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# An empirical study on the measurement and influencing factors of carbon emission efficiency in China's transportation industry

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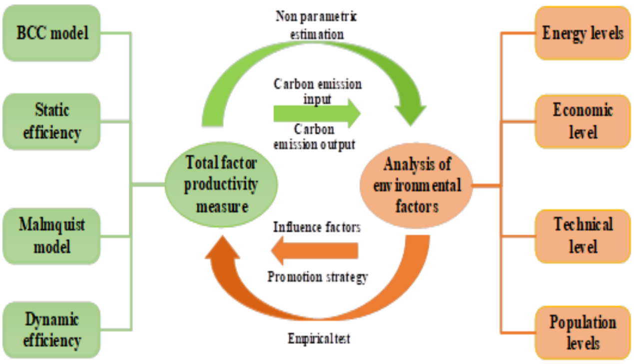
## Graphical abstract




## Abstract

The severe climate problem has forced the Chinese government to put forward the goal of "carbon peak" and "carbon neutrality", and the transportation industry is a key area of carbon emission reduction. Based on this background, this paper introduces the BCC model and the Malmquist-Luenberger index model to measure the carbon emission efficiency of China's provincial transportation industry from the static and dynamic perspectives from 2014 to 2020. At the same time, the Tobit model is used to estimate the influencing factors of carbon emission efficiency. The results show that: (1) the overall transportation carbon emission efficiency level is low. The comprehensive efficiency of 30 provinces is at [0.6634, 0.7154], which needs to be improved urgently. (2) The carbon emission efficiency of transportation is in a growing trend, and the ML index is 1.142, which is significantly higher than 1.0. In addition, the mean value of technical efficiency is 1.015, and the mean value of technological progress efficiency is 1.125. The two factors jointly affect comprehensive efficiency. (3) The carbon emission efficiency of different regions is heterogeneous. The carbon emission efficiency of East China and North China is better than that of Northeast China and South China, while the carbon emission efficiency of Northwest China and Southwest China is at the middle level in China. (4) External environmental factors, such as regional GDP, resident population and consumption level, have a significant impact on the carbon emission efficiency of transportation.

**Keywords:** Transportation industry, carbon emission efficiency, BCC model, malmquist-luenberger index, tobit model

## 1. Introduction

In recent years, global warming has become an obstacle to economic and social development. Reducing the emission of carbon dioxide and other greenhouse gases is an urgent problem for mankind to overcome. In order to overcome this global problem, the United Nations established the *Framework Convention on Climate Change* in 1922. In 2020, the Chinese government set the goal of "carbon peak" by 2030 and "carbon neutrality" by 2060. The transportation industry is a key industry in the national economy and an important source of carbon dioxide emissions. According to relevant statistics, China's carbon emissions from transportation account for 24% of the national total. With the rapid development of automobile transportation, shipping transportation, civil aviation transportation and other businesses, the transportation industry has become a field of the rapid growth of greenhouse gas emissions.

In 2019, the *Outline of Building a Powerful Country in Transportation* proposed to transform transport development from large-scale expansion to high-quality growth, and vigorously develop low-carbon and green transport. Transport carbon emission efficiency is a key indicator to measure the low carbon level of transport, which can fully reflect the technical and energy efficiency of the transport industry. Studying the carbon emission efficiency of transport is conducive to promoting the development of a low-carbon transport industry and effective measures to promote efficient emission reduction.

At present, while the transport industry is developing steadily, it is faced with problems such as decreasing input-output efficiency year by year, gradually failing operating resources, and improper formulation of relevant rules. Transport carbon emission efficiency can reflect the quality of the development of China's transport industry, and improving the total factor growth rate is an effective way to promote the productivity growth of the transport industry. In recent years, domestic and foreign experts and scholars have contributed their strength and wisdom to improve the total factor productivity of the transportation industry. Rebert and other experts and scholars established the definition of transportation productivity to measure the total factor productivity of the transportation industry, and relevant measurement methods were proposed subsequently. In the course of studying the productivity of China's road transportation industry from 2000 to 2004, Liu Yuhai and some other scientists found that the decrease in its productivity was almost caused by the lower level of technological progress.

Domestic and foreign scholars' research on carbon emission efficiency mainly has two research perspectives: total factor and single factor (Trinks A *et al.*, 2020; Hu X *et al.*, 2017). Among them, single-factor carbon emission efficiency first refers to the ratio between GDP and carbon emissions, and then this research has been based on a single factor. Although it has the advantages of simplicity and easy understanding, it has not considered the coupling of related factors (Li *et al.*, 2021; Zhou and Hong, 2018).On the basis of single-factor productivity, total factor productivity (TFP) was proposed. TFP refers to the comprehensive productivity of all factors. Compared with single-factor efficiency, TFP results are more objective and comprehensive, so it is widely used in the study of the change of economic efficiency and the evaluation of environmental quality. For example, whether government-guided funds promote the improvement of enterprise total factors was verified in China (Cheng *et al.*, 2020). The impact of digital financial inclusion development on agricultural total factor productivity has been analyzed (Ren *et al.*, 2022). An undesired SBM model has been constructed to analyze the driving factors of ecological environment by measuring the efficiency of eco-environmental planning in the Beijing-Tianjin-Hebei region from 2009 to 2018 (Sun Yu *et al.*, 2022). The analysis of productivity drivers in the ICE industry has been conducted in recent years (Gokgoz F and Guvercin M.T., 2018). The impact of increases in total factor productivity in industry, agriculture and services on global poverty has been researched (Ivanic M and Martin W, 2018). Based on the consideration of energy consumption and environmental degradation (Bampatsou C and Halkos G, 2019), the total factor productivity was decomposed to further analyze the influencing reasons of productivity. The total factor productivity of 35 NUTS-2 regions in Visegrad Group countries was estimated and its determinants were analyzed (Danska-Borsiak B, 2018).

At present, there are mainly non-parametric and parametric methods for measuring carbon emission efficiency. Non-parametric methods are generally based on data envelopment analysis (DEA). For example, Based on SBM-DEA, X Lin proposed a measurement model of new economy and carbon emissions (Lin X *et al.*, 2020; Guo *et al.*, 2022), which took energy consumption as input, GDP as expected output, and carbon emissions as undesired output, and obtained the efficiency values of each continent. Based on the three-stage SBM-DEA model and ML model, the carbon emission efficiency of 11 provinces and cities in the Yangtze River Economic Belt from 2011 to 2019 was calculated and analyzed dynamically and statically (Iftihar *et al.*, 2018). The parameter method is generally based on stochastic frontier analysis (SFA). For example, SFA was used to measure the regional carbon emission efficiency in China (Sun and Geng, 2017), and the spatial and temporal differences of regional carbon emission efficiency were further analyzed and the convergence test was conducted. The SFA model was constructed and empirical analysis was conducted to explore the relationship among carbon emissions, green total factor productivity and economic growth (Zhan and Zhang, 2016). Compared with SFA, DEA avoids the strong hypothesis bias of SFA and has a better fit for multi-output activities (Zhao *et al.*, 2022; Zhang *et al.*, 2021; Huang *et al.*, 2022). Therefore, generally speaking, DEA is more widely used. However, SFA can directly analyze the influencing factors, which can make up for the shortcomings of DEA in this aspect to a certain extent (Dong *et al.*, 2017; Niu *et al.*, 2022; Li and Zhu, 2020).

In terms of efficiency measurement of carbon emissions in the transportation industry, DEA model is mainly used (Ren *et al.*, 2020; Zhang *et al.*, 2022; Wang *et al.*, 2022), including static analysis and dynamic analysis. Among them, the static efficiency analysis includes Super-SBM and RAM models. For instance, the measurement of the total factor productivity of the transportation industry of provinces and cities in eastern China applied to the Super-SBM and drew a conclusion that the total factor productivity of the transportation industry of provinces and cities in eastern China differed greatly (Lu and Xiao, 2017). The RAM model was used to measure the economy, carbon emissions and joint efficiency of the transportation industry in 30 provinces and municipalities in China (Chen *et al.*, 2019; Peng *et al.*2019). The Super-SBM model was used to evaluate the carbon emission efficiency of the transportation sector in 30 provinces in China from 2004 to 2016, and to examine its spatial dependence and dominant drivers. Among them, ML (Malmquist Luenberger) or GML (Global Malmquist Luenberger) index models are used to study the dynamic efficiency. From the perspective of dynamic analysis alone, the GML index is generally used for measurement (Huang *et al.,* 2018; Yu *et al.*, 2022). For instance, GML index was used to analyze the total factor productivity of Chinese airlines from 2009 to 2013 and its dynamic changes. Based on the panel data of six central provinces from 2005 to 2016, GML index was applied to analyze the dynamic changes of carbon emission efficiency (Sun H *et al.*, 2019). In order to make the measurement analysis of total factor productivity more comprehensive, some scholars conducted dynamic and static comprehensive analysis (Wang and Guo, 2018). The SBM model is used to analyze the carbon emission efficiency statically, and the

ML index model is used to analyze the intertemporal dynamic change. Taking nine national central cities that play a leading role in regional development as the research subjects (Jiang *et al.*, 2020), we used the Super-SBM model and ML productivity index to measure the carbon emission efficiency of the transport industry in the study areas from 2005 to 2016 from static and dynamic perspectives (Ren *et al.*, 2022).

Based on the measurement of carbon emission efficiency, some academics also analyzed the influencing factors. Currently, panel model and Tobit regression model are mainly used to analyze the influencing factors of carbon emission efficiency in the transportation industry (Peng and Wu, 2019). Based on the measurement of the total factor productivity of China's transport industry with DEA-ML model and the performance of convergence analysis via σ convergence tests, a panel data regression analysis approach was used to analyze influential factors. The panel data model was based on the Super-SBM model to assess the energy efficiency of the transportation industry in 11 provinces with special economic zones from 2000 to 2017 and was used to analyze the influencing factors (Xu and Li, 2021). Tobit model was used to analyze the influence of important factors on transport carbon emission efficiency in 15 countries from 2003 to 2010 based on virtual frontier DEA (Cui *et al.*, 2015). Tobit model was used to analyze the key influencing factors of urban transport carbon emissions (Yang *et al.*, 2020).

In conclusion, the academic research on the total factor productivity of transportation carbon emissions has achieved certain results, which provide valuable reference significance for subsequent research. However, most of these studies ignore the important context of carbon constraints and lack research on the latest data. In addition, in terms of research methods, many papers have the problem of a single research method, and do not systematically analyze the level of transportation carbon emission efficiency from static and dynamic perspectives.

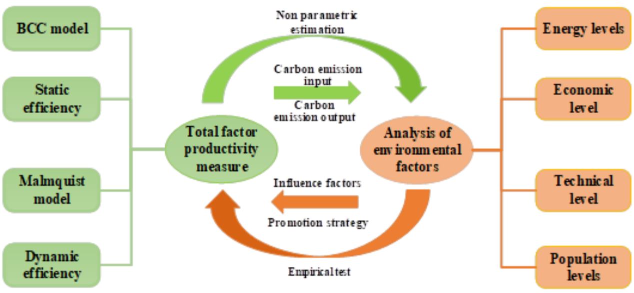



**Figure 1.** The framework and framework of the thesis research

Compared with previous studies, the possible marginal contributions of this paper are as follows: (1) A measurement model of China's transportation carbon emission efficiency based on the BCC model is constructed to assess the level of carbon emission efficiency from a static perspective; (2) Using Malmquist-Luenberger index model and its decomposition efficiency, the dynamic change of transportation carbon emission efficiency was obtained. (3) Tobit model was introduced to analyze the influencing factors of transportation carbon emission efficiency, and the effects of different factors on carbon emission efficiency were explored from an empirical perspective. The basic ideas and framework of this paper are shown in Figure 1.

## 2. Materials and methods

### *2.1. Construction of carbon emission static efficiency model based on BCC model*

Data Envelopment analysis (DEA), a method based on the concept of relative efficiency, can estimate the effectiveness of a DMU based on multiple input and output data. DEA can also be used to analyze the causes and degrees of inefficiency caused by a DMU through redundant input or insufficient output, so as to provide information for decision makers (L.Luo, 2015). It was first proposed as an important non-parametric method for assessing productivity by renowned operations research scientists Chames, Cooper and Rod in 1978 (Gong et al, 2017). DEA model was originally used by Chames to measure the efficiency of public sector and non-profit organizations, and has been widely applied to evaluate the efficiency of banks, universities, hospitals, insurance companies, manufacturing industry, service industry and many other fields. Among the DEA methods, the two most basic models are the CCR model and the BCC model, among which the input-oriented CCR model is the earliest and most widely used model (Du et al, 2022). In the first part of this paper, BCC model was selected to measure the pure technical efficiency (vrste), scale efficiency (scale), comprehensive efficiency (Crste) and returns to scale (VRS) of 30 provinces in China for 7 years, to further determine whether the input scale of each decision-making unit (DMU) was appropriate, and to adjust the direction and strength of input scale. Because when some DMUs do not operate at the optimal scale, the technical efficiency is often affected by the scale efficiency.

$$Min[\theta - \varepsilon(e^T\tau^+ + e^T\tau^-)] = V \tag{1}$$

$$s.t.\begin{cases} \sum_{j=1}^{n} \partial_j \lambda_j + \tau^- = \theta \partial_0 \\ \sum_{j=1}^{n} \rho_j \lambda_j - \tau^+ = \rho_0 \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \geq 0; j = 1, \ldots, n \\ \tau^+ \geq 0, \tau^- \geq 0 \end{cases}$$

Where ε> 0 is a non-Archimedean infinitesimal. When the pure technical efficiency is 1, it means that the decision making unit is technically effective. When the scale efficiency is 1, it means that the decision-making unit is scale effective. When the carbon emission efficiency of a decision making unit is both technology effective and scale effective, it is called an effective unit. When only one of them is valid, the unit is said to be weakly valid; when neither is achieved, the unit is said to be non-valid.

### *2.2. Carbon emission efficiency model construction based on Malmquist-luenberger model*

The carbon emission efficiency of the transportation industry calculated by the BCC model is relative to the static efficiency of the single-year frontier, which cannot completely and truly reflect the intertemporal change of the carbon emission efficiency of the transportation industry. In order to better analyze the dynamic characteristics of carbon emission efficiency in China's transport industry, we measure the dynamic level of carbon emission efficiency of the transportation industry in 30 Chinese provinces with the help of the Malmquist-luenberger index proposed by Chung, Caves and other scientists, which takes into account the undesired output. With reference to the research of Shao and Wang (2020), an output-based Malmquist-luenberger productivity index model from period t to period t+1 can be obtained:

$$ML_t^{t+1} = \left\{ \frac{\left[1 + D_0^t(x^t, y^t, b^t; g^t)\right]}{\left[1 + D_0^t(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})\right]} \times \frac{\left[1 + D_0^{t+1}(x^t, y^t, b^t; g^t)\right]}{\left[1 + D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})\right]} \right\}^{\frac{1}{2}}$$

In the above formula, *x, y* respectively represent the input and output variables of the decision-making unit, and *b* represents the undesired output of the DEA model, and *g* represents the slack variables of different input-output factors. $D_0^t(x^t, y^t, b^t; g^t)$ and $D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})$ represent the distance function in period t and period t+1 respectively. At the same time, $D_0^t(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})$ represents the hybrid distance function with the technology of period t as the reference set for period t+1. $D_0^{t+1}(x^t, y^t, b^t; g^t)$ represents the hybrid distance function with the technology of period t+1 as the reference set for period t. According to this definition, if the value of ML index is greater than 1, it means that the carbon emission efficiency is effective. Otherwise, if the ML index is less than 1, it indicates that the carbon emission efficiency of transportation is insufficient.

*2.3. Influencing factor model construction of carbon emission efficiency based on Tobit model*

Considering the carbon emission efficiency of China's transportation obtained by using BCC model and Malmquist-luenberger index model is greater than 1.0, it has the characteristics of truncating. If the traditional least squares estimation method is used for the estimation of influencing factors, wrong model assumptions may occur, so the obtained results will have obvious bias. Tobit model can be used to solve this problem effectively. Tobit model was proposed by Tobin (1958), which can estimate continuous variables and dummy variables by maximum likelihood estimation. In order to further explore the influencing factors of transportation carbon emission efficiency, the following Tobit model was constructed by referring to Tobin's model:

$$Y_{it} = \begin{cases} Y_{it}^* = \sum_{i=1}^{n} \alpha_t X_{it} + \alpha_0 + \varepsilon_{it}, Y_{it}^* > 0 \\ 0, Y_{it}^* \le 0 \end{cases}$$

In the above formula, $Y_{it}$, $X_{it}$ represent the explained variable and explanatory variable respectively; $\alpha_0$ represents the constant term; $\alpha_t$ represents the coefficient to be estimated. *i*= 1, 2,…,*n* represents the number of decision-making units, that is, the number of research samples; $\varepsilon_{it} \sim (0, \sigma^2)$ represents the stochastic error term.

*2.4. Index selection and data sources*

*2.4.1. Input-output variable selection for DEA model*

According to the traditional production function theory, considering that although the transportation industry itself is a capital-intensive industry, it also requires a large amount of labor, such as loading, unloading and handling operations at stations, storage, passenger service, cruise service and freight intermediary, and the construction of transportation infrastructure is more labor-intensive production and services. Therefore, this paper selects four input indicators, including passenger volume by province, the number of employees in the transportation industry, proportion of transportation land in each province, and energy consumption in the transportation industry. Two output indicators are selected, namely the added value of the transportation industry as the expected output and the carbon emissions of the transportation industry as the non-expected output (Table 1). At the same time, since ML model and BCC require all indicators to be positive, the data on carbon emissions from the transportation sector, which is a non-expected output indicator, was standardized (Han and Fu, 2019).

*2.4.2. Variable selection of Tobit model*

Explained variables: The comprehensive efficiency, pure technical efficiency and scale efficiency of the transportation industry derived from the former BCC model were selected as the explained variables.

Explanatory variables: At present, most studies on the measurement of total factor productivity of transport carbon emissions focus on the influencing factors and measurement of carbon emissions. T.wang (2022) and some other scientists believed that the domestic economic development level, energy utilization efficiency (vehicle technology level), the number and scale of freight transportation enterprises, and the industrial development level are the main factors affecting the carbon emissions of freight transportation in China. Therefore, on the basis of previous studies, this paper selected regional GDP, tertiary industry proportion and consumption level as environmental variables to analyze and study the carbon emission efficiency of transportation in each province based on the characteristics of transportation industry.

*2.4.3. Data sources*

This paper uses methodology of empirical research to measure the carbon emission efficiency of provincial transportation in China, and analyzes the factors affecting the carbon emission efficiency. Considering the availability, scientificity and rationality of the data, the research data in this paper mainly come from *China Statistical Yearbook*, *China Energy Statistical Yearbook* and other channels.

From the descriptive statistics of the main variables in the construction of the model in this paper (see Table 2), it can be seen that the proportion of transportation land is generally low and the polarization is significant, while the energy consumption is in a state of high. Therefore, the green and sustainable development of transportation industry in China is still facing severe challenges. There is clear regional heterogeneity in the value added and GDP of the transport industry.

## 3. Research results

### *3.1. Measurement results of carbon emission static efficiency in China's transportation industry*

Based on the input-output data of each year from 2014 to 2020, the DEA-BCC model was selected and the annual carbon emission efficiency of the transportation industry in 30 provinces of China and its decomposition terms were obtained by using DEAP2.1 software. The decomposition terms include pure technical efficiency and scale efficiency. In order to more intuitively show and compare the carbon emission efficiency of the transportation industry in 30 provinces of China from 2014 to 2020, we use Origin software to plot the results to show the trend of each indicator (Figure 2), and ArcGIS software was used to draw the map (Figure 3). At the same time, the average carbon emission efficiency of the transportation industry by provinces and cities (Table 3) and by regions (Table 4) were calculated.

#### *3.1.1. Analysis of changes in overall efficiency*

This paper presents an overall analysis of the changes of BCC efficiency index in the transportation industry of 30 provinces in China from 2014 to 2020 (Figure 2). Carbon emission scale efficiency of China's transportation industry increased year by year from 2014 to 2017, while the pure technical efficiency and comprehensive efficiency were in a state of fluctuation. Since 2017, the three efficiencies have increased year by year, with the largest increase from 2017 to 2018.From the BCC index value in Figure 2, it is not difficult to find that the slump in the comprehensive efficiency of carbon emissions in China's transportation industry is mainly limited by the scale efficiency. For example, the bottom seven rankings of comprehensive efficiency, Beijing, Heilongjiang, Liaoning, Chongqing, Shaanxi, Sichuan and Gansu, except for Liaoning, have average scale efficiency values below 0.7, and their returns to scale have been increasing during the seven years. Therefore, controlling the number of traditional fuel vehicles and gradually expanding the scale of new energy vehicles are effective ways to improve the carbon emission efficiency.

**Table 1.** Indicator selection

| Input/output indicators | Specific indicator | units |
|---|---|---|
| Input indicators | Passenger volume by province | 10,000 people |
| | Transportation industry employees | 10,000 people |
| | Percentage of transport land | % |
| | Energy consumption | million tons of standard coal |
| Output indicators | Transportation Carbon Emissions | million tons of $CO_2$ |
| | Value added in transportation industry | billion |

**Table 2.** Statistical description of main variables

| Variable sample | number | mean | standard deviation | minimum value | maximum value |
|---|---|---|---|---|---|
| Passenger volume by province | 210 | 57486.5 | 39728.93 | 3559.583 | 180789 |
| Labor force | 210 | 27.78726 | 16.91788 | 2.2935 | 86.41 |
| Transportation land share | 210 | 0.013876 | 0.011938 | 0.00078 | 0.06368 |
| Energy consumption | 210 | 1394.35 | 970.129191 | 127.89 | 4370.21 |
| Carbon emissions of transportation | 210 | 0.687124 | 0.217834 | 0 | 1 |
| The added value of transportation | 210 | 1229.005 | 860.082 | 81.7 | 3636.06 |
| GDP | 210 | 28272.83 | 22135.99 | 2303.32 | 110760.9 |
| Proportion of tertiary industry | 210 | 50.14086 | 8.849359 | 29.7 | 83.8 |
| Permanent resident population | 210 | 4638.09 | 2883.247 | 576 | 12624 |
| Consumption level | 210 | 21216.31 | 28427.81 | 9303.4 | 312947 |

#### *3.1.2. Comparison carbon emission efficiency of transportation in different provinces*

Figure 2 reflects the average and ranking of the comprehensive efficiency of 30 provinces in China from 2014 to 2020. Among them, the estimated value of the comprehensive efficiency of transportation carbon emission in Qinghai, Ningxia, Inner Mongolia Autonomous Region and Hebei Province is 1, indicating that the inputs and outputs of these four provinces are comprehensive and effective, that is, they meet the requirements of both technology and scale. It further indicates that in recent years, the carbon emission efficiency of the transportation industry in these regions has tended to be the optimum, and the efficiency of resource allocation and utilization has been significantly improved, achieving the state of obtaining the highest output with the existing investment.

The average comprehensive efficiency of Shandong, Jilin, Anhui, Hubei and Shanghai ranged from 0.8 to 1 in the seven years, among which the comprehensive efficiency of Anhui, Hubei and Shanghai was more than 0.9, indicating the comprehensive efficiency is relatively effective, while the comprehensive efficiency of Shandong and Jilin is significantly less than 1, indicating non-DEA effective state. The pure technical efficiency of Shanghai and Shandong is both 1, so the comprehensive efficiency is not 1 because of the impact of scale efficiency, which indicates that the management technology level of these two regions is approaching the optimum, but the investment scale is not yet optimal, and the investment scale should be further improved. The scale efficiency of Jilin, Anhui and Hubei provinces is greater than 0.95, and the comprehensive efficiency mainly encumbered by pure technical efficiency. Among them, the pure technical efficiency of Hubei province is 0.567, which is located in the bottom of the pure technology ranking of our provinces. Therefore, these regions should focus on improving pure technical efficiency by optimizing the business environment, upgrading management and technical indicators, and ensuring scientific decision-making, while appropriately upgrading the scale of regional investment to accelerate the growth of scale efficiency. The regions with the average comprehensive efficiency below 0.5 are Beijing, Heilongjiang, Liaoning, Chongqing, Shaanxi, Sichuan and Gansu. The pure technical efficiency of Liaoning and Heilongjiang is 1, while the pure technical efficiency of the other four provinces except Beijing is between 0.8 and 0.94, and the pure technical efficiency of Beijing is 0.796. Therefore, the comprehensive efficiency of these regions has not reached the ideal state due to the influence of insufficient investment scale. These regions should strengthen the management technology level under the active and effective guidance and decision-making of the regional government, so as to promote the improvement of input-output efficiency. However, the comprehensive carbon emission efficiency of the transportation industry in economically developed Beijing is only 0.3078, which is far lower than that in Qinghai, Ningxia and Inner Mongolia Autonomous Region. The reason is that although the transportation is developed in Beijing, the automobile pollution problem caused by the big city disease is serious and the carbon emission efficiency is insufficient. In contrast, Qinghai, Ningxia and Inner Mongolia Autonomous Region have a lower population density and a lower degree of industrialization, so the carbon emissions from automobiles and other transportation are low.

### *3.1.3. Comparison of transport carbon emission efficiency in different regions*

In general, the whole country is divided into six regions according to the geographical location: East China, North China, Northwest China, Southwest China, Northeast China and South China. According to the results, the comprehensive efficiency of all regions shows an overall upward trend. There was a break point in 2017, and in the following three years, the comprehensive efficiency of carbon emission in all regions had a significant improvement, and the comprehensive efficiency of East China, Southwest China, and South China all had a significant continuous increase. There were significant differences in comprehensive efficiency among regions, especially the North-South gap. North China and Northwest China remained at the forefront in the past seven years, and formed a significant gap with Southwest China and South China. East China and Northeast China, which are both eastern regions, showed a polarization. The comprehensive efficiency of East China has been the first in seven years, and has developed in a good trend. However, the comprehensive efficiency of Northeast China fluctuated around 0.549 in recent years, and remained at a low level for a long time.

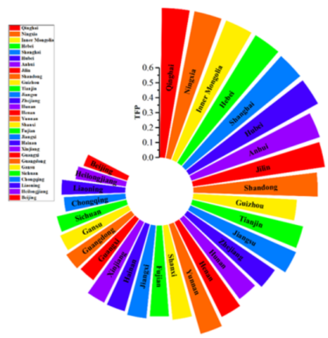


**Figure 2.** Carbon emission rate of transportation by province in China

**Table 3.** Average comprehensive efficiency ranking of provinces from 2014 to 2020

| Region | The comprehensive efficiency | Ranking | Region | The comprehensive efficiency | Ranking |
|---|---|---|---|---|---|
| Qinghai | 1 | 1 | Yunnan | 0.762429 | 16 |
| Ningxia | 1 | 1 | Shanxi | 0.633371 | 17 |
| Inner Mongolia Autonomous Region | 1 | 1 | Fujian | 0.607114 | 18 |
| Hebei | 1 | 1 | Jiangxi | 0.622971 | 19 |
| Shanghai | 0.990171 | 5 | Hainan | 0.604371 | 20 |
| Hubei | 0.984914 | 6 | Xinjiang | 0.601143 | 21 |
| Anhui | 0.905486 | 7 | Guangxi | 0.510457 | 22 |
| Jilin | 0.891257 | 8 | Guangdong | 0.523971 | 23 |
| Shandong | 0.831886 | 9 | Gansu | 0.497629 | 24 |
| Guizhou | 0.6928 | 10 | Sichuan | 0.477057 | 25 |
| Tianjin | 0.7608 | 11 | Shaanxi | 0.4738 | 26 |
| Jiangsu | 0.771429 | 12 | Chongqing | 0.412086 | 27 |
| Zhejiang | 0.705457 | 13 | Liaoning | 0.426743 | 28 |
| Hunan | 0.667914 | 14 | Heilongjiang | 0.339371 | 29 |
| Henan | 0.707571 | 15 | Beijing | 0.3078 | 30 |

As can be seen from Table 4, the carbon emission efficiency of East China, North China and Northwest China is relatively considerable under the influence of scale efficiency in recent years, while the pure technical efficiency is relatively low. Therefore, these three regions should improve the management and technology level of enterprises related to transportation industry and further improve the allocation structure of input factors. The provinces in Southwest China, Northeast China and South China can make full use of technological factors to maximize output, but they should further expand the scale of enterprises related to transportation industry.

### *3.2. Results of Dynamic Measurement of Total Factor Production Efficiency of Carbon Emissions in China's Transportation Industry*

MAXDEA software was used to calculate the carbon emission ML index of transportation industry in 30 provinces in China from 2014 to 2020, and the 30 provinces and cities were divided into seven regions according to their geographical locations.

#### *3.2.1. Results of changes in the overall carbon emission efficiency of the transportation industry*

As shown in Table 5, during the study period, the annual average value of carbon emission ML index of China's transportation industry reached 1.142, with an overall increasing level, and the total factor productivity rises steadily, and the total factor productivity is greater than 1 every year. The mean value of technical efficiency is 1.015, and the average value of technological progress efficiency is 1.125. It can be seen that the improvement of total factor productivity benefits from the joint improvement of the two factors. However, except for 2017-2018, technical progress was higher than technical efficiency, indicating that technical progress is the main factor driving the improvement of total factor productivity. From the perspective of pure technical efficiency and scale efficiency of technical efficiency decomposition, although the annual average value of both is greater than or equal to 1, the annual average value of pure technical efficiency is only 1, indicating that the pure technical efficiency of carbon emissions in transportation industry has not been significantly improved during the study period, and the pure technical efficiency needs to be improved.

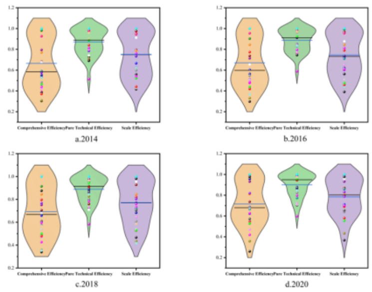


**Figure 3.** Changes of carbon emission BCC efficiency index of China's transportation industry

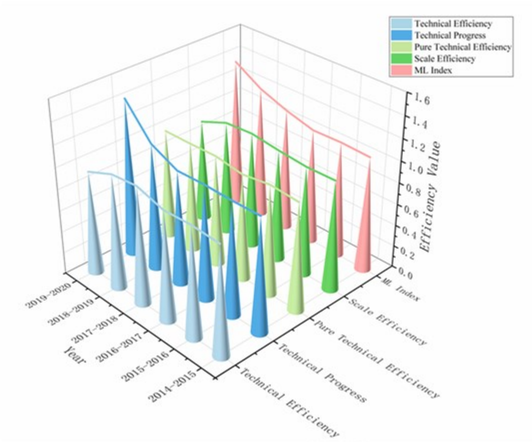



**Figure4.** Changes of carbon emission ML efficiency index of China's transportation industry

**Table 4.** Efficiency rankings by region (by geographic location), 2014-2020

| | Ranking | Region | | Ranking | Region | | Ranking | Region |
|---|---|---|---|---|---|---|---|---|
| The comprehensive efficiency | 1 | East | Pure technical efficiency | 1 | Northeast | The scale efficiency | 1 | East |
| | 2 | North | | 2 | East | | 2 | North |
| | 3 | Northwest | | 3 | Southwest | | 3 | Northwest |
| | 4 | Southwest | | 4 | Northwest | | 4 | Northeast |
| | 5 | Northeast | | 5 | North | | 5 | Southwest |
| | 6 | South | | 6 | South | | 6 | South |

**Table 5.** Statistical table of average ML index from 2014 to 2020

| | Technical efficiency | Advances in technology | Pure technical efficiency | The scale efficiency | Total factor productivity |
|---|---|---|---|---|---|
| 2014-2015. | 1.001 | 1.052 | 0.992 | 1.01 | 1.053 |
| 2015-2016. | 1.017 | 1.047 | 1.012 | 1.005 | 1.065 |
| 2016-2017. | 1.004 | 1.054 | 0.975 | 1.029 | 1.058 |
| 2017-2018. | 1.078 | 1.045 | 1.014 | 1.062 | 1.126 |
| 2018-2019. | 1.051 | 1.159 | 1.006 | 1.045 | 1.217 |
| 2019-2020. | 0.946 | 1.443 | 1.004 | 0.942 | 1.365 |
| average | 1.015 | 1.125 | 1.000 | 1.015 | 1.142 |

It can be seen from Figure 4 that during the study period, the pure technical efficiency index was 0.992 and 0.975 in 2014-2015 and 2016-2017, respectively, reflecting that pure technical efficiency hindered the growth of technical efficiency. In other years, the pure technical efficiency index and scale efficiency index were both greater than 1 and showed an upward trend. Technical efficiency improvs in all years except 2019-2020, while technical progress efficiency stays on the rise and plays a key role in driving the rise of total factor productivity. Since technical progress was improved during the period, and the degree of improvement is basically on the rise, and technical efficiency is also improved during the period except for 2019-2020, the ML index is elevated to a greater extent. It is found that, in different spatial and temporal distributions, the overall transportation industry in China have different degrees of emphasis on the improvement of emission technical efficiency and technological progress, and the coordinated development of the two is conducive to the improvement of total factor productivity. It is worth mentioning that the improvement degree of technical progress efficiency is significantly higher than that of technical efficiency, so more emphasis can be placed on technical efficiency in order to pursue more significant improvements of total factor productivity.

### *3.2.2. Results of carbon emission efficiency of transport industry by province*

It can be seen from Table 6 that the total factor productivity of the other 29 provinces except Guizhou Province is all greater than 1, indicating that under the carbon constraint, China's transportation carbon emission efficiency has improved in the past seven years, and the low-carbon economy has developed significantly. From the perspective of decomposition efficiency, the technical efficiency index of Beijing, Tianjin, Jilin and other regions decreased, and the improvement of TFP was due to the technical progress of transportation industry. The technical progress coefficient decreased in Jiangxi, Sichuan, and Shaanxi, and the total factor productivity increased thanks to the technical efficiency of the transportation industry. In Hebei, Shanxi and other regions, the technical efficiency index and technical progress index both increased. It can be seen that the increase of TFP in these provinces is the result of the joint efforts of technical efficiency and technological progress.

**Table 6.** Statistical table of regional average ML index

| Region | Technical efficiency | Advances in technology | Pure technical efficiency | The scale efficiency | Total factor productivity |
|---|---|---|---|---|---|
| Beijing | 0.963 | 1.066 | 0.982 | 0.980 | 1.026 |
| Tianjin | 0.911 | 1.152 | 0.997 | 0.913 | 1.049 |
| Hebei | 1.000 | 1.085 | 1.000 | 1.000 | 1.085 |
| Shanxi | 1.032 | 1.124 | 1.007 | 1.025 | 1.160 |
| Inner Mongolia | 1.000 | 1.108 | 1.000 | 1.000 | 1.108 |
| Liaoning | 1.013 | 1.023 | 0.996 | 1.017 | 1.036 |
| Jilin | 0.993 | 1.020 | 1.012 | 0.981 | 1.013 |
| Heilongjiang | 0.981 | 1.169 | 1.012 | 0.970 | 1.147 |
| Shanghai | 0.964 | 1.195 | 1.000 | 0.964 | 1.151 |
| Jiangsu | 1.042 | 1.040 | 1.000 | 1.042 | 1.084 |
| Zhejiang | 1.024 | 1.039 | 1.019 | 1.005 | 1.065 |
| Anhui | 1.044 | 1.040 | 1.003 | 1.040 | 1.086 |
| Fujian | 1.023 | 1.060 | 0.985 | 1.039 | 1.084 |
| Jiangxi | 1.054 | 0.982 | 0.991 | 1.063 | 1.035 |
| Shandong | 1.009 | 1.124 | 1.004 | 1.005 | 1.135 |
| Henan | 1.064 | 1.003 | 1.030 | 1.033 | 1.067 |
| Hubei | 1.005 | 1.036 | 1.004 | 1.002 | 1.042 |
| Hunan | 1.002 | 1.024 | 0.981 | 1.021 | 1.026 |
| Guangdong | 1.040 | 1.029 | 0.991 | 1.050 | 1.071 |
| Guangxi | 1.016 | 1.027 | 0.995 | 1.021 | 1.043 |
| Hainan | 1.039 | 1.012 | 1.001 | 1.037 | 1.051 |
| Chongqing | 1.006 | 1.024 | 0.994 | 1.012 | 1.030 |
| Sichuan | 1.029 | 0.983 | 0.974 | 1.056 | 1.011 |
| Guizhou | 0.895 | 1.033 | 0.978 | 0.915 | 0.924 |
| Yunnan | 1.225 | 1.013 | 1.049 | 1.168 | 1.241 |
| Shaanxi | 1.085 | 0.992 | 1.013 | 1.071 | 1.076 |
| Gansu | 1.030 | 1.000 | 1.008 | 1.022 | 1.030 |
| Qinghai | 1.000 | 2.198 | 1.000 | 1.000 | 2.198 |
| Ningxia | 1.000 | 3.446 | 1.000 | 1.000 | 3.446 |
| Xinjiang | 1.007 | 1.200 | 0.989 | 1.019 | 1.209 |
| Northeast | 0.997 | 1.080 | 1.005 | 0.992 | 1.076 |
| East | 1.004 | 1.080 | 0.998 | 1.006 | 1.083 |
| The central region | 1.023 | 1.049 | 0.998 | 1.025 | 1.072 |
| West | 1.029 | 1.392 | 1.000 | 1.028 | 1.421 |
| Mean | 1.015 | 1.125 | 1.000 | 1.015 | 1.142 |

### *3.3. Analysis results of influencing factors of total factor productivity of carbon emissions in China's transportation industry*

#### *3.3.1. Likelihood ratio test of Tobit model data*

First, the overall validity of the Tobit model was analyzed. Table 7 shows the Censor data analysis of the samples. According to the results, the data are complete and there is no left-right censored data. Table 8 shows the results of the Tobit regression model likelihood ratio test. It can be seen from Table 8 that the original hypothesis of the model test here is: the quality of the model is the same when the two explanatory variables (land use ratio, tertiary industry ratio, resident population, consumption level) are included; Here, the p-value is less than 0.05, which indicates that the original hypothesis is rejected, that is, the explanatory variables put into the model are valid and the model construction is meaningful. If AIC or BIC values can be used to compare multiple models, a smaller AIC or BIC value means that the model is relatively better constructed. According to the results, AIC or BIC values were -29.653 and -12.917, respectively, which are both less than 0, indicating that the model is well constructed.

**Table 7.** Summary of censor data samples

| Item | The total sample | Data censored (Uncensored) | Left-censored data | The Right to delete loss (Right - censored) |
|---|---|---|---|---|
| Number | 210 | 210 | 0 | 0 |
| Proportion | 100% | 100.00% | 0.00% | 0.00% |

**Table 8.** Likelihood ratio tests for Tobit regression models

| Model | -2 times the log-likelihood | Chi-square value | *df* | *p* | AIC values | BIC values |
|---|---|---|---|---|---|---|
| Only intercept | 23.838 | | | | | |
| The final model | 39.653 | 15.815 | 4 | 0.003 | -29.653 | -12.917 |

#### *3.3.2. Estimation results based on Tobit model*

According to the regression results in Table 9, the resident population and consumption level have obvious effects on the comprehensive efficiency of transport carbon emissions, indicating that these factors have a significant impact on the carbon emission efficiency of the transport industry. Generally speaking, the higher the population density, the greater the demand for transportation and the more frequent the use of vehicles and other means of transportation, which will increase the carbon emission of transportation. Similarly, the higher the consumption level, the more residents will buy family cars, which will lead to the increase of urban transportation carbon emissions, thus affecting the transportation carbon emission efficiency.

The proportion of land use can reflect the construction quality of transportation infrastructure. Generally, the more perfect the transportation infrastructure is, the more conducive to improving the transportation carbon emission efficiency. From the results, the regression coefficient is 0.016 and the p-value is 0.021, which is significant at 5% level. Therefore, it can also be considered that the proportion of transportation land has a significant positive impact on transportation carbon emission efficiency. Similarly, the ratio of the tertiary industry has a negative impact on the carbon emission efficiency of transportation.

In conclusion, in order to improve the carbon emission efficiency of transportation, it is necessary to strengthen the construction of transportation infrastructure, improve the efficiency of transportation operation, and avoid the waste of energy consumption caused by traffic congestion. At the same time, it is necessary to reduce population density and speed up urbanization construction. For example, in places with high population density, such as Beijing, it will be beneficial to improve the efficiency of transportation carbon emissions by freeing up Beijing's non-capital functions. Finally, as the consumption ability of residents increases, it will help guide residents to consume reasonably and effectively, giving priority to the choice of new green transportation tools such as new energy vehicles. The improvement of transport carbon emission efficiency requires the optimal allocation of multi-factor combinations. Through the improvement of key factors, the transport carbon emission efficiency can be greatly improved.

## 4. Research and discussion

### *4.1. Comparison of transportation carbon emission efficiency in different years*

This paper comprehensively uses the BCC model to measure the carbon emission efficiency of China's transportation, and plots the distribution of comprehensive efficiency, scale efficiency and pure technical efficiency from 2014 to 2020, as shown in Figure 5.

From the calculation results, it can be seen that the change curves of comprehensive efficiency, scale efficiency and pure technical efficiency of China's transportation carbon emission show a trend of increasing, then decreasing and then increasing during 2014-2020. With 2017 being the inflection point, which is approximately a "U-shaped" change. This indicates that, with the continuous optimization of production factors and the rational allocation of resources, the carbon emission efficiency of China's transportation keeps growing. Meanwhile, from 2014 to 2020, the comprehensive efficiency values of East China, North China and Northwest China are all greater than 0.65. This indicates that the carbon emission efficiency of transportation in these regions is higher, and the degree of resource redundancy is lower. The carbon emission efficiency of transportation in Southwest, Northeast, and

South China is less than 0.65, which indicates that there is a high degree of factor redundancy in these regions and there is a large room for improvement. In particular, the efficiency value in 2017 is at the lowest level.

**Table 9.** Summary of Tobit regression analysis results

| Item | Regression coefficient | Standard error | Z value | P values | 95% CI |
|---|---|---|---|---|---|
| Intercept | 0.987 | 0.095 | 10.437 | 0 | 0.802 ~ 1.172 |
| Proportion of land use | 0.016 | 0.007 | 2.312 | 0.021 | 0.002 ~ 0.029 |
| Proportion of tertiary industry | -0.006 | 0.002 | -3.449 | 0.061 | -0.010 ~ -0.003 |
| Population of permanent residents | -0.0013 | 0.001 | -3.071 | 0.004 | 0.000 ~ 0.000 |
| Level of consumption | -0.0026 | 0.003 | 3.556 | 0.008 | 0.000 ~ 0.000 |
| Log (Sigma) | -1.513 | 0.049 | -31.014 | 0 | -1.609 ~ -1.418 |
| McFadden$R^2$ | -0.663 | | | | |
| *Dependent variable: overall efficiency* | | | | | |

From 2014 to 2015, the scale efficiency of transportation carbon emissions shows rapid growth, with the largest increase in North China. From 2015 to 2020, the scale efficiency of East China, Southwest China and North China shows a small range of variation and is generally stable. From 2014 to 2020, the pure technical efficiency of the six regions shows a "U-shaped" or inverted "U-shaped" trend. The changes in Northwest China and East China are more consistent, decreasing first, then increasing, then decreasing and then increasing again. This indicates that the carbon emission efficiency of transportation in China changes significantly from 2014 to 2020, and there are many factors affecting the efficiency, which may be related to the uncertain external environment.

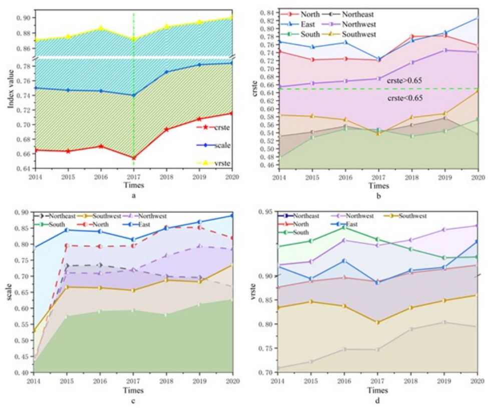


**Figure 5.** Changes of transportation carbon emission efficiency based on BCC model

*4.2. Comparison of ML index of transportation carbon emission in different provinces*

In order to further compare the regional heterogeneity of transportation carbon emission efficiency in China, a map from 2014 to 2020 was drawn with the help of ArcGIS software, as shown in Figure 6. It can be seen from Figure 6 that the carbon emission ML index of Qinghai Province, Henan Province and Chongqing Municipality is lower than 0.732 during 2014-2015, which is at a low level. The ML indexes of Ningxia, Shanxi, Shandong and Guangdong are greater than 1.0, and the change is fast. From 2015 to 2016, the ML indexes of transportation carbon emission in Qinghai, Inner Mongolia, Gansu and Ningxia are lower than 0.7, indicating significant input redundancy. The ML indexes of Liaoning, Beijing, Hebei, Shanxi, Sichuan and Guangxi are greater than 1.0, showing rapid efficiency growth. From 2016 to 2017, the ML indexes of Shanxi, Hebei and Liaoning are less than 0.56, which is at the lowest level, which related to the severe environmental pollution in these regions.

Similarly, the changes of ML index during 2017-2018, 2018-2019 and 2019-2020 can be analyzed. During 2019-2020, the ML indexes of transportation carbon emissions in China are mostly greater than 1.0. Among them, the ML indexes of Xinjiang, Inner Mongolia, Heilongjiang, Beijing, Shandong and Hebei are greater than 1.2, indicating that these regions have made significant achievements in improving transportation carbon emission efficiency. Therefore, from the above analysis, it can be seen that the transport carbon emission efficiency in China presents significant temporal heterogeneity and regional heterogeneity.

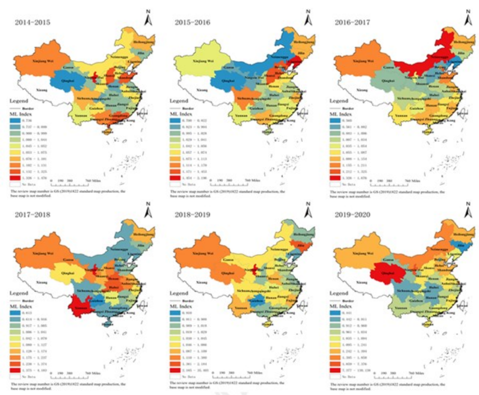


**Figure 6.** ML efficiency Index of China's provincial transport industry from 2014 to 2020

*4.3. Discussion on dynamic efficiency of carbon emissions in Central China*

With a land area of 1.028 million square kilometers and a permanent population of about 368 million, central China is an important region for economic development. The central region mainly includes the six neighboring provinces of Shanxi, Henan, Anhui, Hubei, Jiangxi and Hunan. With the promotion of the strategy of rising central China, carbon emissions in the central region is growing rapidly. Therefore, it is necessary to specifically study the carbon emission efficiency of transportation in the central region. This paper plots the changes in technical efficiency of the six central provinces from 2014 to 2015, 2017 to 2018, and 2019 to 2020, as shown in Figure 7.

From Figure 7, it can be seen that the technical efficiency of the six central provinces increased and decreased during 2014-2015, among which Shanxi showed the largest increase and Henan showed the largest decrease. From 2017 to 2018, the technical efficiency of the six provinces in central China all increased, among which, Henan technical efficiency from the maximum decline during 2014-2015 to the maximum rise today. The technical efficiency of Hubei province tended to be flat, with the smallest increase. From 2019 to 2020, the technical efficiency of the six central provinces also increased and decreased. Among them, Anhui Province shows the largest increase, while Shanxi Province shows the lowest decline.

It can be seen that the changes of technical efficiency in the six central provinces are not stable and do not maintain the good momentum of medium-term development. From the perspective of technological progress, from 2014 to 2015, Shanxi Province showed the largest increase in technological progress, while Hubei Province showed the largest decline. From 2017 to 2018, the technological progress in Hubei Province increased the most, while the technological progress in Henan Province decreased the most. From 2019 to 2020, the technological progress in Shanxi Province increased the most, while the technological progress in Hubei Province decreased the most. During the three years, all the six provinces had rises and falls, and did not achieve technical progress well. Therefore, the improvement of the technical efficiency of the six provinces in central China needs to be strengthened. At the same time, it is urgent to strengthen the development of technical progress.

### *4.4. Analysis of influencing factors of pure technical efficiency of transportation carbon emission*

As can be seen from Table 10, the proportion of land use, GDP, proportion of tertiary industry, resident population and consumption level are taken as explanatory variables, and the pure technical efficiency is taken as the explained variable for Tobit regression analysis. The final specific analysis shows that: The regression coefficient value of land use ratio is 0.010, showing a significance of 0.01 level (z=2.818, p=0.005<0.01), which means that land use ratio will have a significant positive impact on pure technical efficiency. The regression coefficient value of GDP was 0.000, and shows a significance at 0.01 level (z=2.766, p=0.006<0.01), indicating that GDP would have a significant positive impact on pure technical efficiency. The regression coefficient value of the proportion of the tertiary industry was -0.003, and shows a significance of 0.01 level (z=-3.133, p=0.002<0.01), indicating that the proportion of the tertiary industry will have a significant negative impact on pure technical efficiency. The regression coefficient value of the permanent resident population is -0.000, and shows a significance of 0.05 level (z=-2.425, p=0.015<0.05), which means that the permanent resident population will have a significant negative impact on the pure technical efficiency. The regression coefficient value of consumption level is -0.000, but it does not show significance (z=-0.489, p=0.625>0.05), which means that consumption level does not have an impact on pure technical efficiency.

The summary analysis shows that: the proportion of land use and GDP will have a significant positive impact on pure technical efficiency, and the proportion of tertiary industry and permanent population will have a significant negative impact on pure technical efficiency. However, consumption level does not have an impact on pure technical efficiency. In a similar analysis, scale efficiency can be taken as the dependent variable, and the relevant results are shown in Table 11, which will not be described in detail due to space limitation.

**Table 10.** Summary of Tobit regression analysis results (pure technical efficiency)

| Item | Regression coefficient | Standard error | *Z value* | *P values* | 95% CI |
|---|---|---|---|---|---|
| Intercept | 1.018 | 0.048 | 21.021 | 0 | 0.923 ~ 1.113 |
| Proportion of land use | 0.01 | 0.003 | 2.818 | 0.005 | 0.003 ~ 0.016 |
| GDP | 0 | 0 | 2.766 | 0.006 | 0.000 ~ 0.000 |
| Proportion of tertiary industry | -0.003 | 0.001 | -3.133 | 0.002 | -0.005 ~ -0.001 |
| Permanent residents | 0 | 0 | -2.425 | 0.015 | -0.000 ~ -0.000 |
| Level of consumption | 0 | 0 | -0.489 | 0.625 | -0.000 ~ 0.000 |
| Log (Sigma) | -2.215 | 0.049 | -45.384 | 0 | -2.310 ~ -2.119 |

*Dependent variable: pure technical efficiency*

**Table 11.** Summary of Tobit regression analysis results (scale efficiency)

| Item | Regression coefficient | Standard error | *Z value* | *P value* | 95% CI |
|---|---|---|---|---|---|
| Intercept | 1.081 | 0.085 | 12.721 | 0 | 0.914 ~ 1.247 |
| Proportion of land use | 0.007 | 0.006 | 1.211 | 0.226 | -0.004 ~ 0.019 |
| GDP | 0 | 0 | 1.804 | 0.071 | -0.000 ~ 0.000 |
| Proportion of tertiary industry | -0.006 | 0.002 | -3.869 | 0 | -0.009 ~ -0.003 |
| Permanent residents | 0 | 0 | -2.036 | 0.042 | -0.000 ~ -0.000 |
| Level of consumption | 0 | 0 | -0.159 | 0.874 | -0.000 ~ 0.000 |
| Log (Sigma) | -1.652 | 0.049 | -33.861 | 0 | -1.748 ~ -1.557 |
| McFadden $R^2$ | -0.211 | | | | |

*Dependent variable: scale efficiency*

## 5. Research conclusions

In this paper, the DEA-BBC model, DEA-ML model and Tobit model were comprehensively used to estimate the change rate of carbon emission efficiency and total factor productivity of the transport industry in 30 provincial administrative regions in China during 2014-2020, and three other factors besides input-output were introduced to analyze the effects of various factors on the comprehensive efficiency of carbon emission.

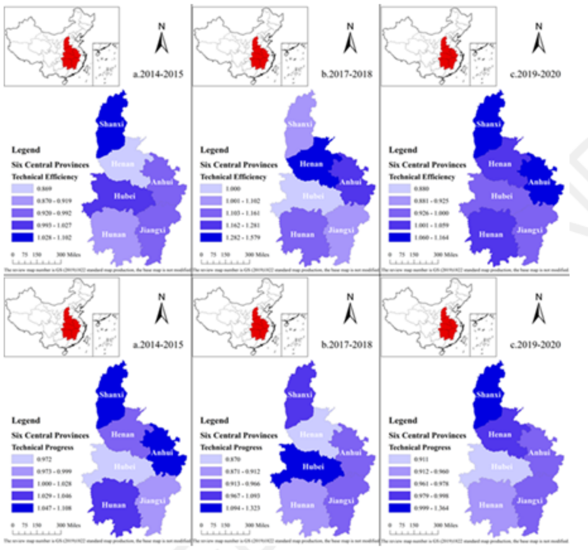



**Figure 7.** Changes of technical efficiency in central China

Analysis from static model. On the whole, there is still a large room for improvement in the comprehensive efficiency of China's transportation carbon emissions, and the gap between them and the optimal production frontier is obvious. According to the measurement results of BCC model, only Qinghai, Ningxia, Inner Mongolia Autonomous Region and Hebei Province have comprehensive transportation carbon emission efficiency greater than 1.0, which is in an effective state.

From the dynamic model analysis. Except Guizhou province, the total factor productivity of transportation carbon emissions in other provinces showed an upward trend. The progress of the pure technical efficiency of carbon emission is not obvious, which limits the technical efficiency to a certain extent. Technological progress is the driving factor for the increase of total factor productivity. The technical efficiency of the decomposition of total factor productivity of carbon emissions in all regions decreased in Northeast China, but increased in other regions. The technological progress index showed an overall upward trend, especially in the western region, where the index value reached 1.392, much higher than other regions.

Analysis from the influencing factors. The external environment, such as the proportion of land use, the proportion of the tertiary industry in GDP, and the resident population, has a significant impact on the carbon emission efficiency of transportation. Therefore, in order to improve the efficiency of transportation carbon emissions, it is necessary to strengthen the construction of transportation infrastructure, improve the efficiency of traffic operation, and avoid the waste of energy caused by traffic congestion. At the same time, it is necessary to reduce population density and speed up urbanization. Improving transportation carbon emission efficiency requires multi-factor combination and optimal allocation. Through the improvement of key factors, transportation carbon emission efficiency can be greatly improved.

Therefore, in order to promote the low-carbon development of the transportation industry, it is urgent to optimize the industrial structure, promote the use of clean energy and renewable energy in the transportation industry, improve the total factor productivity of carbon emissions by optimizing the energy consumption structure, improve the smooth flow rate of transportation and the efficiency of transportation organization, and avoid unnecessary energy consumption and carbon emissions. Finally, it is necessary to strengthen inter-regional cooperation, expand the overall scale of production, and improve scale efficiency.

### Competing interests

The authors have no conflicts of interest to declare.

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