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Evaluation Analysis of the Operational Efficiency and Total Factor Productivity of Container Terminals in China

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Abstract: As crucial international trade and global logistics players, container terminals worldwide handle more than 80% of the global merchandise trade. After analyzing and summarizing the previous studies, we use container terminal companies as the research object to fill the gap left by previous studies. Based on the above research status, this study analyzes the operational efficiency and total factor productivity of 32 container terminal companies in China using the super -efficiency DEA–SBM model and the Malmquist index method. The results show that (1) the operational efficiency level of 32 container terminals in China from 2017 to 2020 has a huge gap, and 15 container terminal companies have operational efficiency below 0.6, which indicates that most container terminals have excess inputs and a waste of resources. (2) The container terminals in the Bohai Rim, Pearl River Delta and Yangtze River Delta regions have higher operational efficiency. This shows that the development of container terminals cannot be separated from the economic hinterland of the cities where the ports are located. (3) The Malmquist index analysis shows a 2.8% decrease in total factor productivity, a 3.2% increase in the composite technical efficiency index and a 5.8% decrease in the technological progress index, which indicates that most container terminal companies have imperfect management practices and decision making. Based on the study's results, this research provides relevant and feasible recommendations for policymakers who formulate policies for the development of the shipping industry to promote high quality and sustainable development of the shipping industry and the economy.

Keywords: container terminal; operational efficiency; super-efficiency DEA–SBM model; Malmquist total factor productivity index

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1. Introduction

As the pillar industry of international trade, the shipping industry is directly related to the production, life, economic and social sustainable development of people worldwide [1]. The operational efficiency of ports is an essential indicator of a country's shipping industry development. Worldwide, more than 85% of international trade is conducted by sea freight [2]. As a key player in international trade and global logistics, container terminals are critical nodes in the maritime supply chain. Container terminals are essential infrastructure serving maritime and international trade, and their performance depends mainly on the development of the world economy and trade. International trade, global supply chains and the economic integration of different countries rely heavily on efficient container terminals and their associated supply chains. Container terminals around the world handle over 80% of global merchandise trade, and well-functioning and efficient container terminals are a powerful driver of global economic growth [3].

Competition among global container terminals is currently fierce, especially in the container market segment. More than ever, container terminals and their stakeholders need to be reassessed regarding their role in the global maritime supply chain [4]. In 2021, the global container shipping market demand continued to be strong. According to the Ministry of Transport of China, global full container ships reached 5515, 24.97 million TEU, and capacity scale increased by 4.1% compared to the last year [5]. However, due to the recurrence of the COVID-19 epidemic, congestion in the ports of some countries in the US and Europe has increased. This has led to the obstruction of the logistics supply chain, severe loss of ship capacity, a serious imbalance between the supply and demand of shipping capacity and a general increase in global shipping prices. As a result of the effective prevention and control of the epidemic, China still holds 7 of the top 10 ports and 28 of the top 100 ports in the world, with the 3 ports of Shanghai, Ningbo Zhoushan and Shenzhen still experiencing high growth rates from a large base [6]. In 2021, China completed port cargo throughput of 15.55 billion tons, which, according to preliminary statistics, increased by 6.8% compared to the last year. The port throughput of foreign trade cargo was about 4.7 billion tons, an increase of 4.5% from the last year. Container throughput was 280 million TEUs, which was up 7% from the last year. The port's foreign trade container throughput is about 160 million standard containers, which is an increase of 7.5% yearly [7]. Improving environmental performance and meeting established global sustainability benchmarks and targets, such as the Sustainable Development Goals, are increasingly considered key to port planning, investment and strategic positioning. Therefore, measuring and assessing container terminals' operational and economic performance and social and environmental performance is essential [8].

With the rapid development of China's economy, China's container terminals are in a fiercely competitive market environment. Market demand, on the one hand, drives economic growth. However, the rapid expansion of market capacity also intensifies market competition and blindly increases investment among container terminal companies, leading to operational inefficiency and a waste of resources [9]. How to evaluate and improve the operational efficiency of China's container terminals is key to changing the status quo of China's port industry, which is "large in scale but not competitive in the market" and is related to the survival and development of the port itself and stable economic growth. Improving operational efficiency is not only an important issue of concern for many container terminals but also one of the core issues of port operation theory [10]. In the rapid development of container terminals, we should not only focus on the growth of container throughput, but we should also pay attention to the operational efficiency of terminals. Otherwise, this can easily lead to problems of the scale of the port, "blind expansion", "excess berth throughput capacity" and other problems of resource waste [11].

The domestic and foreign studies on the quantitative evaluation of container terminal operation efficiency follow two ideas of efficiency evaluation, i.e., the production function method, which requires parameter estimation, and the data envelopment analysis method, which does not require parameter estimation. The DEA method is more suitable for operational efficiency evaluation because it can handle multiple input and output situations and does not need to explicitly give the relationship between inputs and outputs [12,13]. The existing domestic and foreign studies on the operational efficiency of container terminals mainly focus on the analysis of port efficiency. Liu [2] used a three-stage DEA model to evaluate the changes in operational efficiency for the period of 1998–2001 for 10 significant ports in the Asia–Pacific region. The results show that different models lead to different results. The three-stage DEA approach is the most efficient, indicating that the efficiency values, excluding statistical noise and errors, are more accurate. Lu et al. [14] used three models, BCC, CCR and super-efficiency, to evaluate and analyze the operational efficiency of the world's leading container ports, to analyze causes and to suggest improvements. Carine [15] used three models, BCC, CCR and super-efficiency, to evaluate the operational efficiency of container ports in 2012 with 16 container ports in sub-Saharan Africa. The results show that the inefficiencies of the selected ports were due to insufficient scale. Pinto et al. [16] used a DEA model to evaluate virtual terminals' equipment efficiency (OEE) worldwide. Dong et al. [17] used the DEA–SBM model to evaluate and analyze the environmental performance and operational efficiency of 10 major container ports along the Maritime Silk Road (MSR). The results show that the operational efficiency of the selected 10 ports outperformed the environmental performance. Liu et al. [18] assessed and analyzed the overall technical efficiency (OTECH), pure technical efficiency (PTECH) and scale efficiency (SECH) of 6 pilot free trade zones' ports in China from 2010 to 2017 using the super-efficiency DEA–SBM model to reveal their development.

In previous studies on container terminals, operational efficiency is usually evaluated and analyzed on a port unit. After analyzing the results of previous studies, we found that port-based studies do not fully reflect the actual operational efficiency. Therefore, we take the container terminal company as the research object to bridge the shortage in previous studies. This study analyzes the operational efficiency and total factor productivity of 32 container terminal companies in China in 2017–2020 using the super-efficiency DEA–SBM model and Malmquist index method. By analyzing and studying the operational efficiency of container terminals, we analyze the reasons affecting efficiency and propose improvement suggestions to achieve high-quality development of the shipping industry to promote high-quality and sustainable development of the global economy.

The content of the study is as follows: First, we briefly introduce the prior research and theoretical knowledge related to the operational efficiency of container terminals. Then, the corresponding measurement and evaluation methods and indicators for each variable in this paper are introduced, as well as the data sources and descriptions. After this, the analysis and empirical study of the corresponding data are conducted. Finally, we present the conclusion section, research limitations and future research directions.

2. Literature Review

Operational efficiency is an organization's ability to produce high-quality services or products while minimizing the waste of time, effort and materials [2]. In management, operational efficiency is the ratio between the inputs needed to keep an organization running and the outputs it delivers [19]. Inputs refer to things that are put in for normal operations, such as costs, employees and time. Outputs refer to things that are produced or acquired, such as products, quality, revenue, customer acquisition and customer retention. Operational efficiency is gained by a company cost-effectively streamlining its underlying operations while eliminating redundant processes and waste. Generally, this is achieved by focusing on resource utilization, production, inventory management and distribution [20]. In recent years, port operational efficiency has received considerable attention. Related studies can be divided into three research directions: the service operation perspective for evaluating port performance, the governance perspective for measuring port performance, and research of port environmental performance [17]. Wanke and Barros [21] used input/output factor extraction to calculate DEA efficiency estimates to assess the impact of public–private partnerships on major public ports in Brazil. Ding et al. [22] used the data envelopment analysis method (DEA) and the Malmquist productivity index (MPI) to assess the operational efficiency and total factor productivity changes in 21 small and medium-sized container terminals in China. Suárez-Alemán et al. [23] used the DEA–Malmquist index to analyze the operational efficiency of container ports in developing countries around the world. Kutin et al. [24] used the traditional output-oriented BCC and CCR models to analyze the relative efficiency of 50 container ports and terminals in the Association of Southeast Asian Nations (ASEAN). Ha et al. [25] proposed a port performance measurement tool from the perspective of different stakeholders. They established the interdependence between the port performance measurement indicators and the weight combination model of the interdependent measurement indicators, as shown in Table 1.

Table 1. Summary of operational efficiency in the literature.

Ref.	Research Subjects	Mode	Method
Liu [2]	Terminal operational efficiency	Asia's top 10 ports	DEA–CCR DEA–BCC
Lu et al. [14]	Container terminal operational efficiency	World's leading container seaports	DEA–CCR DEA–BCC
Carine [15]	Container terminal operational efficiency	Container ports in sub-Saharan Africa	DEA–CCR DEA–BCC Super DEA
Dong et al. [17]	Container terminal operational efficiency	Container ports along the Maritime Silk Road (MSR)	DEA–SBM
Liu et al. [18]	Terminal operational efficiency	China's six new free trade zones	DEA–SBM
Wanke et al. [21]	Terminal operational efficiency	Public-private ports in Brazil	DEA–CCR
Ding et al. [22]	Container terminal operational efficiency	21 coastal small and medium-sized port container terminals in China	DEA–CCR DEA–BCC DEA–Malmquist
Suárez-Alemán et al. [23]	Container terminal efficiency	Container terminals in developing countries	DEA–Malmquist
Kutin et al. [24]	Container terminal efficiency	50 ASEAN container ports and terminals	DEA–CCR DEA–BCC

From previous studies, it is known that DEA methods are widely used to measure efficiency problems. However, there are still the following shortcomings: First, most of the previous studies assess operational efficiency based on ports. Container terminals are composed of several container terminal companies, and the operational efficiency varies widely among companies. This can lead to the container terminal data not genuinely reflecting the actual situation. To compensate for previous studies' shortcomings, we take container terminal companies as the research object. Secondly, most of the previous studies on operational efficiency were static analyses and lacked the dynamic analysis of operational efficiency. The development of container terminals is a continuous process, and static measurement methods cannot accurately reflect the evolution of the operational efficiency of each container terminal company. Third, the traditional DEA model was basically chosen in previous studies. The traditional DEA model requires radial improvements of inputs and outputs, ignoring the effect of slack, which leads to deviations between the measured and actual efficiency values.

Based on the shortcomings of previous studies, the SBM model is selected in this paper to make the efficiency values vary with the slackness of inputs and outputs. According to the requirements of the container terminal operation efficiency evaluation model, the super-efficiency DEA model is combined with the SBM model to establish the super-efficiency DEA–SBM model. The super-efficiency DEA–SBM model avoids the bias caused by radial and angular selection and can obtain more accurate input–output efficiency. The Malmquist index is then used to analyze the dynamic changes in the operational efficiency of each container terminal company.

3. Materials and Methods

3.1. Materials

The data source used in this study is the National Bureau of Statistics of China and the *National Statistical Yearbook*, as well as the *Provincial and Municipal Statistical Yearbook* revised by the provincial statistical bureaus [26]. The timespan of the sample selection is 2017–2020. Due to some companies' lack of original data, only 32 container terminal companies in China are selected for the study. The data from the National Bureau of Statistics and the *National Statistical Yearbook* are more complete, and the official statistics are highly accurate and authoritative, guaranteeing the analysis results' accuracy.

Based on previous literature and data availability, this study selects four indicators as input indicators: the number of employees, the number of berths, the total length of berths and the amount of loading and unloading equipment. The container terminal throughput and net cargo weight are taken as output indicators, as shown in Table 2.

Table 2. Operational efficiency evaluation indicators.

Type of Indicator	Name of Indicator	Unit
Input Indicators	Number of employees (*X1*)	People
	Number of berths (*X2*)	Pcs
	Total length of berth (*X3*)	Meter
	Amount of loading/unloading equipment (*X4*)	Set
Output Indicators	Container throughput (*Y1*)	10,000 TEU
	Net weight of cargo (*Y2*)	10,000 tons

3.2. Methods

3.2.1. Super-Efficiency DEA–SBM Model

Data envelopment analysis (DEA) is a nonparametric efficiency analysis method proposed by Charnes et al. [27] to deal with multiple inputs and outputs. The DEA method projects decision-making units (DMUs) onto the frontier surface through linear programming and judges the relative effectiveness of DMUs based on their distance from the frontier surface. The DEA method is an essential tool for evaluating the relative efficiency between decision-making units (DMUs) with multiple inputs and outputs and has been widely used in various fields. As a non-parametric evaluation tool, DEA does not require a priori information about the production technology and cannot be underestimated in terms of avoiding subjective factors, simplifying operations and reducing errors [28]. The main principle of the traditional DEA model is that, when a DMU has a particular input or output, the production frontier of the evaluated data is established by analyzing the DMU through a transformed linear programming model and projection analysis. The relative efficiency value of each DMU can be obtained by comparing the distance between each DMU and the established production frontier to represent its relative efficiency. Furthermore, by comparing the situation of each DMU with the "best production" represented by the production frontier, we can find the causes of inefficiencies and then obtain some management recommendations to improve efficiency [28].

In order to fit the development status of container terminals, we need to enhance the practical significance of the terminal infrastructure by the operational efficiency of container terminals from the perspective of inputs and outputs. On the other hand, we also need to consider the slackness of inputs and outputs fully. Since the traditional efficiency measurement model only considers the proportional improvement of inputs or outputs, the obtained efficiency is often overestimated, leading to the inaccuracy of efficiency evaluation [29]. The traditional DEA model requires the radial improvement of inputs and outputs and ignores the influence of slack, which leads to bias between the measured value and the actual efficiency value [30]. To solve this problem, Tone [31] proposed a non-radial SBM model based on slack variables, which makes the efficiency values vary with the input and output slackness. Based on the requirements of the container terminal operation efficiency evaluation model, the super-efficiency SBM model was established by combining the super-efficiency DEA model and the SBM model. The super-efficiency DEA–SBM model avoids the bias caused by radial and angle selection and can obtain more accurate input–output efficiency [32].

Assuming the existence of n DMUs using m classes of inputs and s classes of outputs, an input vector $X = (x_{ij}) \in R^{m\times n}$ and an output vector $Y = (y_{ij}) \in R^{s\times n}$, the model can be expressed as:

$$\begin{cases} \min\rho = & \frac{1-\frac{1}{m}\sum_{i=1}^{m} S_i^-/x_{ik}}{1+\frac{1}{q}\sum_{r=1}^{q} S_i^+/y_{ik}} \\ \text{s.t.} & x_k = X\lambda + s^- \\ & y_k = Y\lambda + s^+ \\ & \lambda \geqslant 0, s^+ \geqslant 0, s^- \geqslant 0 \end{cases}$$

where ρ is the efficiency evaluation index; x_k and y_k are the input and output vectors of the decision unit, respectively; x_{ik} and y_{ik} are the elements of the input and output vectors, respectively; X and Y are the input–output matrices; s^- and s^+ denote the input–output slack variables; and λ is the column vector. When $\rho \geq 1$, it indicates that the decision unit is efficient; when $0 \leq \rho < 1$, it suggests that the decision unit needs to improve the input–output ratio further to achieve the best efficiency [33,34].

3.2.2. The Malmquist Total Factor Productivity Index Model

The DEA method can only compare the magnitude of the relative efficiency of decision units in the same period. It cannot observe the dynamic trend of efficiency in different periods [35]. Total factor productivity refers to the combined productivity of all factors in the system of production units. It is the efficiency of the utilization of all material elements except labor and capital. This paper analyzes the dynamics of port efficiency by introducing the Malmquist productivity change index proposed by Färe and Grosskopf [36] based on the Malmquist [37] study.

The Malmquist index method uses the ratio of distance functions to measure the total factor productivity change ($TFPCH$) from period t to period $t+1$, which can be decomposed into the product of the integrated technical efficiency change index ($EFFCH$) and the technical progress change index ($TECH$). The $EFFCH$ can be further decomposed into a scale efficiency change index ($SECH$) and a pure technical efficiency change index ($PTECH$).

$$TFPCH = EFFCH \times TECH = SECH \times PTECH \times TECH$$

The Malmquist index model is constructed as follows:

$$m_i(x_{t+1}, y_{t+1}, x_i, y_i) = \frac{d_i^t(x_t, y_t)}{d_i^{t+1}(x_{t+1}, y_{t+1})} \times \frac{d_i^{t+1}(x_{t+1}, y_{t+1}/VRS)}{d_i^t(x_t, y_t/VRS)} \times \left[\frac{d_i^t(x_t, y_t)}{d_i^{t+1}(x_t, y_t)} \times \frac{d_i^t(x_{t+1}, y_{t+1})}{d_i^{t+1}(x_{t+1}, y_{t+1})}\right]^{1/2} \quad (1)$$

where di_i denotes the input-oriented distance function; the first term is *SECH*; the second term is *PTECH*; and the third term is *TECH*. If the Malmquist index is greater than 1, it indicates an upward trend in *TFP*. If it is less than 1, this indicates a downward trend in *TFP*, and if it is equal to 1, this indicates a constant *TFP* [36].

4. Empirical Analysis

4.1. Descriptive Statistics

After the data were organized, we performed descriptive statistics. In the statistical table, Min represents each indicator's minimum value; Max represents each indicator's maximum value; Mean represents each indicator's mean; Median represents each indicator's median; and SD represents each indicator's standard deviation. The results of the descriptive statistics show that there is a huge gap between the inputs and outputs of the 32 container terminal companies in China. The descriptive statistical analysis of the input and output variables is as follows, as shown in Table 3.

Table 3. The descriptive statistics of the sample.

	Min	Max	Mean	Median	SD
X1	54.00	2268.00	552.59	438.00	438.05
X2	2.00	30.00	5.59	4.00	4.75
X3	269.00	7382.00	1603.88	1090.00	1437.46
X4	6.00	327.00	64.20	44.00	61.84
Y1	30.46	1334.90	349.87	257.63	306.26
Y2	365.14	13,273.00	3480.30	2771.40	2893.81

4.2. Pearson Correlation Analysis

Pearson correlation tests [38] were performed to ensure the validity of the selected input and output metrics. The results of the correlation test show that the correlation coefficients of the four input indicators (number of employees, the number of berths, the total length of berths and the number of loading and unloading equipment) and the two output indicators (container throughput and net weight of cargo) are positive. The correlation coefficients are positive and more significant than 0.7, indicating that the input and output indicators are positively correlated with each indicator and that the correlation is high. It also passed a two-tailed test at the 0.01 significance level, indicating a significant relationship between the input–output indicators. This is consistent with the homogeneity assumption required by DEA analysis [39]. The Pearson correlation test ensured the validity of the input and output indicators, as shown in Table 4.

Table 4. Pearson correlation analysis of inputs and outputs.

	X1	X2	X3	X4	Y1	Y2
X1	1	0.708 **	0.827 **	0.869 **	0.852 **	0.761 **
X2	0.708 **	1	0.802 **	0.772 **	0.781 **	0.756 **
X3	0.827 **	0.802 **	1	0.935 **	0.880 **	0.855 **
X4	0.869 **	0.772 **	0.935 **	1	0.879 **	0.837 **
Y1	0.852 **	0.781 **	0.880 **	0.879 **	1	0.932 **
Y2	0.761 **	0.756 **	0.855 **	0.837 **	0.932 **	1

Note: ** at the 0.01 level (two-tailed), the correlation is significant.

4.3. Evaluation of Container Terminals' Operational Efficiency

After the Pearson correlation test was passed, the operational efficiency of 32 container terminal companies in China was measured using the super-efficiency DEA–SBM model of MAXDEA software. The results show that the operational efficiency of 32 container terminals in China shows an overall trend of increasing and decreasing from 2017 to 2020. The number of terminals with an efficiency above 1 in 2017–2020 was 11, 8, 9 and 9. A total of 7 container terminals with efficiency had averages above 1 in 2017–2020, and they are located in Shanghai, Guangzhou, Wuhan and Tianjin. A total of 9 container terminals were between 0.7 and 1; 11 were between 0.4 and 0.7; and 5 were between 0.1 and 0.4. In terms of overall efficiency changes, the operational efficiency of the 32 container terminals in China in 2017–2020 shows an overall trend of first decreasing and then increasing. In terms of efficiency changes, the operating efficiency of container terminals in the southern region (Xinhaida, Yidong, Zhenghe, Jiujiang) increased significantly, and the operational efficiency of ports in the northeastern region (Dalian, Jinzhou, Yingkou, Xinshiji) decreased significantly. From the results, the terminals with high operational efficiency are concentrated in the economically developed Bohai Economic Belt (Dalian, Jinzhou, Yingkou, Xinshiji), the Pearl River Delta region (Nansha, Haigang, Xinhaida) and the Yangtze River Delta region (Guandong, Yidong, Hudong, Zhendong, Mingdong, Shengdong, Zhenghe). Economically developed areas have a good foundation of urban construction and huge market demand. However, this could also lead to a corresponding decrease in resources and market demand in the surrounding areas. This caused the low efficiency of terminal operation in the surrounding areas, as shown in Table 5.

4.4. Malmquist Total Factor Productivity Index

To further investigate the spatial and temporal variation of container terminals' operational efficiency, the Malmquist Total Factor Productivity Index (TFPI) model was used to obtain the results of TFPI and its decomposition index for 32 container terminals in China and to analyze their spatial and temporal variation characteristics.

Table 5. China's 32 container terminals' operational efficiency values for 2017–2020.

DMU	2017	2018	2019	2020	Average
Dalian	1.033	1.068	0.845	0.488	0.858
Dongguan	0.608	0.518	0.620	0.647	0.598
Nansha	1.307	1.417	1.387	0.705	1.204
Guangzhou	0.373	0.365	0.467	0.588	0.448
Haigang	1.598	0.722	1.724	0.938	1.245
Jinzhou	1.025	1.093	1.015	0.392	0.881
Xinshidai	0.474	0.281	0.708	0.574	0.509
Taipingyang	0.270	1.006	0.377	0.449	0.525
Zhaoshang	0.547	0.560	0.590	0.696	0.598
Meizishan	0.486	0.566	0.486	0.560	0.524
Zhoushan	0.577	0.547	0.576	0.678	0.594
Xiamen	0.338	0.254	0.272	0.302	0.291
Xinhaida	0.519	0.628	0.729	1.081	0.739
Jiujiang	0.187	0.319	0.411	0.547	0.366
Guandong	1.002	0.909	1.004	1.029	0.986
Yidong	0.765	0.910	1.239	1.113	1.007
Zhendong	1.016	0.866	0.922	1.021	0.956
Hudong	0.702	0.698	0.699	0.779	0.720
Mingdong	1.148	1.407	1.472	1.495	1.380
Pudong	0.637	0.617	0.609	0.727	0.647
Shengdong	1.087	0.857	0.913	1.004	0.965
Shekou	0.530	0.549	0.569	0.616	0.566
Zhenghe	0.877	1.149	1.080	1.001	1.027
Tianjin	0.493	0.528	0.536	0.730	0.572
Lianmengguoji	1.035	0.967	1.044	1.145	1.048
Jinyang	0.304	0.371	0.319	0.364	0.340
Wuhan	1.043	1.152	1.232	1.027	1.113
Yantian	0.541	0.534	0.554	0.616	0.561
Yingkou	0.933	0.868	0.644	0.768	0.803
Xinshiji	1.079	1.085	0.657	0.775	0.899
Yongjia	0.305	0.332	0.296	0.304	0.309
Hongwan	0.408	0.361	0.338	0.356	0.366
Average	0.726	0.734	0.760	0.735	0.739

The Malmquist index total factor productivity results are as follows: (1) The mean value of the total factor productivity index from 2017 to 2020 was 0.972, with a change of 2.8%. This indicates that the total factor productivity index of operational efficiency had a slight difference in change across periods, with an overall decreasing trend. After showing an increase in efficiency from 2017–2019, it showed a decreasing trend in 2019–2020. This indicates that the port did not reasonably consider operational efficiency while improving competitiveness during the research period. (2) The average value of pure technical efficiency from 2017 to 2020 was 1.01, with a change of 1%; the average value of the scale efficiency index was 1.022, with a change of 2.2%. Improving pure technical efficiency and scale efficiency has a positive effect on promoting port operation efficiency. Scale efficiency is slightly higher than pure technical efficiency, indicating that the ports paid more attention to improving technical levels under the existing scale conditions. (3) The average integrated technical efficiency value in the research period was 1.032, with an average increase of 3.2%, which is higher than the average value of the technical progress index. This indicates the more significant development potential of the technology level under the premise of technology development and scale development. (4) The comprehensive technical efficiency change index, scale efficiency index and pure technical efficiency index are all higher than the average value of the total factor productivity index. This indicates that the dominant port operation efficiency improvement is technological development and the scale of the port. The comprehensive technical efficiency index and pure technical efficiency index of the port have been increasing yearly, which is consistent with the phenomena of the continuous improvement of infrastructure, information level and a reduction in the port transportation costs of each port in recent years, as shown in Table 6.

Table 6. China's 32 container terminals' Malmquist index summary.

DMU	EFFCH	TECH	PECH	SECH	TFPCH
Dalian	0.844	1.017	0.948	0.891	0.859
Dongguan	1.022	0.962	1	1.022	0.983
Nansha	0.953	0.871	1	0.953	0.83
Guangzhou	1.163	0.95	1.078	1.078	1.105
Haigang	0.984	0.766	0.99	0.995	0.754
Jinzhou	0.745	0.98	1	0.745	0.73
Xinshidai	1.044	0.997	1	1.044	1.041
Taipingyang	1.195	0.975	1	1.195	1.165
Zhaoshang	1.159	0.877	1.1	1.053	1.016
Meizishan	1.084	0.906	1.05	1.032	0.982
Zhoushan	1.128	0.872	1.077	1.047	0.983
Xiamen	0.98	0.932	1	0.98	0.913
Xinhaida	1.161	0.874	1	1.161	1.015
Jiujiang	1.487	0.905	1	1.487	1.345
Guandong	1	0.985	1	1	0.985
Yidong	1.051	0.961	1	1.051	1.01
Zhendong	1	0.973	1	1	0.973
Hudong	1.089	0.92	1.086	1.003	1.002
Mingdong	1	1.017	1	1	1.017
Pudong	1.101	0.885	1.042	1.056	0.975
Shengdong	1	0.945	1	1	0.945
Shekou	1.029	1	1.05	0.98	1.029
Zhenghe	1.01	1.029	1	1.01	1.04
Tianjin	1.113	0.927	1.059	1.051	1.032
Lianmengguoji	1	1.042	1	1	1.042
Jinyang	1.053	0.96	0.993	1.061	1.012
Wuhan	1	1.031	1	1	1.031
Yantian	1.042	0.975	1	1.042	1.015
Yingkou	0.964	0.886	1	0.964	0.854
Xinshiji	0.936	0.931	1	0.936	0.871
Yongjia	1.002	0.956	0.957	1.047	0.957
Hongwan	0.9	0.899	0.901	0.998	0.809
Average	1.032	0.942	1.01	1.022	0.972

5. Conclusions

5.1. Research Summary

This paper uses the panel data of 32 container terminal companies in China from 2017 to 2020 as a sample based on previous studies. The super-efficiency DEA–SBM model is applied to reveal the operational efficiency of these container terminals, and the Malmquist index is used to analyze the trend of efficiency dynamics.

The results of this research indicate that: (1) There is a huge gap between the operational efficiency levels of 32 container terminals in China in 2017–2020. There are 15 container terminal companies with an operational efficiency below 0.6, indicating that most container terminals have over-input and a waste resources. (2) The operational efficiency of the port clusters in the Yangtze River Delta and the Pearl River Delta is higher. In comparison, efficiency in the northeastern region is generally lower, indicating that the development of container terminals is inextricably linked to the economic hinterland of the cities where the ports are located. (3) The Malmquist index analysis total factor productivity of 32 container terminals in China decreased by 2.8% in 2017–2020, the comprehensive technical efficiency index increased by 3.2% and the technical progress index decreased by 5.8%. The decline in the technological progress index indicates that most container terminal companies have poor management practices and decision making.

5.2. Discussion

In previous studies on container terminals, the operational efficiency of container terminals was studied for the whole terminals [14–17]. Container terminals are composed of several container terminal companies, and the operational efficiency of each company varies greatly. This may result in the container terminal data not truly reflecting the actual situation. In our study, we take container terminal companies as the research object to fill the gap in the study of container terminal operation efficiency. The results show that the operational efficiency of container terminals is closely related to the economy of the regions where they are located, and the operational efficiency of container terminals in economically developed regions is higher [9,17,40]. However, economically developed areas also lead to lower markets and resources in the surrounding areas, which causes inefficiency in some areas. The Malmquist index analysis shows that the combined technical efficiency index of 32 container terminals in China increased by 3.2%, and the scale efficiency increased by 2.2% from 2017 to 2020. This is generally consistent with the results of Liu [41], which indicate that the technology investment and infrastructure of each container terminal in China are developed. The difference is that the total factor productivity rose in the study with container terminals as the subject of study [41]. In our study, the total factor productivity of 32 container terminal companies in China decreased by 2.8%, and the efficiency of technological progress decreased by 5.8%, indicating that most container terminal companies have poor management practices and decisions. This shows that the reasons for the inefficiency of the operations of the container terminal companies come from the company managers and policymakers. Due to the characteristics of container terminals, high efficiency and high automation are a measure of the success of a container terminal prerequisite. Therefore, how to manage with high efficiency is the question that each manager needs to think about.

5.3. Policy Recommendations

As an essential connection point of the global economy, container terminals are directly related to the economic development of countries. Although this study takes container terminal companies as the research object, the development of container terminals cannot be achieved without the support of national policies. The following recommendations are based on the research results and the actual situation.

(1) Clarify the positioning of each port, reasonably allocate port resources and elements, further strengthen infrastructure construction, form economies of scale and promote the steady improvement of port operation efficiency. Promote the development of an open economy, create a fair operating environment, actively participate in the construction of infrastructure and the improvement of domestic and international transportation systems, and enhance the ability of ports to adapt to the new development concept.

(2) In terms of regional construction, strengthen regional cooperation and realize the integrated development of ports and cities. Take advantage of the restricted location to learn specialized division of labor, promote resource integration and industry chain mythology, and strengthen the coordinated development of ports and cities.

(3) In terms of technology, strengthen critical technology research and development, encourage technology industry reform, upgrade port equipment and build infrastructure that meets the requirements of technological transformation and industry development.

(4) In terms of terminal management and operation, strengthen management and avoid poor decision making. In response to the input redundancy situation, it is necessary to prevent over-investment in port infrastructure construction and to give full play to the functions of existing port infrastructure.

5.4. Limitations and Future Research

This paper measures the operational efficiency and total factor productivity of 32 container terminals in China for 2017–2020. This paper adopts the method of empirical analysis. The limitations mainly come from the collection and acquisition of data, the choice of research methods and the academic ability of the authors. Therefore, this paper has some shortcomings, and we hope to further research the following areas.

(1) In the selection of the operational efficiency evaluation model, the selection of super-efficiency SBM model is used. Besides the DEA model, there are gray evaluation methods, indicator evaluation methods, stochastic frontier methods, etc. There is no comparative study of these evaluation methods, so it is necessary to analyze their advantages and disadvantages further and to improve the evaluation method.

(2) In the selection of operational efficiency evaluation indicators, only four input variables and two output variables are selected. Factors such as environmental factors and undesired outputs are not considered. As an essential link to the global economy, container terminals bring problems such as environmental pollution and resource waste while promoting global development. Therefore, in future research, more reasonable evaluation indicators can be constructed in conjunction with the actual situation, and factors such as non-desired outputs can be taken into account to more accurately evaluate port operation efficiency.

(3) For some of the evaluation indicators selected for operational efficiency, the data after 2020 have not been published to reflect the current situation fully. Given the data collection limitations, this paper uses the National Bureau of Statistics data for 2017–2020. This may have led to the lack of continuity and validity of the data used in this paper, which can further deepen studies in the future.

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