Three-stage DEA Model on the Low-carbon Logistics Efficiency in Ten Coastal Provinces of China

Qingyu Zhang*, Jieshan Mai and Yulin Li
College of Management, Research Institute of Business Analytics and SCM, Shenzhen University, China
Email: q.yu.zhang@gmail.com

Abstract. As China's economy rapidly grows, the tertiary industry has developed vigorously, and at the same time there has been a huge demand for the logistics industry. The coastal logistics industry, which uses water transportation as its main mode, has brought about carbon emissions that cannot be ignored due to its high energy consumption and high pollution. This paper focused on efficiency research and was based on the concept of green logistics. By using the three-stage DEA model which selecting the data of China's coastal provinces from 2015 to 2017, the research shows that environmental factors and random disturbances have important effects on the evaluation of efficiency. Finally, this paper put forward suggestions for improvement based on empirical results.

Keywords. Low carbon logistics efficiency, Three-stage DEA, Coastal provinces, Carbon dioxide emissions.

1. Introduction
In the national policy "the 13th Five-Year Plan for the Development of Commercial Logistics", China is required to adhere to green development and ensure the low-carbon and sustainable development of various industries. But the logistics industry cannot develop without the consumption of gasoline, kerosene, diesel and fuel oil, which is the main cause of aggravating the earth's greenhouse effect. Among them, coastal provinces have more developed logistics industry than some inland provinces due to their convenient waterway transportation, and the environmental pollution is more serious. The development of China's coastal provinces represents the future development of China. Therefore, suggestions and measures are proposed by studying the logistics industry level of China's coastal provinces, which can bring reference significant to the logistics industry construction of other provinces and further stimulate the development of China's overall logistics industry. In view of this, this paper takes the data of Hebei, Liaoning, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong and Guangxi in the coastal areas of China from 2015 to 2017 as the research object. We will adopt the three-stage DEA method to analyze the logistics efficiency of each province under the constraint of carbon emission and put forward corresponding suggestions.

2. Literature Review
Data Envelopment Analysis (DEA) has a wide variety of applications and has special advantages when analyzing multiple inputs and multiple outputs. Karahan and Mehmet [1] used the DEA to analyze the application data obtained from health enterprises to obtain the performance and efficiency levels of 1,533 public hospitals in 81 provinces of Turkey. The results can be used to improve the operational efficiency of hospitals. Wahyudi and Azizah [2] used DEA to calculate bank efficiency...
scores for the five ASEAN countries, including Philippines, Indonesia, Malaysia, Singapore and Thailand. The results showed that the efficiency level of Banks in various countries is relatively high.

People have gradually realized that the improvement of the quality of life is accompanied by the growing climate problem, which has set off the "low-carbon revolution". Therefore, all mankind has entered a new era based on "low energy consumption, low pollution, and low emissions." The development of logistics as a high-end service industry must also take a low-carbon path and focus on the development of low-carbon logistics. At present, the literature on low-carbon logistics is still scarce. Ma [3] used the three-stage DEA method to conduct static analysis and evaluation of regional logistics efficiency by considering CO2 emissions when analyzing the efficiency of low-carbon logistics in Chinese provinces. Li [4] introduced the logistics carbon emissions and logistics GDP as input and output indicators into the low-carbon logistics efficiency evaluation system, and conducted an empirical analysis of the low-carbon logistics efficiency of 31 provinces in China based on the DEA model. It is found that the efficiency level of low-carbon logistics in China is significantly different in different regions and the overall level is low.

3. Research methods

DEA model is the abbreviation of Data Envelopment Analysis, which is a method of efficiency evaluation. This method mainly evaluates the relative efficiency of multiple inputs and multiple outputs. The system of inputs and outputs is called a decision unit, or DMU for short. Using the DEA model to analyze the logistics efficiency can not only know the level of logistics efficiency in the studied area, but also find out the reasons and improvement directions that lead to the status quo of logistics.

In the first stage of this paper, an input-oriented BCC model is adopted. However, due to the limitation of BCC model, the input relaxation value calculated in the first stage is affected by management inefficiency, environmental factors and random errors. Therefore, the second stage analysis is carried out to separate the efficiency value affected by external factors.

The SFA model constructed using the input relaxation variable of each DMU as the dependent variable is as follows:

\[ S_{ik} = f^*(Z_i; \beta^*) + v_{ik} + u_{ik} \]

\[ i = 1, 2, \ldots, n, k = 1, 2, \ldots, m \]  

(1)

\( S_{ik} \) represents the kth input relaxation variable of the ith DMU; \( f^*(Z_i; \beta^*) \) represents the effect of environmental variables on \( S_{ik} \); \( v_{ik} \) represents a random error and follows a normal distribution with a mean of 0; \( u_{ik} \) represents the management inefficiency and follows a semi-normal distribution.

Further, according to the regression results of SFA model, the input of DMU can be adjusted as follows:

\[ \hat{x}_i = x_{ik} + [\max_k \{Z_i \hat{\beta}^*\} - Z_i \hat{\beta}^*] + [\max_k \{v_{ik}\} - v_{ik}] \]

\[ i = 1, 2, \ldots, n, k = 1, 2, \ldots, m \]  

(2)

\( \hat{x}_i \) represents the actual value of the KTH input of the ith DMU, \( x_{ik} \) represents the adjusted input, \([\max_k \{Z_i \hat{\beta}^*\} - Z_i \hat{\beta}^*]\) represents the adjustment of all DMU to a homogeneous environment, and \([\max_k \{v_{ik}\} - v_{ik}]\) represents the adjustment of the random error of all DMU to the same situation, so that each DMU is in the same external environment.

In the third stage, the adjusted input value is used to replace the traditional BCC model again.
4. Research Data

4.1. The Choice of Input and Output Indicators
The input and output indicators of the DMU are the key factors to measure the efficiency, so the selection of input and output indicators is crucial to the efficiency measurement result. Through a large amount of literature review, we find that scholars generally regard the transportation industry, the warehousing industry, and the postal industry as the general term of the logistics industry. This article also adopted the same definition. After sorting out the relevant research and evaluation indicators, and taking into account the availability of the indicators, and the quantitative relationship between the number of indicators and the DMU, the article selected the the investment in fixed assets in the logistics industry (IFA), the carbon dioxide emissions (CDE) and the highway mileage (HM) as input indicators, selected the output value in the logistics industry (OV) and the rotation volume of goods transport (RVT) as output indicators.

4.2. The Selection of Environment Indicators
The environmental variables selected in this paper were the education funding (EF) and regional GDP (RG). They have a substantial impact on the efficiency of low-carbon logistics, but they are not subjectively controllable in the sample and are not controlled in the short term.

4.3. Data Sources
The research object of this article is the ten coastal provinces of China. The research data were selected from the China Statistical Yearbook, and the China Energy Statistical Yearbook. Among them, the carbon emission indicator has no direct data source and needs to be calculated. Firstly, the terminal consumption data of diesel oil, gasoline, fuel oil, kerosene, and natural gas in the logistics industry of each province was obtained by inquiring the China energy statistical yearbook. Then, the carbon dioxide emission coefficient was obtained by referring to Zhu [5] and the results are shown in table 1. Finally, the carbon emissions of the logistics industry in each province were calculated.

Table 1. Carbon Dioxide Emission Coefficients.

| Fuel        | Gasoline | Kerosene | Diesel oil | Fuel oil | Natural gas |
|-------------|----------|----------|------------|----------|-------------|
| Unit        | KgCO₂/kg | KgCO₂/kg | KgCO₂/kg   | KgCO₂/kg | KgCO₂/m³    |
| Emission coefficient | 3.02     | 3.1      | 3.16       | 3.24     | 2.19        |

5. Empirical analysis

5.1. The Traditional DEA BCC Model
In the first stage, we used Deap2.1 to add the input index and output index of the logistics industry in ten coastal provinces to the model for calculation. Since the input factor are variable factors, and the output factors cannot be changed generally, it is more meaningful to choose the input orientation. The results of the first stage are shown in table 2. The all-inclusive technical efficiency is composed of pure technical efficiency and scale efficiency, which reflects the maximum output ratio achieved by the local logistics industry under the current technology. From table 2, we can find that with the fast technological development in China, the average of the pure technical efficiency of ten coastal provinces shows an increasing trend. However, the average scale efficiency does not increase significantly, which indicates that there is a phenomenon of blind expansion of the scale of logistics industry on the whole.
Table 2. The First Stage DEA Estimation Results.

|        | 2015 | 2016 | 2017 |
|--------|------|------|------|
|        | OTE  | PTE  | SE   | OTE  | PTE  | SE   | OTE  | PTE  | SE   |
| Tianjin| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000|
| Hebei  | 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000|
| Liaoing| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000|
| Shandong| 0.750| 0.795| 0.944| 0.778| 0.907| 0.858| 0.646| 1.000| 0.646|
| Jiangsu| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000| 1.000|
| Zhejiang| 0.750| 0.795| 0.944| 0.778| 0.907| 0.858| 0.646| 1.000| 0.646|
| Fujian | 0.696| 0.833| 0.835| 0.771| 0.903| 0.853| 0.775| 0.931| 0.832|
| Guangdong| 0.795| 1.000| 0.795| 0.867| 1.000| 0.867| 0.800| 1.000| 0.800|
| Guangxi| 0.457| 0.767| 0.886| 0.753| 0.850| 0.886| 0.723| 0.843| 0.858|
| Mean   | 0.834| 0.896| 0.923| 0.860| 0.922| 0.925| 0.813| 0.929| 0.873|

OTE-comprehensive technical efficiency value; PTE-pure technical efficiency value; SE-scale efficiency value.

5.2. Establish SFA Model for Regression Analysis

We borrow the results obtained in the first stage to isolate the relaxation variables for each input variable. The Frontier 4.1 program was used to perform SFA analysis to obtain the influence of environmental factors on input relaxation, as shown in Table 3. The regression coefficients of the two environmental variables on the analysis of input relaxation reflect the corresponding degree and direction of their influence on input relaxation.

Table 3. The SFA Analysis Results

| Dependent Variable Year | Constant | EF    | RG    | σ²     | γ     | LOGL | LR    |
|-------------------------|----------|-------|-------|--------|-------|------|-------|
| FIA Slack 2015          | -108.778*** | 2.687*** | -86.058*** | 325879.330*** | 0.999*** | -69.836 | 6.366*** |
| FIA Slack 2016          | -144.894*** | 3.664*** | -119.960*** | 439068.520*** | 0.999*** | -71.405 | 6.299*** |
| FIA Slack 2017          | -139.136*** | 5.759*** | -200.076*** | 685177.220*** | 0.999*** | -73.251 | 6.967*** |
| CDE Slack 2015          | -176.018*** | 2.118* | -55.454*** | 291931.670*** | 0.999*** | -69.470 | 5.998*** |
| CDE Slack 2016          | -131.438*** | 4.118*** | -138.691*** | 163540.590*** | 0.999*** | -71.405 | 6.299*** |
| CDE Slack 2017          | -117.464*** | 5.446*** | -192.932*** | 181619.650*** | 0.999*** | -73.251 | 6.967*** |
| HM Slack 2015           | -2232.676*** | 13.195 | 2537.830* | 3269401800*** | 0.999*** | -115.536 | 7.102*** |
| HM Slack 2016           | -27383.581*** | 5.323 | 3177.908*** | 2870084800*** | 0.999*** | -115.065 | 6.740*** |
| HM Slack 2017           | -7829.496*** | 358.215*** | 12855.321*** | 762647810*** | 0.999*** | -108.839 | 5.941*** |

***, **, * Significant at the 1%, 5%, 10% level, respectively.

From Table 3, it can be found that most of the parameters in the SFA regression model can pass the significance test, indicating that the model regression effect is good, and the environmental variables selected in this paper have significant correlation with input redundancy. According to the SFA regression results, analyze the impact of various environmental variables on the input indicators:

1) Education funding was a negative factor for the input target over the three-year period. Because in the table 3, the regression coefficients of the relaxation variables of the input index are positive. The results show that the increase in education funding will increase the fixed-assets investment in the logistics industry, the carbon dioxide emissions and the highway mileage, and reduce the management efficiency. It is worth noting that the impact of education funding on the slack variable of highway.
mileage was not significant in 2015 and 2016, but showed a significant impact in 2017. Aiming at this problem, we can discuss it further in the future.

2) The influence of regional GDP on the relaxation variables of fixed assets in the logistics industry and carbon dioxide emissions in logistics industry increases year by year, and it is a favorable factor. However, the regression coefficients between regional GDP and the relaxation variable of highway mileage changed from positive to negative during the three-year period, indicating that the growth of regional GDP greatly improved the efficiency of low-carbon logistics.

5.3. Adjusted DEA
After adjusting the initial data in the second stage, excluding environmental factors and random interference input variable values, the logistics efficiency analysis of the ten provinces along the coast of China was performed again. Using DEAP 2.1 software again, the results are shown in table 4. Obviously, the pure technical efficiency after the adjustment is higher than that before the adjustment, which indicates that the development of the technical efficiency in ten coastal provinces is restricted by external environmental factors. After the adjustment, the scale efficiency of all provinces increased, but that of Guangxi decreased. This indicates that external environmental factors and random error factors have positive impacts on the scale efficiency of logistics industry in Guangxi.

Table 4. The Third Stage DEA Estimation Results.

|        | 2015  | 2016  | 2017  |
|--------|-------|-------|-------|
|        | OTE   | PTE   | SE    | OTE   | PTE   | SE    | OTE   | PTE   | SE    |
| Tianjin| 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Hebei  | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Liaoning| 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Shandong| 0.754 | 0.795 | 0.947 | 0.781 | 0.912 | 0.857 | 0.728 | 1.000 | 0.728 |
| Jiangsu| 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.895 | 1.000 | 0.895 |
| Shanghai| 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Zhejiang| 0.757 | 0.803 | 0.942 | 0.857 | 0.886 | 0.967 | 0.834 | 0.904 | 0.922 |
| Fujian | 0.775 | 0.840 | 0.922 | 0.872 | 0.909 | 0.959 | 0.885 | 0.971 | 0.912 |
| Guangdong| 0.849 | 1.000 | 0.849 | 0.944 | 1.000 | 0.944 | 0.891 | 1.000 | 0.891 |
| Guangxi | 0.461 | 0.607 | 0.759 | 0.471 | 0.641 | 0.735 | 0.516 | 0.644 | 0.801 |
| Mean   | 0.859 | 0.905 | 0.942 | 0.893 | 0.935 | 0.946 | 0.875 | 0.952 | 0.915 |

OTE—comprehensive technical efficiency value; PTE—pure technical efficiency value; SE—scale efficiency value.

We can find that Tianjin, Hebei, Liaoning and Shanghai are among the ten coastal provinces with the highest comprehensive technical efficiency of logistics before and after the adjustment. Their efficiency level has been in the forefront of efficiency for three successive years, indicating that the logistics industry input of these four provinces has been fully utilized and the optimal output has been achieved in three years. The reason is that Tianjin and Hebei belong to the Beijing-Tianjin-Hebei Urban Agglomeration, and their low-carbon logistics development is not only planned by themselves, but also planned by multiple regions. Therefore, their cooperation and exchanges promote the interconnected development of the whole Beijing-Tianjin-Hebei Urban Agglomeration, which is an important measure to optimize the allocation of resources. During the 12th five-year plan period, Liaoning pointed out that it should economize on resources, build and develop green transportation, and make efforts to apply technologies and equipment such as energy conservation, emission reduction and recycling into practice. To some extent, this has brought a positive effect on the efficiency of low-carbon logistics. As a national logistics node city, Shanghai is committed to
strengthening the fine-tuning and upgrading of the logistics industry structure. The mean comprehensive technical efficiency of other coastal provinces increased after adjustment.

6. Discussion and Concluding Remarks
In this paper, a three-stage DEA model is used to treat pollutants as input and carbon dioxide emission as one of input indexes. From the empirical results, we can draw the following conclusions: First, Tianjin, Hebei, Liaoning and Shanghai have the highest efficiency of low-carbon logistics, indicating that the input of logistics industry in these four regions has made full use of 2015-2017 and achieved the best output, which needs to be maintained. And Guangxi's low-carbon logistics has the lowest efficiency, indicating that Guangxi needs to improve the local technical level and optimize technical processes. Finally, after the elimination of environmental factors and random errors, it can be seen that the main reason for the low efficiency of low-carbon logistics in China's coastal provinces is the low efficiency of pure technology, which indicates that we should devote ourselves to improving the technology of logistics industry.

In order to implement the sustainable development policy, I make the following three suggestions: First, we can improve logistics efficiency by strengthening internal cooperation in various coastal provinces. For example, Guangdong can use Guangxi's land resources to relieve its own pressure. Guangdong’s advanced logistics information level and management experience can be shared by Guangxi. Second, adjust the regional energy consumption structure of the logistics industry to improve energy efficiency. As the energy consumption in coastal areas is mainly reflected in the main form of water transport, and a large amount of energy such as diesel and gasoline is consumed, these fossil fuels are the main cause of the greenhouse effect. Therefore, we must actively develop and call for the use of energy-saving and emission-reduction technologies and renewable energy technologies. Finally, the government should learn from foreign carbon guidance policies and speed up the formulation and improvement of "carbon emissions tax" collection standards. Through the above measures to increase the efficiency of low-carbon operation of logistics companies.

Acknowledgment
The authors are grateful to the research funding by National Natural Science Foundation of China (#71572115); Major Program of Social Science Foundation of Guangdong (#2016WZDXM005); Natural Science Foundation of SZU (# 836).

References
[1] Karahan K and Mehmet J 20119 Using data envelopment analysis to measure the technical efficiency of public hospitals in Turkey Veri Zarflama Analizi ile Türkiye’deki Kamu Hastanelerinin Teknik Etkinliğinin Ölçülmesi 19 373-387
[2] Setyo T W 2018 A comparative study of banking efficiency in Asean-5: The data envelopment analysis (DEA) approach Journal of Indonesian Economy & Business 33 168-186
[3] Ma S 2019 Study on Efficiency evaluation of low carbon logistics in ten provinces of China in the background of the "Belt and Road" North China University of Water Resources and Electric Power 1-12
[4] Li Y 2014 Research on the efficiency of low carbon logistics in china based on DEA China Market 23-25
[5] Zhu Q R 2010 Study on CO_2 emission in China's export trade Chinese Industrial Economy 55-64