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# PORT EFFICIENCY EVALUATION BASED ON THREE-STAGE DEA MODEL

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Abstract. *Port efficiency is one of the indicators for evaluating the development level of various ports. In order to improve the accuracy of port efficiency evaluation, based on the traditional data envelopment analysis (DEA) model, this paper uses the three-stage DEA method to study the comprehensive efficiency, scale efficiency and pure technical efficiency of six perennial 100-million-ton ports in Liaoning Province and Shandong Province. The results show that there are great differences in the level of each port, and there is a mismatch between scale and input-output. From the third stage of DEA, it can be concluded that the hinterland environment has a great impact on the improvement of port efficiency. Finally, countermeasures and suggestions are put forward on how to improve port efficiency.*

**Keywords:** Three-stage DEA, Port efficiency, SFA, Evaluation

1. **Introduction.** Port efficiency is a comprehensive reflection of port competitiveness, management capabilities, and reasonable allocation of input-output resources. Especially in the context of rapid economic growth and accelerated trade growth, the evaluation method of port efficiency is a hot spot in port development theory [1]. At present, the research methods of port efficiency are mainly divided into two categories: parametric method and non-parametric method [2].

The parametric method mainly includes linear regression method, stochastic frontier analysis method (SFA) and neural network method. Kuang and Chen [3] use the neural network method to measure the port efficiency in China; although it gets rid of the influence of artificial subjective factors and fuzzy random factors, the differentiation degree of port efficiency is poor. Therefore, there is very little literature on the use of neural network method to study port efficiency. At present, SFA is used by Medda and Liu [4], Trujillo et al. [5], Ai and Zhou [6] as the most commonly used parameter method. However, the disadvantage of the parametric method is that it is easy to be affected by subjective factors when selecting indicators and influencing factors, and the form of the function needs to be artificially determined, which is not objective.

The non-parametric method mainly includes data envelopment analysis (DEA) and balanced scorecard (BSC). Non-parametric method does not have the subjective influence of parametric method, so it is also a widely used research method of port efficiency at present, such as Wang and Zhang [7], Almawsheki and Shah [8], Zhang and Fan [9], and Li [10]. In recent years, there is much foreign literature using DEA to study port efficiency. Kyu [11], Wang and Hou [12], and Wang et al. [13] use DEA method to establish an evaluation model of port economic development effectiveness, and evaluate port management efficiency and environmental efficiency. Although there is much literature on DEA, the effects of external environmental factors and random errors are ignored. For this reason,

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many scholars use three-stage DEA to study port efficiency after excluding external factors and random errors. For example, Fried [14] puts forward a three-stage DEA model to evaluate the efficiency of the ten ports in the Pacific Ocean. At the same time, compared with the results of the traditional DEA model, it is considered that the evaluation result of the three-stage DEA model is more objective. Wu [15], Zhu and Gai [16], Yang [17], Lu and Zhang [18], and Wang and Liang [19] also carry out similar calculations. This method eliminates the errors caused by external environmental factors and random errors in port efficiency evaluation. Compared with the traditional CCR, BBC model, the evaluation results are more objective and authentic.

For this reason, this paper adopts the three-stage DEA model for China's major coastal ports of Liaoning Peninsula and Shandong Peninsula efficiency measure. In the first stage using the BCC model each measure ports efficiency value, and then in the second stage using SFA regression, eliminate the influence of environmental factors and random error. It is concluded that the adjusted input value, putting the value to the new BCC model, is calculated, to obtain more accurate measurement results and improve the efficiency of path.

## 2. Research Methods and Data.

### 2.1. Research methods.

The data envelopment analysis model was first proposed by Charnes et al. [20] in 1978. This model has been widely used in various fields, and more than a dozen different improved models have evolved. The three-stage DEA model was first proposed by Fried [14] in 2002. Due to the application of the stochastic frontier analysis (SFA) theory, this model can overcome the influence of environmental variables and errors in the traditional DEA model, thereby enabling more accurate evaluation.

In the first stage, the traditional DEA model is used to analyze the port efficiency. This paper uses the BCC model from the input angle to analyze. The model is more mature, and its principles and methods are not repeated.

In the second stage, the SFA method is used to regression of the environmental variables, and it is concluded that the environmental factors are worth affecting the input redundancy. The input relaxation variables in the first stage are divided into three effects: environmental factors, management inefficiency and random factors. The SFA regression function is as follows:

$$S_{ni} = f(Z_i; \beta_n) + v_{ni} + \mu_{ni} \quad i = 1, 2, \ldots, N;\ n = 1, 2, \ldots, N \tag{1}$$

Among them, $S_{ni}$ is the slack value of the $n$-th input of the $i$-th decision-making unit, $Z_i$ is the environmental variable, $\beta_n$ is the coefficient of the environmental variable, $v_{ni}$ represents random interference, and $\mu_{ni}$ indicates management inefficiency.

SFA regression can eliminate the impact of environmental variables and random factors on efficiency, and adjust all decision-making units in the same external environment. The adjustment formula is as follows:

$$\begin{aligned} X_{ni}^A &= X_{ni} + \left[\max\left(f\left(Z_i; \hat{\beta}\right)\right) - f\left(Z_i; \hat{\beta}\right)\right] + [\max(v_{ni}) - v_{ni}] \\ i &= 1, 2, \ldots, N;\ n = 1, 2, \ldots, N \end{aligned} \tag{2}$$

Among them, $X_{ni}^A$ is the input after adjustment, $X_{ni}$ is the input before adjustment, $\left[\max\left(f\left(Z_i; \hat{\beta}\right)\right) - f\left(Z_i; \hat{\beta}\right)\right]$ is to adjust the external environmental factors, and $[\max(v_{ni}) - v_{ni}]$ is to put all decision-making units under homogeneous conditions. In order to adjust according to the above formula, random factors and management inefficiency must first be separated, so the separation formula derived by Luo [21] is used:

$$E(\mu|\epsilon) = \sigma_* \left[ \frac{\phi\left(\partial\frac{\epsilon}{\mu}\right)}{\varphi\left(\frac{\alpha\epsilon}{\mu}\right)} + \frac{\alpha\varepsilon}{\mu} \right] \tag{3}$$

Among them, $\sigma_* = \frac{\sigma_\mu \sigma_v}{\sigma}$, $\sigma = \sqrt{\sigma_\mu^2 + \sigma_v^2}$, $\alpha = \sigma_\mu/\sigma_v$. The calculation formula of random error term $\mu$ is as follows:

$$E[v_{ni}|v_{ni} + \mu_{ni}] = s_{ni} - f(Z_i; \beta_n) - E[\mu_{ni}|v_{ni} + \mu_{ni}] \tag{4}$$

In the third stage, the adjusted input data is used instead of the original input data, and the BCC model of input angle is applied again. At this time, the calculated efficiency value has excluded the influence of environmental factors and random factors, and can objectively reflect the efficiency of each unit.

The operation tools used in this paper are Deap2.1 and FRONTIER4.1 software.

2.2. **Selection of indicators.** Data envelopment analysis studies the multi-input and multi-output model, so the selection of input-output indicators is particularly important for the evaluation results. At present, in the literature of using DEA method to study port efficiency, most scholars select input indicators from three aspects of capital, labor and equipment, among which the length of the wharf and the number of berths are the most important indicators. For the output index, most of the relevant literature takes the cargo throughput as the output index, and some of the literature container throughput and port profit value as the output index. In view of the objectivity and availability of the data, this paper selects berth length and number of berths as input indicators and cargo throughput as output indicators.

The selection of environmental variables has an impact on port efficiency but is not within the subjective controllable range of the sample, including natural and social environmental factors. Therefore, this article selects the year-end total population (RKS), gross domestic product (GDP), total import and export investment (TZZE), average salary of transportation employees (PJGZ), and foreign investment (WSTZ) as environmental variables.

2.3. **Data sources.** In view of the availability and completeness of the data, this paper selects the input-output and environmental variable data of six ports in Shandong Peninsula and Liaoning Peninsula from 2014 to 2018. The data come from "China Statistical Yearbook", "China Port Statistical Yearbook" and provincial and municipal statistical yearbooks.

## 3. **Empirical Analysis.**

3.1. **Stage 1: DEA analysis.** This section focuses on six container ports in Shandong Province and Liaoning Province from 2014 to 2018, including Dalian (DL), Yingkou (YK), Jinzhou (JZ), Yantai (YT), Qingdao (QD), Rizhao (RZ). In the first stage, the Deap2.1 software is used to analyze the port efficiency level of six ports in Shandong Peninsula and Liaoning Peninsula from 2014 to 2018. The results are shown in Table 1.

Table 1 shows the comprehensive efficiency, pure technical efficiency and scale efficiency of each port calculated by the BCC model from 2014 to 2018. According to the definition of the DEA model, when the comprehensive technical effect of the calculated decision-making unit is 1, the DEA of the decision-making unit is valid, otherwise it is invalid. It can be calculated from Table 1 that in the past five years, the overall comprehensive efficiency value of the port is 0.723, the pure technical efficiency value is 0.811, and the scale efficiency value is 0.899. Therefore, the overall efficiency of the ports of Shandong Province and Liaoning Province is higher, in which the level of scale efficiency is relatively higher than that of pure technical efficiency, so it is necessary to pay attention to the improvement of pure technical efficiency. The ineffectiveness of the comprehensive efficiency

TABLE 1. Efficiency values of the six major ports in 2014-2018

| | 2014 | | | 2015 | | | 2016 | | | 2017 | | | 2018 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Port | TE | PTE | SE | TE | PTE | SE | TE | PTE | SE | TE | PTE | SE | TE | PTE | SE |
| DL | 0.401 | 0.461 | 0.870 | 0.392 | 0.458 | 0.855 | 0.431 | 0.492 | 0.877 | 0.526 | 0.574 | 0.917 | 0.456 | 0.499 | 0.915 |
| YK | 0.734 | 0.736 | 0.997 | 0.741 | 0.743 | 0.996 | 0.788 | 0.791 | 0.996 | 0.957 | 0.958 | 0.998 | 0.824 | 0.837 | 0.984 |
| JZ | 0.642 | 1.000 | 0.642 | 0.614 | 1.000 | 0.614 | 0.656 | 1.000 | 0.656 | 0.936 | 1.000 | 0.936 | 0.817 | 1.000 | 0.817 |
| YT | 0.503 | 0.552 | 0.912 | 0.548 | 0.593 | 0.924 | 0.568 | 0.602 | 0.943 | 0.445 | 0.450 | 0.988 | 0.562 | 0.572 | 0.983 |
| QD | 0.831 | 1.000 | 0.831 | 0.800 | 1.000 | 0.800 | 0.843 | 1.000 | 0.843 | 0.886 | 1.000 | 0.886 | 0.782 | 1.000 | 0.782 |
| RZ | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

Note: TE is the comprehensive efficiency value, PTE is the pure technical efficiency value, SE is the scale efficiency value.

of the ports in the two provinces is caused by the ineffectiveness of DEA in terms of pure technical efficiency and scale efficiency.

In addition, the comprehensive efficiency of Rizhao Port in each year is 1. The comprehensive efficiency of DEA is effective and the level of development is high. Except for Rizhao Port, the efficiency values of the ports in the two provinces have different degrees of room for improvement. The failure of other ports to achieve DEA effectiveness may be due to the ineffectiveness of scale efficiency DEA, the ineffectiveness of pure technical efficiency DEA, or the influence of environmental variables and random interference factors.

3.2. **Stage 2: Results of SFA regression analysis.** The quantity of terminal relaxation variable (Y1) and terminal length relaxation variable (Y2) obtained in the first stage is taken as the explained variable, and the year-end total population (RKS), gross domestic product (GDP), imports and the total amount of export investment selected above (TZZE), the average wage of employees in the transportation industry (PJGZ) and the amount of foreign investment (WSTZ) are used as explanatory variables. This article uses FRONTIER4.1 for SFA regression and the results were shown in Table 2.

TABLE 2. Results of SFA stochastic frontier analysis

| | (Y1) wharf number | (Y2) relaxation variable |
|---|---|---|
| C | 159.69052(159.690)*** | 19533.785(16.019)*** |
| X1(RKS) | −0.32529049(−0.512) | −17.415033(−1.253)*** |
| X2(GDP) | 0.02625774(0.399) | 1.8198063(2.072)** |
| X3(TZZE) | −6.81722E-07(−0.284) | −3.15416E-05(−0.682) |
| X4(PJGZ) | −8.04808E-05(−0.097) | 0.017181842(0.314) |
| X5(WSTZ) | 8.99592E-07(0.006) | −6.88942E-05(−0.032) |
| gamma | 0.84293699 | 0.94351589 |
| LR test of the one-sided error | 22.117273 | 34.77427 |

Note: * indicates that the significant level is at least 10%; the t value is in parentheses.
** indicates that the significant level is at least 5%; the t value is in parentheses.
*** indicates that the significant level is at least 1%; the t value is in parentheses.

As can be seen from Table 2, the LR test values are 22.117273 and 34.77427 respectively, the model passes the test, the estimated values of constant parameters in the model are statistically significant, and the gamma values are 0.8429 and 0.9435 respectively, indicating that the regression effect of the model is very good and has strong explanatory power. As can be seen from Table 2 above, the statistical significance of each environmental variable index of the number of wharfs is not significant, indicating that environmental factors have little impact on the number of wharfs. Therefore, it is of little significance to analyze the number of wharfs using SFA.

Since the environment variable is the regression of each input relaxation variable, when the regression coefficient is negative, it means that increasing the environment variable can reduce the redundancy of input index, which is conducive to reducing the waste of each input variable. When the regression coefficient is positive, the reverse is true. From the relaxation variable of the wharf length, we can get that the statistics of the population and GDP of the port city are significant, and the influence is great. Among them, the population of the city where the port is located is a favorable factor for the relaxation variables of the number of wharves and the length of wharves. It may be that with the increase of the total population and the growth of consumer demand, the demand for passenger and freight transport will increase accordingly, which in turn increases the input-output capacity of the port. The regional GDP is a disadvantageous factor to the number and length of wharves, which may be because with the growth of GDP, the investment of coastal ports increases, but the throughput level does not increase in proportion, resulting in a waste of port investment resources. At the same time, we can see from Table 2 that the total amount of import and export investment, the average salary of transportation employees and the amount of foreign investment have little influence on the relaxation variable of wharf number and wharf length.

Based on the above analysis, it can be seen that various environmental factors have different degrees and directions of influence on the port. So the third stage of DEA model analysis is carried out to eliminate the influence of environmental variables and random errors, so that all decision-making units face the same environment.

3.3. **Stage 3: Calculation of the efficiency of DEA model in the third stage.** After excluding the impact of environmental factors and random errors on port logistics, the adjusted input and original output are substituted into the BCC model to obtain the three-stage efficiency and the results are shown in Table 3.

Table 3. The third stage efficiency value of the six major ports in 2014-2018

| | 2014 | | | 2015 | | | 2016 | | | 2017 | | | 2018 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Port | TE | PTE | SE | TE | PTE | SE | TE | PTE | SE | TE | PTE | SE | TE | PTE | SE |
| DL | 0.946 | 0.978 | 0.968 | 0.937 | 0.975 | 0.961 | 0.936 | 0.973 | 0.962 | 0.954 | 0.989 | 0.965 | 0.978 | 0.982 | 0.996 |
| YK | 0.878 | 0.998 | 0.880 | 0.904 | 0.998 | 0.906 | 0.897 | 0.998 | 0.898 | 0.890 | 1.000 | 0.890 | 0.900 | 0.999 | 0.901 |
| JZ | 0.313 | 1.000 | 0.313 | 0.308 | 1.000 | 0.308 | 0.298 | 1.000 | 0.298 | 0.365 | 1.000 | 0.365 | 0.357 | 1.000 | 0.357 |
| YT | 0.680 | 0.994 | 0.684 | 0.724 | 0.997 | 0.726 | 0.733 | 0.998 | 0.735 | 0.761 | 0.984 | 0.773 | 0.993 | 0.994 | 0.999 |
| QD | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| RZ | 0.888 | 1.000 | 0.888 | 0.904 | 1.000 | 0.904 | 0.896 | 1.000 | 0.896 | 0.889 | 1.000 | 0.889 | 1.000 | 1.000 | 1.000 |

Through the analysis of Table 3, the specific conclusions are as follows.

1) Compared with the overall efficiency of the first stage, the value of pure technical efficiency of each port in the third stage is generally at a higher level, and the overall value of comprehensive efficiency changes greatly before and after adjustment, which proves that the pure technical inefficiency of DEA in each port comes from environmental factors and random interference. Comparing the two stages, it can be seen that the input redundancy phenomenon of Dalian Port and Yingkou Port is more serious. The result of the first stage is further confirmed that the port resource input and output levels do not match, and the high input-output ratio makes the DEA of the two ports invalid.

2) After adjustment from 2014 to 2018, the pure technical efficiency of Jinzhou Port and Qingdao Port is always in the DEA effective state compared with the invalid state of the first stage DEA, which indicates that the scale efficiency becomes effective after excluding the environmental variables, and proves that the environment of the port hinterland affects its scale development. However, after the adjustment from 2014 to 2018, the pure technical efficiency of Rizhao Port remains at 1, but the comprehensive technical efficiency decreases and is ineffective, indicating that the environmental variables cover up the mismatch

between its scale and input-output, and it is in a state of increasing scale. It is proved that Rizhao Port still has room for development in terms of scale.

3) Through the comparison of the scale efficiency of each port in one or three stages, except Qingdao Port, the scale efficiency of each port decreases obviously, which shows that the crux of the problem faced by the major ports in Shandong Province and Liaoning Province lies in the scale efficiency of the port. One of the main reasons for the decline of efficiency after adjustment is that ports are in a homogeneous environment and the investment structure of ports does not match its development scale.

4. **Research Conclusions and Countermeasures and Suggestions.** Based on the three-stage DEA model, this paper studies and analyzes the efficiency of six perennial 100-million-ton ports in Shandong Province and Liaoning Province from 2014 to 2018. The results show that in the past years, the efficiency level of each port is on the high side and has a good development prospect, but some ports such as Dalian Port and Yingkou Port have the problems of input congestion or low output level, the waste of port resources is serious, and the overall efficiency of the port is relatively low. In the third stage, the port efficiency of Qingdao Port and Jinzhou Port changes from DEA ineffective to DEA effective, so the hinterland environment has a certain impact on port efficiency, and port competitiveness can be enhanced by adapting to the external environment.

In view of the above conclusions, the following suggestions are put forward.

1) Do a good job in the integration of resources to avoid waste of resources. The port has the situation of input redundancy and low scale efficiency, which is closely related to the ratio of input and output. Liaoning and Shandong should allocate resources rationally and improve the efficiency of resource allocation and scale efficiency.

2) Actively carry out inter-regional cooperation, focusing on the development of inter-provincial port logistics cooperation mechanism. The ports of different provinces within the same port group should clearly define their own position, and the ports of each province should have a reasonable division of labor. At the same time, build a cross-provincial logistics system to improve the development level of the port logistics industry.

3) Improve the port collection and distribution facilities and improve the port financing system. The location conditions and traffic environment of the port hinterland play an important role in the development of the port, so the tilt of port collection and distribution facilities should be strengthened for Qingdao, Jinzhou, Rizhao, Yantai and other ports and key port areas.

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