 million tons); M_1, M_2, M_3 are the proportion of petroleum products, coal and natural gas consumption, respectively, to the total energy consumption of the transportation industry; For the transportation energy carbon emission factor, that is, the carbon emissions of transportation energy consumption accounted for the total energy consumption; α is the model coefficient; $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9$ are respectively Elastic coefficients of $A, T, S, H, M_1, M_2, M_3$ and F ; ε is the model error term.

When performing the metrological analysis, the logarithm of the two sides of the formula 3 is obtained, and the following equation is obtained:

$$\ln C = \beta_1 \ln P + \beta_2 \ln A + \beta_3 \ln T + \beta_4 \ln S + \beta_5 \ln H + \beta_6 \ln M_1 + \beta_7 \ln M_2 + \beta_8 \ln M_3 + \beta_9 \ln F + \ln k \quad (4)$$

In equation (4): $\ln C$ is the dependent variable, $\ln P, \ln A, \ln T, \ln S, \ln H, \ln M_1, \ln M_2, \ln M_3$ and $\ln F$ As an independent variable, $\ln k$ is a constant, and thus a multivariate linear fitting analysis of Equation 4 is required.

In 1970, Hoed and Kennard [10] proposed Ridge Regression, an improved OLS regression method designed for collinear data analysis. Ridge regression gives up the unbiasedness of LS. When the model has multiple collinearity problems, the ridge parameter can be introduced on the diagonal of the independent variable normalization matrix (the parameter must be a normal number) to ensure the obtained regression coefficient. Stability and reliability, while the standard deviation of the regression coefficients is also less than OLS. It can be seen that the ridge regression fits the ill-conditioned data much better than LS.

3. Numerical experiments

Based on the collected data, combined with the STIRPAT model, in order to eliminate the multicollinearity between variables, this paper uses the ridge regression with biased estimation to fit the model. Let the regression coefficient k of the ridge be $[0, 0.1]$ and the step size be 0.001, and the corresponding trend of the ridge map and the determinable coefficient R^2 will be obtained, as shown in

Fig. 1 and Fig. 2. At the same time, it can be found from these two figures that when $k = 0.05$ and $R^2 = 0.997$, the ridge parameter and the determinable coefficient of the model tend to be stable. The specific results are shown in Tables 1 to 3.

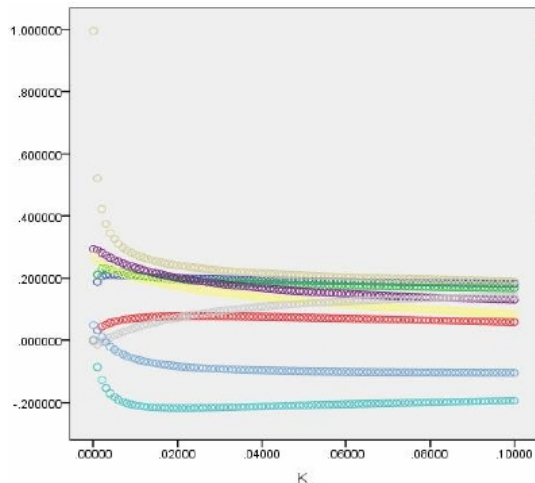


Figure 1. Ridge trace chart

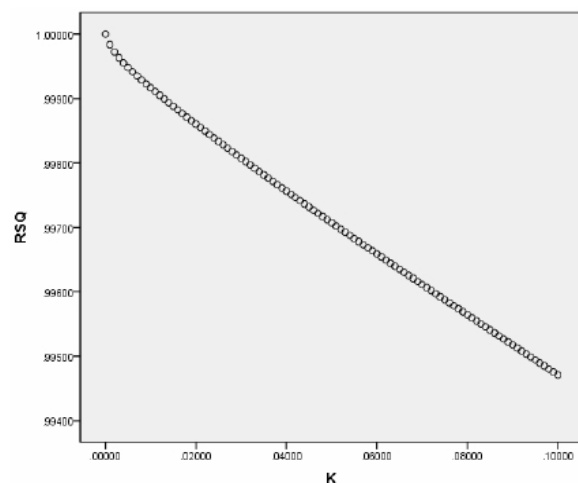


Figure 2. The change of determination coefficient R^2

Table 1. Summary Model

Model	R	R^2	Adjustment R^2	Standard estimated error
1	0.998268	0.996540	0.991349	0.036446

Table 2. Anova

Model	sum of square	df	Mean square	F	Sig
Return	2.295	9	0.255	191.9965033	0.000
Residual	0.008	6	0.001		
Total	2.303	15			

Table 3. The estimation results of ordinary least square

Variable	Coefficient	Standard error	Standard coefficient	t statistic	Sig	VIF
Constant	-28.251	7.453	0.000	-3.790	0.00907	
$\ln P$	3.161	0.228	0.204	13.881	0.00000	0.373
$\ln A$	0.168	0.017	0.186	9.915	0.00006	0.613
$\ln T$	0.223	0.021	0.223	10.825	0.00004	0.733
$\ln S$	0.582	0.150	0.171	3.871	0.00826	3.385
$\ln H$	0.521	0.139	0.142	3.759	0.00941	2.469
$\ln M_1$	1.449	0.550	0.080	2.632	0.03894	1.603
$\ln M_2$	0.058	0.020	0.126	2.841	0.02951	2.590
$\ln M_3$	-0.094	0.024	-0.165	-4.271	0.00526	3.383
$\ln F$	-2.192	0.651	-0.108	-3.369	0.01507	1.780

It can be seen from Table 1 and Table 2 that the model's coefficient of determination R^2 is 0.997, close to 1, and F statistics is 165.3507052, Sig. (F statistic) = 0. The equation passes the significance test, indicating the overall fit of the model. Very high. It can be seen from Table 3 that all variables have Sig. values less than 5%, all passed the t test, and the VIF of all variables is also less than the maximum

tolerance of 10. Therefore, the model can explain the relationship between energy consumption carbon emissions and its influencing factors in China's transportation industry. The standardized regression equation is as follows:

$$\ln C = 3.161 \ln P + 0.168 \ln A + 0.223 \ln T + 0.582 \ln S + 0.521 \ln H + 1.449 \ln M_1 - 0.104 \ln M_2 + 0.058 \ln M_3 - 2.192 \ln F - 28.251$$

From the results of the regression equation, it can be seen that the influencing factors of China's transportation industry's carbon emissions in 2003-2017 are in descending order of absolute value: population size (3.161), transportation energy carbon emission factor (-2.192), petroleum product consumption. Volume ratio (1.449), transportation intensity (0.582), transportation energy intensity (0.521), transportation industry added value (0.223), per capita GDP (0.168), natural gas consumption (-0.094), coal consumption Ratio (0.058). Among them, the elasticity coefficient of population size, per capita GDP, transportation industry added value, transportation intensity, transportation energy intensity, petroleum product consumption ratio and coal consumption ratio is positive, indicating that these seven influencing factors and transportation A positive correlation between carbon emissions from energy consumption indicates that a 1% increase in population size will result in an increase of 3.161% in carbon emissions; a 1% increase in GDP per capita will result in an increase in carbon emissions by 0.168%; a 1% increase in the value added of the transportation industry will result in Carbon emissions increased by 0.223%; 1% increase in transportation intensity will lead to an increase of 0.582% in carbon emissions; 1% increase in traffic energy intensity will lead to an increase of 0.521% in carbon emissions; a 1% increase in the consumption of petroleum products will lead to carbon emissions. The increase in volume is 1.449%; a 1% increase in coal consumption will result in a 0.058% increase in carbon emissions. The coefficient of elasticity of natural gas consumption and the carbon emission factor of transportation energy are negative, indicating that it is negatively correlated with the carbon consumption of energy consumption in the transportation industry, which indicates that the consumption of natural gas increases by 1%, which will lead to carbon emissions from transportation. The volume is reduced by 0.094%; while the transportation energy carbon emission factor is increased by 1%, it will lead to a 2.192% reduction in traffic carbon emissions. The above analysis shows that the proportion of coal consumption and natural gas consumption has a very weak impact on carbon emissions, mainly because in the energy structure of the transportation industry, the consumption of petroleum products accounts for more than 83%, while coal and natural gas account for the ratio is very low, and the effect can be weak. Although the consumption of natural gas is increasing year by year, petroleum products will still be the most important energy source for transportation in a long period of time. Therefore, in the following study, the transportation energy structure is represented by the proportion of petroleum products consumption; the other influencing factors have obvious effects on the increase and decrease of carbon emissions, among which the population size, the proportion of petroleum products consumption and the carbon emission factors of transportation energy are the most significant.

4. Conclusion

Based on the STIRPAT model and the industry characteristics of China's transportation industry, this paper constructs the STIRPAT model for the development of China's transportation industry, and carries out the ridge regression analysis on the influencing factors of energy consumption carbon emissions in the transportation industry, and draws the influence degree of each influencing factor. From large to small, the population size, transportation energy structure, transportation intensity, transportation energy intensity, transportation industry added value and per capita GDP. All of the above factors are the main influencing factors of carbon emissions from energy consumption in China's transportation industry. The effects of carbon emission increase and decrease are obvious. Among them, the influence of population and energy structure is the most significant, but the proportion of natural gas consumption and coal consumption is proportional. The extent of the impact is very weak.

This paper conducts a detailed study on the factors affecting the carbon emissions of China's transportation industry, and proposes corresponding policy recommendations for the carbon emission reduction of China's transportation industry based on the influencing factors. However, due to data reasons, the analysis of provincial influence factors has not been studied in more depth, which makes it impossible to propose more detailed policy recommendations at the provincial level. Therefore, in future research, policy recommendations can be refined to the provincial level based on comprehensive and in-depth research on provincial impact factors in order to propose more practical emission reduction targets.

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