

Article

Operational Efficiency Evaluation and Persistence Analysis for Chinese Port-Listed Companies Using the Network SBM Model

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Abstract

Ports play a crucial role in global maritime logistics systems, and evaluating their operational efficiency is essential for improving resource allocation. However, existing studies often treat port operations as a black box, limiting the understanding of internal mechanisms and sources of inefficiency. Using panel data from 17 Chinese port-listed companies from 2018 to 2023, this study applies a network slacks-based measure (SBM) model to evaluate operational efficiency within a two-stage framework. The service stage transforms labor, fixed assets, and berth length into cargo and container throughput, while the profitability stage converts these outputs into revenue and net profit. The results show that overall operational efficiency remains relatively low. Profitability-stage efficiency is generally lower than service-stage efficiency, indicating that inefficiency mainly arises from the limited ability to convert operational performance into financial outcomes. Significant differences are also observed across regions and operational scales. To further capture persistence, this study evaluates the dynamic performance of efficiency by considering both growth and fluctuation over time. The findings indicate that most inefficient ports exhibit weak persistence, reflecting limited capacity to maintain stable efficiency improvements. This study provides a stage-based analytical framework for identifying inefficiency sources and offers insights for enhancing both efficiency and the long-term stability of port operations.

Keywords: operational efficiency; port-listed companies; persistence; network SBM model

1. Introduction

With the continuous expansion of global maritime trade and the growing demand for port modernization, port companies have become increasingly important within global supply chains [1]. Ports not only serve as critical logistical hubs but also face growing challenges related to sustainable development and operational performance [2,3]. In particular, sustainable port development requires not only high operational efficiency but also the ability to maintain stable performance over time under changing market conditions. Correspondingly, port companies face the urgent issue of how to maintain efficient operations in management practice [4]. As management guru Peter Drucker once noted, “If you cannot measure it, you cannot improve it.” Naturally, the operational efficiency of port companies needs to be accurately evaluated first.

In the literature, the evaluation of port efficiency can be broadly classified into single-factor methods and multi-factor methods. The traditional single-factor efficiency evaluation



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only considers a specific indicator, such as vessel turnaround time [5], berth productivity, or crane productivity [6]. While this method has certain practical value, it cannot comprehensively reflect the complex operational system of the port, particularly in identifying efficiency issues at different stages [7]. Later, an increasing number of scholars adopted multi-factor frontier analysis methods such as data envelopment analysis (DEA) and stochastic frontier analysis (SFA) [8,9]. These methods can effectively combine multiple input and output factors, thereby providing more accurate results for the comprehensive efficiency assessment of ports [10].

Although previous studies have substantially improved the measurement of port efficiency, an important question remains unanswered. Existing research primarily evaluates how effectively ports transform physical resources into operational services, while paying limited attention to whether these service outputs can be successfully converted into financial value.

As a result, it remains unclear whether the low operational efficiency observed in many ports originates from deficiencies in service provision or from weaknesses in profitability generation. This distinction is theoretically important because the two inefficiency sources imply fundamentally different resource allocation mechanisms and managerial strategies. It is also practically important because ports with strong operational capabilities may still fail to achieve satisfactory financial performance.

Understanding the source of inefficiency is critical because different inefficiency sources require fundamentally different managerial interventions and resource allocation strategies. Accordingly, this study addresses the following research question: Where does port inefficiency primarily originate? Does inefficiency arise from the inability to transform operational resources into service outputs, or from the inability to convert service outputs into financial returns? Answering this question contributes to the port efficiency literature by shifting the focus from efficiency measurement to inefficiency diagnosis, thereby revealing where value-creation bottlenecks emerge within port operations.

The main contributions of this study are summarized as follows:

First, this study advances the port efficiency literature by identifying the internal source of inefficiency through a two-stage value-creation framework. Drawing on the Resource-Based View (RBV), port operations are conceptualized as a process in which physical resources are transformed into operational services and subsequently into financial outcomes. This framework enables the distinction between service-stage inefficiency and profitability-stage inefficiency, thereby providing new insights into where value-creation bottlenecks emerge within port operations.

Second, this study complements conventional efficiency assessment by introducing an efficiency persistence perspective. While most port efficiency studies focus on cross-sectional efficiency levels, this study further examines whether efficiency improvements can be maintained with relative stability over time. This perspective provides additional insights into the long-term resilience of port operational performance.

The rest of this study is organized as follows. Section 2 presents the literature review on efficiency in the port industry. Section 3 establishes the methodology by introducing the network SBM model and the measure for efficiency persistence. Section 4 provides a detailed description of the two-stage operational process of port companies as well as the selection of input and output variables. Section 5 reports the efficiency evaluation results. Section 6 discusses these findings in depth and derives practical managerial implications. Finally, Section 7 concludes this paper.

2. Literature Review

In recent years, increasing attention has been paid to persistence in port operations, particularly in terms of balancing efficiency performance with long-term development and environmental considerations. To evaluate the operational efficiency of ports, scholars generally employ either single-factor or multi-factor measurement frameworks. In the traditional single-factor measurement, indicators such as vessel turnaround time, berth or crane productivity, and cargo dwell time remain widely applied. For example, Zhang and Kim [6] focused on quay crane productivity and propose optimization strategies to maximize dual-cycle operations, thereby reducing ship service time and improving berth utilization efficiency. Saurí and Martín [11] investigated container dwell time in import yards at marine terminals and demonstrate that longer container stays intensify yard congestion and rehandling activities, thereby deteriorating terminal operational performance and highlighting the critical role of dwell-time management in port efficiency improvement. Meanwhile, Yoon et al. [12] applied machine learning models to predict vessel dwell times at Busan New Port, demonstrating how time-based metrics can be used to quantify port-level service effectiveness with high temporal resolution. These indicators are intuitive, transparent, and easy to benchmark operationally, making them useful for managerial decision-making. However, single-factor measurement ignores the multi-input, multi-output nature of port operations, oversimplifies complex production systems, and may lead to biased efficiency results.

To address these limitations, recent studies increasingly adopt multi-factor frontier approaches, particularly the parametric SFA and the nonparametric DEA. For instance, Delfin-Ortega [13] employed an SFA metafrontier framework to evaluate efficiency in maritime transport and finds that large hub ports exhibit higher efficiency and smaller technology gaps, while less advanced ports display lower efficiency. Compared with traditional ratio-based or deterministic approaches, SFA offers a more realistic assessment because it can consider multiple inputs and outputs. However, SFA still depends on predefined functional forms, which makes the results sensitive to model specification. In addition, traditional SFA models are relatively limited in their ability to handle multi-stage production processes. In contrast, DEA serves as a non-parametric approach that avoids functional-form misspecification and accommodates multiple inputs and outputs. In recent years, the DEA method has become one of the most rapidly expanding analytical frameworks for evaluating port operational efficiency [14,15]. DEA-based studies on port efficiency are generally categorized into two streams according to the production process: single-stage and two-stage models.

The single-stage DEA model remains a fundamental tool for evaluating port operational efficiency, offering a direct and transparent means to assess performance. Early research, such as Roll and Hayuth [16], applied DEA to port performance comparisons and identified substantial efficiency disparities caused by differences in governance structures and scale. Wu and Goh [17], employing a DEA-based efficiency framework for container ports across emerging and advanced markets, demonstrated that ports in advanced economies achieve superior and more stable efficiency due to stronger infrastructure endowments and managerial capabilities. Sun et al. [18] extended the single-stage approach to include environmental factors, revealing that stricter ecological constraints significantly lower the average efficiency of Chinese port companies.

As for the two-stage efficiency measurement, most studies divide the port production process into a service or operational stage and an outcome or transformation stage to examine the efficiency within the port system. Wanke [19] divided port operations into the first stage of physical infrastructure efficiency and the second stage of shipment consolidation efficiency, applied a two-stage network DEA model to Brazilian ports and found that

infrastructure utilization efficiency was considerably higher than shipment consolidation efficiency. Nguyen and Tsai [20] divided container port operations into a building capacity stage and a utilizing capacity stage, finding that a multiplicative two-stage network data envelopment analysis (DEA) approach provides more accurate diagnostic insights into the underlying causes of technical inefficiencies that are often masked in traditional single-stage analyses. While previous studies mainly focused on overall port performance as a single process, this comprehensive framework concurrently examines technical efficiency, pure technical efficiency, and scale efficiency. The decomposition reveals that the overall underperformance of Southeast Asian container ports is primarily driven by technical inefficiency in the building capacity phase rather than the utilizing capacity phase, and that inadequate scale operation remains a significant constraint for long-term productivity. Krmarc and Djordjević [21] divided port operations into an operational production stage and a transformation stage, finding that the two-stage approach provides more accurate diagnostic insights into environmental inefficiencies that are often overstated in single-stage analyses. While these studies extend efficiency analysis to environmental and regional persistence contexts, they mainly focus on static performance and provide limited insights into the dynamic persistence of operational efficiency over time.

There is also a strand of research devoted to the port–regional system model. For instance, Chen and Lam [22] developed a two-stage SBM-DEA framework to link port operations with urban persistence, using data from 20 major global port cities. Their results showed that ports such as Singapore and Busan achieve high operational efficiency but low environmental performance, indicating that rapid port expansion may outpace sustainable urban governance. Wang et al. [23] employed a two-stage network DEA model to assess European port–regional systems and confirmed that operational efficiency systematically exceeds environmental efficiency, revealing a continuing gap between production capacity and ecological management.

Here we focus on analyzing the studies by Wanke [19] and Nguyen and Tsai [20]. Both of these papers utilize two-stage evaluation frameworks to identify internal operational bottlenecks. Wanke [19] divides port operations into physical infrastructure and shipment consolidation stages. Similarly Nguyen and Tsai [20] explore capacity building and capacity utilization phases. These existing models share a fundamental limitation as they concentrate exclusively on the physical and infrastructural aspects of maritime logistics. They primarily assess the capability to transform fixed assets into physical throughput. Furthermore their evaluations are completely static and cannot capture performance stability over time. Our research offers distinct advantages by explicitly integrating the financial value-creation process into the efficiency evaluation. Rather than concluding the assessment at physical cargo handling we adopt a network slacks-based measure model that links a foundational service stage directly to a profitability stage. This structural innovation uncovers the widespread phenomenon where massive cargo throughput fails to generate proportional economic returns. Moreover this study overcomes the static nature of previous research by introducing a dynamic persistence metric. By evaluating both the growth and fluctuation of efficiency across multiple years our framework provides deeper insights into the long-term operational resilience of port companies.

Existing two-stage DEA studies have primarily focused on infrastructure utilization [19], port–city sustainability interactions [22], or port–region coordination systems [23]. Although these studies successfully decompose port-related activities into multiple stages, they mainly examine operational, environmental, or regional development processes. However, they seldom examine whether operational outputs can be successfully converted into financial value. In contrast, the present study conceptualizes port operations as a value-creation process in which physical resources are transformed into operational ser-

vices and subsequently into financial outcomes. By explicitly incorporating a profitability stage, this study investigates whether inefficiency originates from service provision or from the conversion of services into financial returns. Therefore, the contribution of this study lies not in the application of a two-stage DEA model itself, but in addressing a different research question concerning the internal source of inefficiency within port companies.

In summary, mapping the methodological evolution of port efficiency evaluation reveals two specific, critical gaps. First, conceptually, the existing two-stage literature predominantly focuses on physical infrastructure utilization or environmental trade-offs, largely neglecting the subsequent value-creation phase: how these operational services are translated into corporate financial profitability. Second, methodologically, prior studies lack a systematic approach to measure the dynamic persistence of efficiency—namely, the capacity to maintain stable improvements over time—leaving a gap in understanding long-term operational resilience.

To address these research gaps, this study uses the Resource-Based View (RBV) as a guiding theoretical framework. As proposed by Wernerfelt [24] and Barney [25], the RBV suggests that a firm achieves competitive advantage and strong financial performance by effectively configuring its strategic resources and internal capabilities. In port operations, foundational resources mainly include physical infrastructure like berths and fixed assets alongside human capital. These elements are necessary to generate physical service outputs. However, the RBV highlights that merely collecting these highly imitable and homogeneous resources does not automatically create sustained economic value. If ports cannot turn their operational capacity into value-adding market capabilities, they risk misallocating resources and failing to capture financial returns. Building on this theoretical logic, our study applies a network SBM model to examine a two-stage process. We first assess the utilization of foundational resources in the service stage. Next, we evaluate the capacity to capture financial value from these services in the profitability stage. We also introduce a persistence indicator to track the temporal stability of this resource-to-profit conversion. This approach theoretically clarifies how physical endowments are converted into resilient financial performance.

3. Methodology

3.1. SBM Model

Since the seminal work of Charnes et al. [26], in which the DEA method is first proposed through the Charnes–Cooper–Rhodes (CCR) model, the methodology evolves through theoretical refinements and practical extensions. To overcome the restrictive assumption of constant returns to scale embedded in the CCR framework, Banker et al. [27] introduced the BCC model, which incorporates variable returns to scale (VRS) and thereby broadens DEA's applicability to production systems of heterogeneous sizes. Nevertheless, both the CCR and BCC models remain radial in nature, requiring proportional adjustments of all inputs and outputs and thus limiting their capacity to capture slack inefficiencies observed in practice. To address this limitation, Tone [28] developed the SBM model, which provides a comprehensive non-radial framework capable of directly incorporating slack variables, distinguishing efficient from near-efficient decision-making units (DMUs) and handling undesirable outputs.

Assume that there exist n DMUs. Each DMU uses m inputs to generate g outputs. The input and output matrices are expressed as $X = (x_{ij}) \in R^{m \times n}$ and $Y = (y_{rj}) \in R^{r \times n}$. The production possibility set P can be defined as

$$P = \{(x, y) | x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\} \quad (1)$$

where λ is a non-negative weight vector, representing the intensity of each DMU in constructing the optimal production frontier.

Based on Tone [28], the non-oriented SBM model is presented by Formula (2).

$$\begin{aligned} \rho_o^{SBM} = \min & \frac{1 - \frac{1}{m} \left(\sum_{i=1}^m \frac{s_i^-}{x_{io}} \right)}{1 + \frac{1}{g} \left(\sum_{r=1}^g \frac{s_r^+}{y_{ro}} \right)} \\ \text{s.t. } & X\lambda + s^- = x_o, \\ & Y\lambda - s^+ = y_o, \\ & e\lambda = 1, \\ & \lambda, s^-, s^+ \geq 0. \end{aligned} \quad (2)$$

where s^- and s^+ are slack variables of inputs and outputs. The subscript o denotes the evaluated DMU. The objective value ρ_o^{SBM} denotes the efficiency for the evaluated DMU, ranging from 0 and 1. The evaluated DMU will be evaluated as efficient when it contains neither redundant inputs nor insufficient outputs, i.e., $\rho_o^{SBM*} = 1$. When $\rho_o^{SBM*} < 1$, the evaluated DMU is regarded as inefficient. If the constraint $e\lambda = 1$ is deleted, the CRS setting of the SBM model can be obtained.

3.2. Network SBM Model

Compared with a single-stage production system, the multi-stage system is more complex, making it difficult to accurately measure efficiency at each stage as well as overall operational efficiency. To this end, Tone and Tsutsui [29] extended the SBM model to the network SBM model. This network structure enables the model to capture the internal flow of resources and inter-stage linkages, providing a more detailed representation of operational processes.

Assume that there are k ($k = 1, \dots, K$) stages in the network production system. After externally assigning the weight w^k of each stage k in the operational efficiency assessment, the non-oriented network SBM model based on the VRS assumption is shown in Formula (3).

$$\begin{aligned} \rho_o^{NSBM} = \min & \frac{\sum_{k=1}^K w^k \left[1 - \frac{1}{m_k} \left(\sum_{i=1}^{m_k} \frac{s_i^{k-}}{x_{io}^k} \right) \right]}{\sum_{k=1}^K w^k \left[1 + \frac{1}{g_k} \left(\sum_{r=1}^{g_k} \frac{s_r^{k+}}{y_{ro}^k} \right) \right]} \\ \text{s.t. } & X^k \lambda^k + s^{k-} = x_o^k, \\ & Y^k \lambda^k - s^{k+} = y_o^k, \\ & e\lambda^k = 1 (k = 1, 2, \dots, K), \\ & \lambda^k, s^{k-}, s^{k+} \geq 0, (\forall k). \end{aligned} \quad (3)$$

where $X^k = (x_1^k, \dots, x_n^k) \in R^{m_k \times n}$, $Y^k = (y_1^k, \dots, y_n^k) \in R^{r_k \times n}$, $\sum_{k=1}^K w^k = 1$, $w^k \geq 0 \forall k$. The meaning of the parameters is the same as that in Formula (2). Based on Tone and Tsutsui [29], the constraint associated with the link variable $Z_o^{(k,h)}$ should be included in Formula (3) as shown below:

$$Z^{(k,h)} \lambda^h = Z^{(k,h)} \lambda^k, (\forall (k, h)), \quad (4)$$

where $Z^{(k,h)} = (z_1^{(k,h)}, \dots, z_n^{(k,h)}) \in R^{t_{(k,h)} \times n}$. Formula (4) expresses the “free” case that the linking activities are free while keeping the continuity between inputs and outputs. This means the intermediate products may change (increase or decrease) in the optimal solution of Formula (3).

The objective value ρ_o^{NSBM} denotes the operational efficiency for the evaluated DMU. The evaluated DMU will definitely be considered as overall efficient when $\rho_o^{NSBM*} = 1$. When $\rho_o^{NSBM*} < 1$, the evaluated DMU is regarded as inefficient. The efficiency ρ_o^{k*} at stage k can be defined by:

$$\rho_o^{k*} = \frac{1 - \frac{1}{m_k} \left(\sum_{i=1}^{m_k} \frac{s_i^{k-*}}{x_{io}^k} \right)}{1 + \frac{1}{g_k} \left(\sum_{r=1}^{g_k} \frac{s_r^{k+*}}{y_{ro}^k} \right)} \quad (k = 1, 2, \dots, K) \quad (5)$$

where s^{k-*}, s^{k+*} represents the optimal input and output slacks for the abovementioned Formula (3).

In this study, the network SBM model is applied to a two-stage operational process to capture the internal structure of port operations. That is, $k = 1, 2$. The evaluated DMU will be considered efficient at stage k when $\rho_o^{k*} = 1$. When $\rho_o^{k*} < 1$, the evaluated DMU is regarded as inefficient at stage k .

3.3. Measure for the Persistence of Operational Efficiency

Persistence in operational efficiency reflects whether a port company can maintain a stable efficiency path over time and whether its efficiency shows an improving or declining trend. In this study, the persistence of operational efficiency is measured from two aspects. The first aspect is the fluctuation of operational efficiency, measured by the variance of annual operational efficiency from 2018 to 2023. In this study, the median value is used as the benchmark for judging the level of variance. A smaller variance indicates that the operational efficiency of the port company is more stable over time, while a larger variance indicates stronger fluctuation.

The second aspect is the changing trend of operational efficiency, measured by the regression coefficient β obtained from a simple linear regression, as shown in Formula (6).

$$OE_{\delta t} = \alpha_{\delta} + \beta_{\delta} t + \varepsilon_{\delta t} \quad (6)$$

where t is coded as the years from 2018 to 2023, δ represents the δ th port company. α_{δ} is the intercept, β_{δ} is the regression coefficient, and $\varepsilon_{\delta t}$ is the random error term. The value of β_{δ} reflects the average annual change in operational efficiency. A positive β_{δ} indicates an upward trend in operational efficiency, while a negative β_{δ} indicates a downward trend.

Based on the two indicators, this study presents the persistence characteristics of port operational efficiency through a scatter plot. The horizontal axis represents the variance of operational efficiency, and the vertical axis represents β . This method avoids judging persistence only by the efficiency difference between the beginning and the end of the period. It also retains information on yearly fluctuation during the whole observation period. In this way, port companies with low variance and positive β can be regarded as having relatively strong efficiency persistence, since their efficiency improves while remaining stable. Port companies with high variance and positive β show improvement but lack stability. Port companies with low variance and nonpositive β are relatively stable but show weak improvement. Port companies with high variance and negative β face both instability and a declining efficiency trend.

4. Port Operational Process and Variable Selection

4.1. Two-Stage Operational Process of Port Companies

In the literature, many studies adopt a two-stage DEA framework to analyze port operations because it captures how resources are transformed into services and subse-

quently into economic outcomes [14,22,30]. Following these studies, this study divides the operational process of port companies into two key stages: the service stage, which focuses on transforming input resources (fixed assets, berth length, and labor) into service outputs (cargo throughput and container throughput); and the profitability stage, which emphasizes converting these intermediate outputs into financial outcomes (operating revenue and net profit). This structure enables a consistent assessment of service-stage efficiency and profitability-stage efficiency and facilitates stage-specific diagnostics, as illustrated in Figure 1.

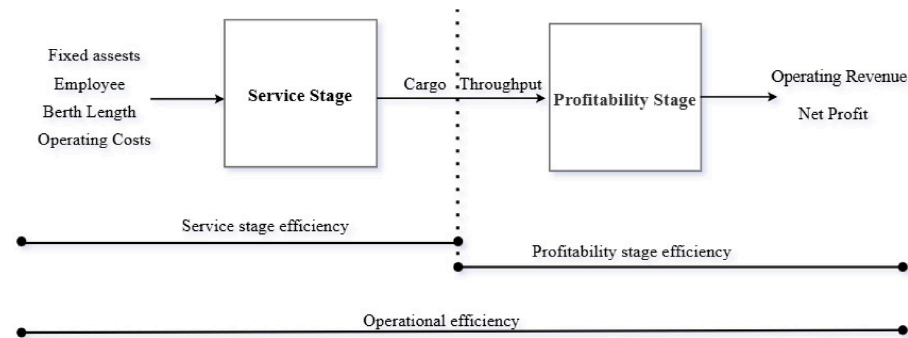


Figure 1. The operational process of port companies.

4.2. Input and Output Variables

To better evaluate the operational efficiency of port companies, appropriate input and output indicators must be identified. Recent studies employ a variety of input–output combinations depending on the analytical framework and data availability, as summarized in Table 1. Based on existing studies, this paper selects appropriate input and output indicators for the two-stage operational process of ports, which are strictly categorized into three groups: inputs, intermediates, and outputs, as systematically detailed in Table 2. In the service stage, port companies allocate physical and infrastructure inputs to generate operational services. The inputs include berth length, employees and fixed assets [19,21,22,31–33]. The service outputs are cargo throughput and container throughput, which capture the realized volume of operational services produced by these core inputs [19,22,31–33].

Table 1. Input–output variables.

Studies	Inputs	Intermediates	Outputs
[19]	Number of berths, warehousing area, yard area, solid bulk frequency, container frequency	Solid bulk frequency, container frequency	Solid bulk throughput, container throughput
[21]	Total number of cranes, total number of terminals, vessels arrived	Goods received, goods forwarded, total energy consumed per ton of volume throughput	Total number of vehicles, total emissions produced per year
[22]	Terminal area, berth length, number of quay cranes	Annual container throughput	GDP, exhaust emissions & wastes
[29]	Number of container berths, container berth length, number of quay cranes	/	Container throughput, CO ₂ emissions
[30]	Cost of port security measures, container facilities infrastructure cost, dredging cost, berth length, number of cranes, container terminal acreage	/	Net income, container throughput
[31]	Berth length, average depth, berth number	/	Container throughput
[32]	Number of terminals, capital expenditure, vessels arrived	Goods received, goods forwarded, energy consumed per ton of throughput	Total number of vehicles/trucks, operating profit, total CO ₂ emissions per year

Table 2. Description of the variables.

Variable Type	Variable	Description	Unit
Input	Employees	Reflects the total number of employees in each port company, used as a proxy for labor input	10 ³ Persons
	Fixed assets	Residual value of fixed assets after depreciation, serving as a proxy for capital input	10 ⁸ CNY
	Berth length	Total available berth length of each port, representing port infrastructure capacity	m
Intermediate	Operating costs	Total expenses incurred in daily port operations, serving as a proxy for operational input	10 ⁸ CNY
	Cargo throughput	Total volume of goods handled by the port, reflecting operational performance	10 ⁴ t
	Operating revenue	Income derived from regular port operations, including loading, unloading, logistics, and related services	10 ⁸ CNY
Output	Net profit	Remaining profit or loss after revenues and expenses are accounted for, indicating profitability	10 ⁸ CNY

In the profitability stage, the operational service output from the first stage is converted into financial outcomes through port service charges and related logistics activities. The most frequently used economic outputs are net income and operating profit, which reflect profitability performance [32,34]. Therefore, this two-stage framework describes how core capacity inputs generate operational throughput, and how this throughput is subsequently translated into financial profitability.

In China, 17 listed port companies are broadly representative of the national port industry in terms of throughput scale, cargo mix (containers and major bulk cargoes), and corporate governance. As listed firms, these port companies provide audited and standardized operational and financial disclosures, which ensure the construction of a reliable dataset. The samples cover leading hub ports and regional ports of different sizes, giving sufficient information to identify stage efficiency differences over 2018–2023. Notably, this specific data period covers the outbreak, persistence, and aftermath of the COVID-19 pandemic, thereby capturing its potential impacts on international supply chain disruptions and port operations while maintaining data reliability and comparability.

Regarding data sources, data on fixed assets, number of employees, operating revenue, and net profit are obtained from each company's annual reports, while data on berth length and cargo throughput are collected from the Port Yearbooks (2019–2024) and official websites. Table 3 reports the descriptive statistics of the variables in 2018, 2020, and 2022.

Table 3. Descriptive statistics.

Year	Input					Intermediate	Output	
	Factor	Employees	Fixed Assets	Berth Length	Operating Costs	Cargo Throughput	Operating Revenue	Net Profit
	Unit	10 ³ Persons	10 ⁸ CNY	m	10 ⁸ CNY	10 ⁴ t	10 ⁸ CNY	10 ⁸ CNY
2018	Max	16.37	318.40	43,056.00	307.50	7.76	380.40	143.30
	Min	0.78	18.66	4881.00	2.91	0.13	4.04	0.19
	Avg	6.68	127.98	18,083.74	84.29	3.00	96.80	18.63
	Std. Dev.	4.83	90.84	10,982.54	74.68	2.24	90.59	34.10
2020	Max	17.79	392.00	55,601.00	215.30	9.20	261.19	105.70
	Min	0.85	22.26	4881.00	5.26	0.25	5.31	0.94
	Avg	7.10	151.00	19,657.21	82.50	3.19	96.58	20.50
	Std. Dev.	5.13	109.61	14,233.01	60.97	2.45	71.59	27.36
2022	Max	17.07	438.70	53,730.00	283.90	10.40	372.80	201.20
	Min	0.89	22.44	4881.00	6.38	0.41	7.98	1.26
	Avg	7.58	165.74	19,799.50	96.64	3.53	114.22	28.59
	Std. Dev.	5.38	122.33	13,977.63	81.02	2.82	99.68	49.70

5. Results Analysis

5.1. Overall Analysis of Port Operational Efficiency

In the calculation process of the network SBM model, we set the weights $w^1 = w^2 = 0.5$ to indicate that the two stages are of equal importance. This equal weight setting is widely applied in two-stage DEA studies, such as the framework proposed by Chen et al. [35]. Based on the collected data, this study obtains the overall operational efficiency of ports as well as stage-specific efficiency for port companies. Table 4 reports the efficiency values for 17 port companies from 2018 to 2023. First, an overall analysis is conducted based on the average operational efficiency scores over the study period. The companies are categorized into two groups: those with efficiency scores above and below the sample average.

Table 4. Efficiency results of port companies during 2018–2023.

Port	2018			2019			2020			2021			2022			2023			2018–2023		
	E1	E2	OE	E1	E2	OE	E1	E2	OE	E1	E2	OE	E1	E2	OE	E1	E2	OE	E1	E2	OE
YTP	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
BGP	0.8121	0.1262	0.2030	0.7063	0.1992	0.2834	0.7427	0.2339	0.3303	0.8679	0.1439	0.2350	0.7590	0.1232	0.1930	0.8141	0.1290	0.2073	0.7837	0.1592	0.2420
XMG	0.6158	0.0637	0.0968	0.6130	0.1199	0.1727	0.6415	0.1372	0.1981	0.6422	0.1114	0.1646	0.6001	0.0866	0.1275	0.6148	0.1312	0.1873	0.6212	0.1083	0.1578
CMPG	0.4422	0.3160	0.3463	0.6109	0.4622	0.5092	0.6017	0.5032	0.5362	0.6416	0.4358	0.4982	0.5817	0.4218	0.4693	0.4667	0.4702	0.4691	0.5575	0.4349	0.4714
NJP	1.0000	0.0602	0.1135	1.0000	0.0560	0.1060	1.0000	0.0586	0.1107	1.0000	0.0429	0.0822	1.0000	0.0319	0.0619	1.0000	0.0534	0.1015	1.0000	0.0505	0.0960
RZP	1.0000	0.1073	0.1938	0.8732	0.1762	0.2806	0.9680	0.1838	0.3056	1.0000	0.1275	0.2262	0.7328	0.1122	0.1748	1.0000	0.1218	0.2172	0.9290	0.1381	0.2330
SIPG	0.6210	1.0000	0.8105	0.5551	1.0000	0.7775	0.5486	1.0000	0.7743	0.5738	1.0000	0.7869	0.5140	1.0000	0.7570	0.4387	1.0000	0.7194	0.5419	1.0000	0.7709
JZP	1.0000	0.1529	0.2653	1.0000	0.1328	0.2345	1.0000	0.1493	0.2598	1.0000	0.0688	0.1287	1.0000	0.0678	0.1270	1.0000	0.0567	0.1073	1.0000	0.1047	0.1871
CQP	1.0000	0.2411	0.3885	1.0000	0.2999	0.4614	1.0000	0.2112	0.3488	1.0000	0.1291	0.2287	1.0000	0.2155	0.3545	1.0000	0.4244	0.5959	1.0000	0.2535	0.3963
TJP	0.8390	0.1306	0.2125	0.8277	0.1573	0.2485	0.7915	0.2020	0.3011	0.9034	0.1485	0.2461	0.9427	0.1028	0.1811	0.7580	0.1771	0.2645	0.8437	0.1531	0.2423
TSP	0.8176	0.2752	0.3922	0.8933	0.4142	0.5545	0.5002	0.5493	0.5319	0.3861	0.3759	0.3787	0.3895	0.2731	0.2981	0.5481	0.3236	0.3785	0.5891	0.3685	0.4223
LYGP	0.8466	0.0109	0.0199	0.8487	0.0224	0.0405	0.8950	0.0550	0.0988	0.9128	0.0589	0.1064	0.5375	0.0613	0.0887	0.9257	0.0871	0.1542	0.8277	0.0493	0.0848
NBP	0.6086	0.3226	0.3924	0.4539	0.4476	0.4496	0.4541	0.5048	0.4878	0.5077	0.3817	0.4165	0.4543	0.3472	0.3748	0.3384	0.4814	0.4350	0.4695	0.4142	0.4260
GZP	0.5919	0.1428	0.1989	1.0000	0.1448	0.2530	0.8710	0.1773	0.2817	0.9775	0.1185	0.2094	0.8606	0.1013	0.1711	0.6223	0.1486	0.2099	0.8206	0.1389	0.2207
QDP	0.5901	0.4014	0.4554	1.0000	0.3516	0.5203	0.9444	0.4580	0.6107	0.9481	0.3395	0.4937	0.8010	0.3466	0.4636	0.6520	0.4343	0.5002	0.8226	0.3885	0.5073
QHDP	0.6693	0.1115	0.1674	1.0000	0.1411	0.2474	1.0000	0.1655	0.2840	1.0000	0.1178	0.2107	1.0000	0.1288	0.2282	0.8326	0.1931	0.2966	0.9170	0.1430	0.2390
LNP	0.6212	0.1095	0.1601	0.8105	0.1464	0.2313	0.5846	0.3679	0.4262	0.6569	0.1847	0.2584	0.6492	0.1165	0.1720	0.5006	0.1617	0.2089	0.6372	0.1811	0.2428
MEAN	0.7691	0.2689	0.3186	0.8349	0.3101	0.3747	0.7967	0.3504	0.4051	0.8246	0.2815	0.3336	0.7543	0.2669	0.3084	0.7360	0.3173	0.3560	0.7859	0.2992	0.3494

Note: E1 means service-stage efficiency, E2 means profitability-stage efficiency, and OE means operational efficiency.

Figure 2 illustrates the distribution of operational efficiency. The average operational efficiency is 0.3494, reflecting a relatively low level of operation across the port system.

Among the 17 companies, 58.82% perform below the mean, while 41.18% perform above it. This suggests that the majority of ports still face significant challenges in achieving balanced operational outcomes. These limitations are likely attributable to factors such as disparities in infrastructure quality, varying investment levels, and differences in managerial efficiency among the ports. In terms of operational efficiency, YTP shows the highest values, indicating relatively strong coordination between service provision and financial performance. In contrast, LYGP records the lowest value, suggesting persistent inefficiencies in both operational performance and profit generation.

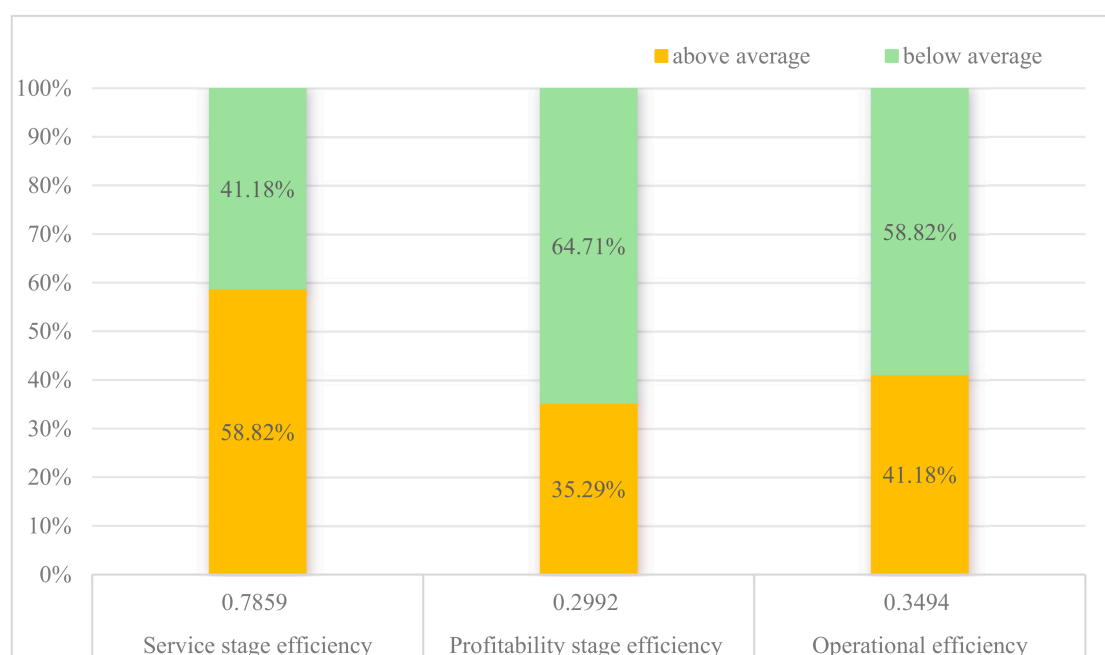


Figure 2. Overview of port operational efficiency.

The average service-stage efficiency is 0.7859, representing the strongest performance among the operational stages. According to the data, 58.82% of ports perform above the mean, while 41.18% perform below it, indicating that most ports have established a stable operational foundation. However, gaps in efficiency persist due to differences in capacity utilization, technological advancement, and labor productivity. The highest-performing ports in terms of service-stage efficiency are YTP, JZP, NJP, and CQP, while NBP exhibits the lowest performance, suggesting a need for improvements in infrastructure deployment and operational scheduling to enhance service productivity.

By contrast, the average profitability-stage efficiency is 0.2992, with 35.29% of ports performing above the mean and 64.71% below it. This suggests that although many ports demonstrate solid service capabilities, a significant portion of them struggle to translate operational activities into sufficient financial returns. The highest-performing ports at this stage are YTP and SIPG, while LYGP exhibits the lowest performance, revealing weaknesses in market connectivity and limited diversification of revenue sources.

Figure 3 illustrates the trends in service-stage efficiency, profitability-stage efficiency, and operational efficiency. In general, the operational efficiency remains at a relatively low level, showing only minor fluctuations throughout the period. Specifically, the operational efficiency increased steadily from 2018 to 2020, reaching its peak around 2020, before gradually declining in 2021 and 2022, and then stabilizing again in 2023. This pattern suggests that although ports make progress in improving their overall operational performance, operational efficiency remains constrained by the difficulty of maintaining balanced growth between the two stages.

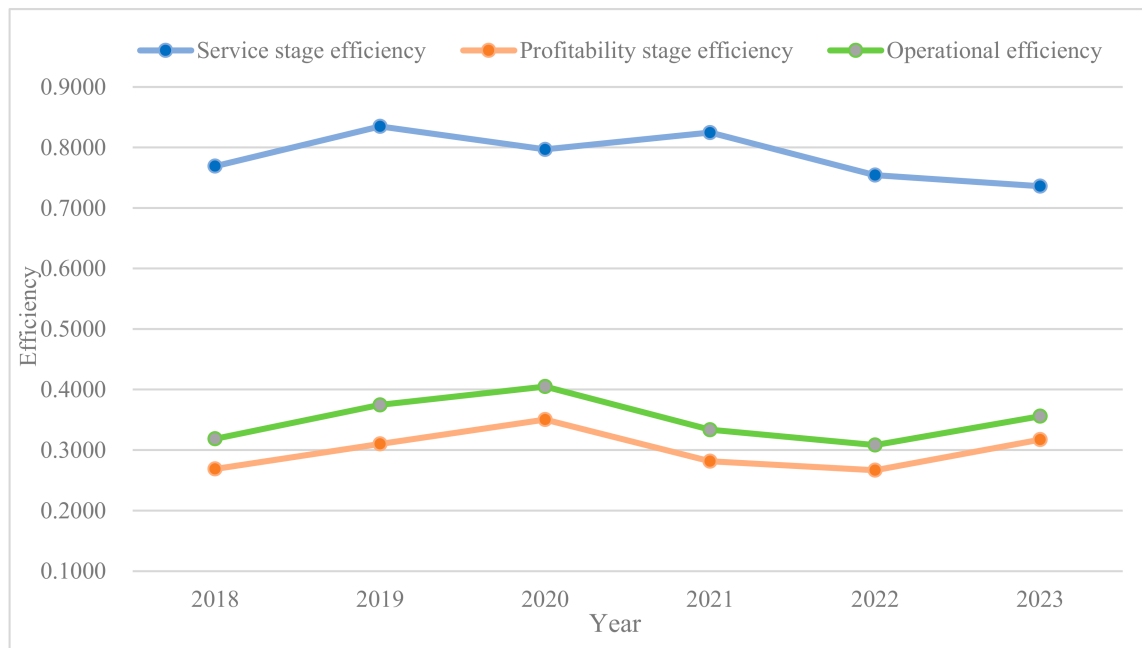


Figure 3. Trends of operational efficiency during 2018–2023.

Regarding service-stage efficiency, it exhibits early growth by increasing from 2018 and peaking in 2019. However, it demonstrates noticeable fluctuation, thereafter, dropping in 2020 and briefly recovering in 2021, before gradually declining to reach its lowest level in 2023. This trend indicates that although service-stage efficiency consistently remains the highest among all metrics, maintaining stability and driving further improvements have become increasingly difficult. This downward shift in recent years is possibly due to insufficient infrastructure renewal, constraints on capacity utilization amid fluctuating trade volumes, and limited technological innovation to handle operational bottlenecks.

In contrast, the profitability-stage efficiency demonstrates more noticeable volatility with a distinct peak and trough. It increases steadily from 2018 to 2020, reaching its highest level in 2020, then declines significantly, hitting its lowest point in 2022 before rebounding again in 2023. This fluctuation reveals that while many ports improved their financial performance during the early part of the study period, likely due to favorable market conditions and increased trade volume, the subsequent downturn reflects persistent challenges in sustaining profitability, possibly related to slowing trade growth, intensified competition, or rising operational costs. The recovery in 2023 indicates a partial rebound in financial performance, suggesting that ports are adapting to changing market conditions through service diversification and improved revenue management.

Overall, the trend analysis shows that while service-stage efficiency remains relatively stable, profitability-stage efficiency serves as the primary driver of fluctuations in operational efficiency. The decline in overall performance after 2020 highlights the need for stronger integration between operational services and profit generation, emphasizing the importance of improving profitability-stage efficiency to support long-term operational performance and competitiveness in the port industry.

5.2. Classification Analysis

This study conducts a detailed classification analysis of port operational efficiency of port companies across two dimensions: geographical region and operational scale, to gain a comprehensive understanding of efficiency.

5.2.1. Analysis from a Geographical Region

The regional classification highlights substantial efficiency heterogeneity across Chinese coastal areas. The 17 port companies are distributed among three major clusters: the Bohai Rim Port Cluster (BRPC), including RZP, QDP, QHDP, LNP, TJP, TSP, and JZP; the Yangtze River Economic Belt Port Cluster (YREBPC), comprising SIPG, NBP, NJP, LYGP, and CQP; and the Southeast Coastal Port Cluster (SCPC), consisting of XMG, GZP, YTP, CMPG, and BGP. Their efficiencies are illustrated in Figure 4. The results reveal noticeable regional disparities in port operational efficiency.

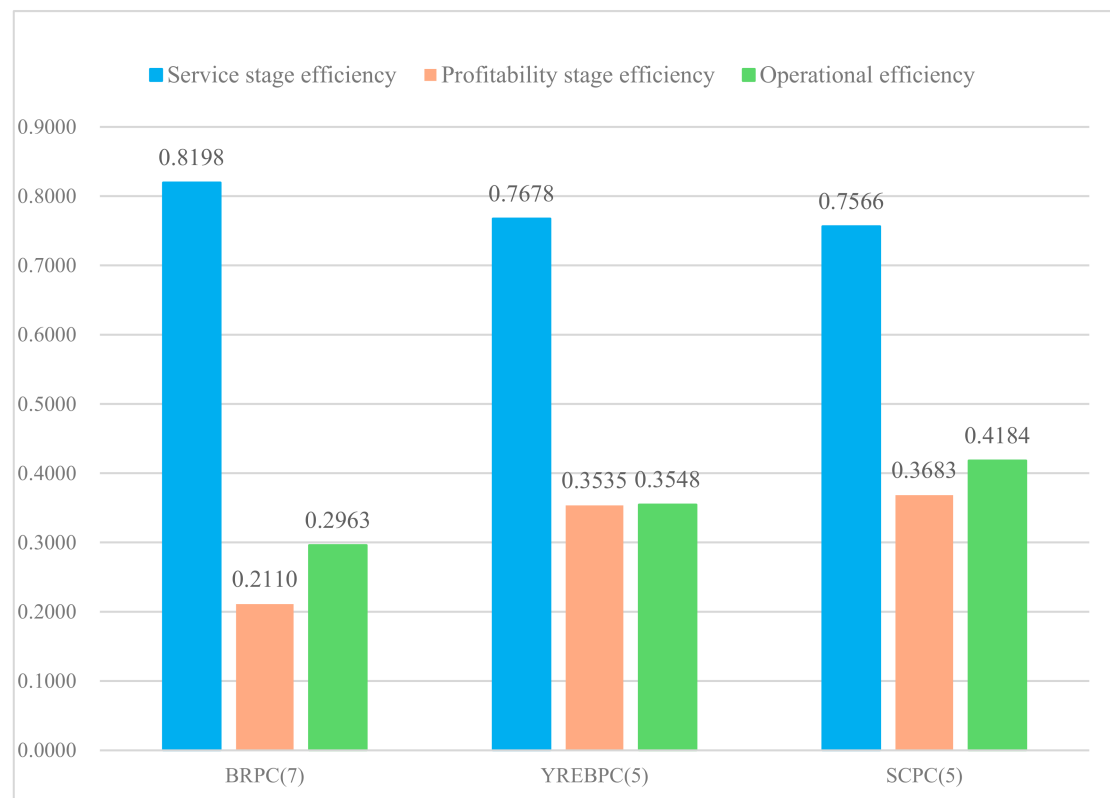


Figure 4. Efficiency overview of three port clusters.

Overall, SCPC exhibits the highest operational efficiency (0.4184), followed by YREBPC (0.3548), while BRPC lags behind (0.2963). The superior operational efficiency of the SCPC primarily results from its synergistic advantages in geography, economic structure, and policy. Its prime location along major international shipping lanes, coupled with a hinterland specializing in high-value exports, enables superior resource utilization and profitability. In contrast, the diminished operational efficiency observed in the BRPC is underpinned by a structural economic composition that constrains profit generation, specifically a heavy reliance on low-margin bulk commodities and intense intra-regional competition.

In the service stage, BRPC is clearly the best (0.8198), YREBPC is a close second (0.7678), and SCPC is the lowest (0.7566). The performance of these port clusters is directly related to their main functions and daily operations. The BRPC benefits from handling a massive and consistent volume of bulk cargo like coal and iron ore, allowing for highly standardized, large-scale throughput operations that drive its superior service-stage efficiency. On the other hand, the SCPC mainly deals with a complex mix of containerized goods. While highly valuable, these operations require intricate, flexible logistics and coordination,

which can introduce processing bottlenecks. This operational complexity explains its comparatively lower score in service efficiency.

Regarding the profitability stage, SCPC clearly leads (0.3683), YREBPC closely follows (0.3535), and BRPC is far behind (0.2110). This pattern is primarily attributed to their distinct economic specializations and cargo value. The SCPC's advantage derives from its focus on high-value containerized goods and advanced value-added logistics services, creating a robust profit margin and strong revenue base. Similarly, YREBPC maintains strong profitability through its expansive, economically vibrant hinterland along the Yangtze River. In contrast, BRPC's lower performance reflects its heavy reliance on essential but low-margin bulk commodities, alongside intense regional competition, which together severely constrain its profit generation efficiency.

5.2.2. Analysis from an Operational Scale

The classification by operational scale highlights the efficiency disparities among port companies grouped by cargo throughput capacity. Based on cargo throughput levels for 2023, the 17 sample port companies are divided into three groups. The first is the small-scale port group with throughput levels of 0–2 billion tons, including six ports (YTP, XMG, NJP, JZP, CQP, and LYGP). The second group is the medium-scale port group, with throughput levels of 2–5 billion tons, including five ports (BGP, RZP, TJP, TSP, and QHDP). The third group consists of large-scale ports with annual throughput exceeding 5 billion tons, including six ports (CMPG, SIPG, NBP, GZP, QDP, and LNP). Their efficiency performance over the study period is presented in Figure 5. The results reveal a clear divergence in operational performance across different scales.

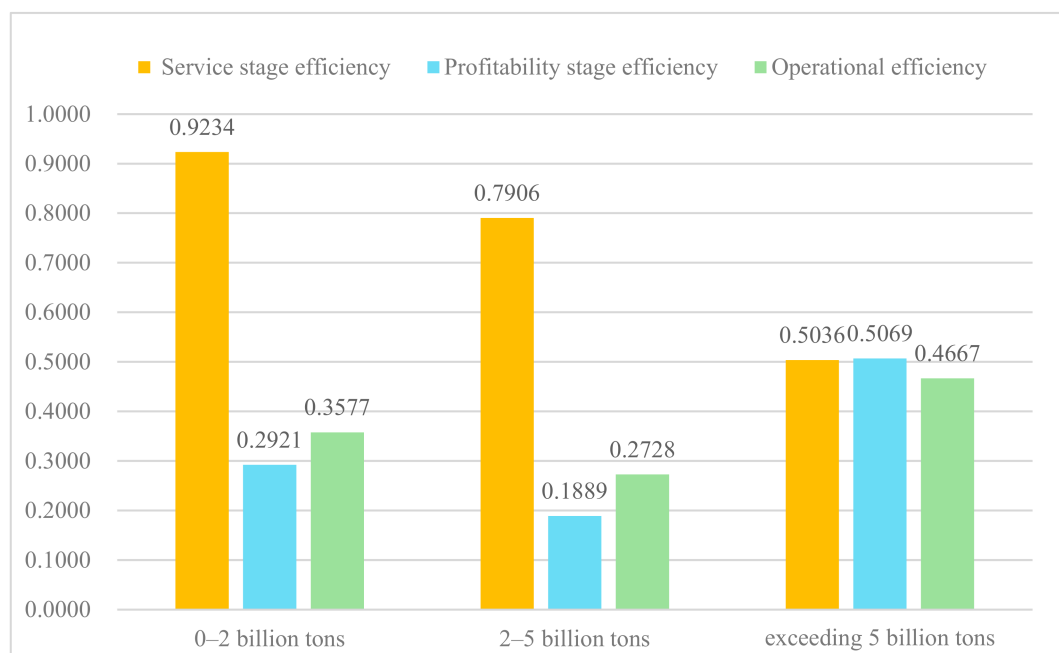


Figure 5. Efficiency overview of three port groups.

From the perspective of operational efficiency, the large-scale port group achieves the highest efficiency (0.4667), followed by the small-scale port group (0.3577), while the medium-scale port group records the lowest efficiency (0.2728). The superior performance of large-scale ports stems from their mature economies of scale, extensive global networks, and advanced automation, which optimize overall resource utilization. The small-scale ports also perform relatively well; commonly functioning as vital feeders or specialized terminals, their compact scale facilitates agile management and allows them to capitalize

on specific local advantages. Conversely, medium-scale ports face the most acute strategic dilemma. Often propelled by local government development strategies to invest heavily in capacity expansion, this pursuit frequently leads to overcapacity and intense homogeneous competition with neighboring ports. Caught between the targeted agility of small-scale ports and the established dominance of large hubs, medium-scale ports suffer from severe inefficiencies, manifesting in the lowest overall score.

From the perspective of service-stage efficiency, the small-scale port group exhibits the highest efficiency (0.9234), followed by the medium-scale port group (0.7906), while the large-scale port group records the lowest efficiency (0.5036). The small-scale ports excel in service-stage efficiency due to their operational simplicity and targeted functions. Handling a limited and predictable cargo mix allows for highly streamlined processes, minimal internal coordination overhead, and a sharp focus on rapid turnaround for specific vessels, resulting in lean and effective operations. In contrast, the large-scale port group suffers from the lowest service-stage efficiency. This underperformance is primarily due to the inherent complexity of managing massive hub operations. Processing an immense volume of diverse cargo types and coordinating across numerous intersecting shipping routes often leads to congestion, operational friction, and intricate internal coordination challenges, which inherently depress their service conversion efficiency compared to smaller, specialized peers.

From the perspective of profitability-stage efficiency, the large-scale port group exhibits the highest efficiency (0.5069), followed by the small-scale port group (0.2921), while the medium-scale port group records the lowest efficiency (0.1889). The robust profitability of large-scale ports is driven by overwhelming economies of scale, strong market pricing power, and the ability to offer comprehensive, high-value integrated logistics services, ensuring strong revenue generation that easily offsets maintenance costs. The small-scale ports maintain moderate profitability by operating with low overhead and catering to stable, specialized niche markets. Meanwhile, medium-scale ports exhibit the lowest profitability. This reflects the heavy financial burden of continuous infrastructure expansion and high operational expenditures incurred in their attempt to upgrade to hub status. Lacking the massive, stable cargo volumes and pricing dominance of large ports to offset these capital investments, their profit generation efficiency remains severely constrained.

5.3. Persistence Analysis for Efficiency

Figure 6 presents the persistence pattern of operational efficiency for the 17 listed port companies from 2018 to 2023. In this figure, the variance threshold is set at the median value (i.e., 0.0023) of all variances for port companies, which is used to distinguish between low fluctuation and high fluctuation in operational efficiency. The regression coefficient β is used to identify the direction of efficiency change, with positive values indicating an upward trend and negative values indicating a downward trend.

First of all, in the low variance and positive β region, the port companies show the best persistence in operational efficiency. LYGP, QHDP, XMG, and TJP are in this region. Their efficiency changes are relatively stable, and the overall trend is upward. This means that these port companies have not only kept small fluctuations during the period, but also improved their efficiency over time. Among them, LYGP has the highest β value, which indicates a more obvious improvement trend. TJP has the lowest β value (i.e., 0.0001), suggesting that its efficiency is stable but the improvement is limited.

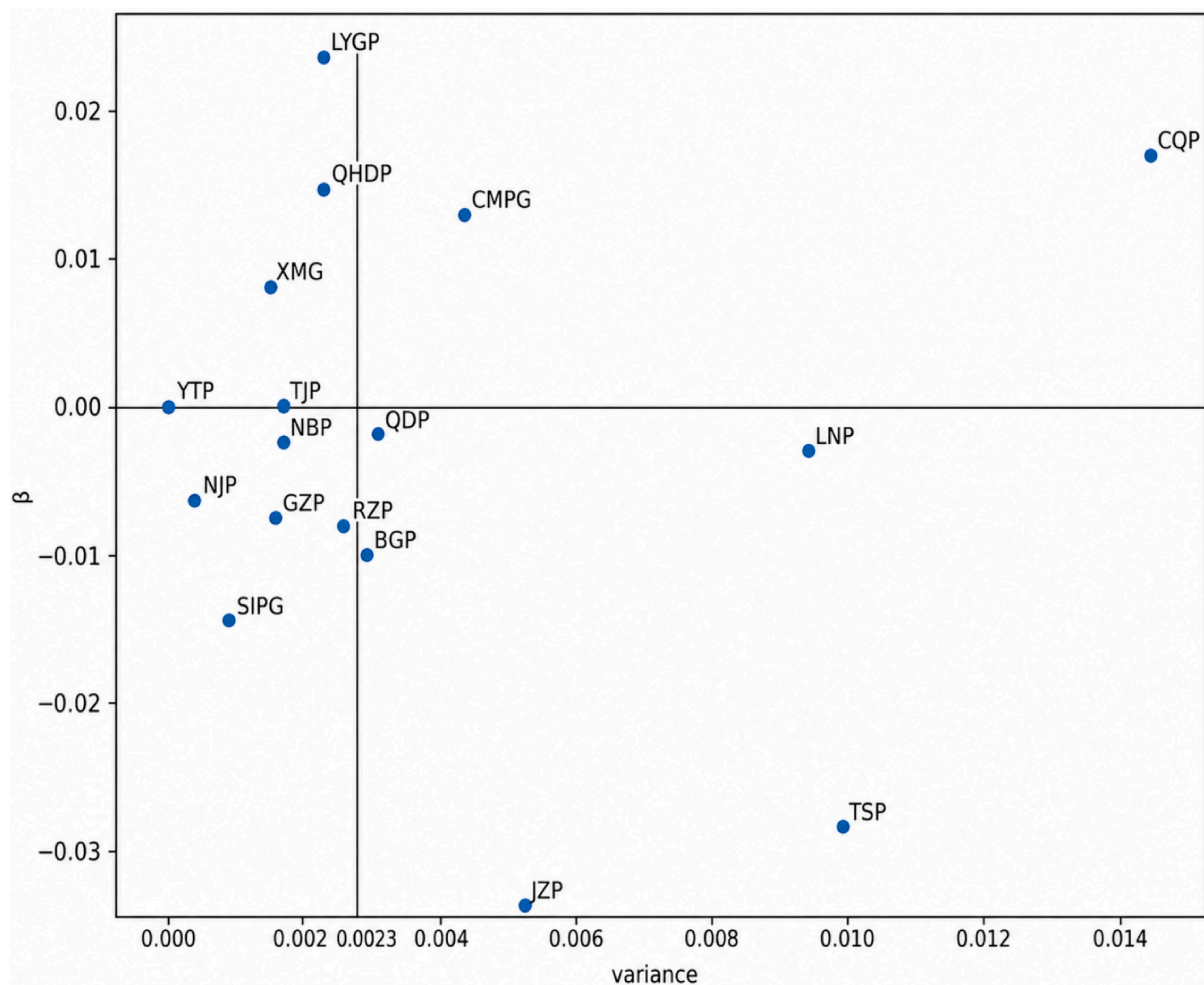


Figure 6. Scatter plot of variance and β values for 17 port companies.

Second, in the high variance and positive β region, CQP and CMGP show an upward trend, but their efficiency changes are less stable. CQP has the largest variance in the sample, which means its efficiency fluctuates strongly across different years. Although its β value is positive, the improvement process is not smooth. CMGP also shows improvement, but the fluctuation is higher than the median level. These port companies have growth potential, but they still need to improve the stability of their operations.

Third, in the low variance and negative β region, the port companies have relatively stable efficiency, but they show a slight downward trend. NBP, NJP, GZP, SIPG, and RZP are mainly located in this region. Overall, these port companies perform steadily, but their ability to improve efficiency is limited.

Fourth, in the high variance and negative β region, the port companies face both fluctuation and decline. QDP, BGP, LNP, TSP, and JZP are in this region. Their efficiency changes are not stable, and the overall trend is downward. JZP and TSP are the most obvious cases, as they have large variance and strongly negative β values. This suggests that their efficiency performance varies greatly across years and weakens over time. These port companies should pay more attention to controlling fluctuations and preventing further efficiency decline.

Notably, YTP is located at the boundary line, with zero variance and a β value of zero. This is because YTP maintained efficient operational efficiency throughout the observation period and can be regarded as a benchmark port company with the most stable performance.

5.4. Result Comparison

To verify the robustness of the evaluation results, we designed nine distinct scenarios labeled S1 through S9, and their specific parameters are detailed in Table 5. Scenario S1 serves as the benchmark using the two-stage network slacks-based measure model. It assigns equal weights to the service and profitability stages while utilizing fixed assets, employees, operating costs, and berth length as inputs, cargo throughput as the intermediate variable, and operating revenue alongside net profit as final outputs. Scenarios S2 through S5 test the sensitivity of the stage weights by adjusting the service and profitability ratios to 0.1 and 0.9, 0.3 and 0.7, 0.7 and 0.3, and 0.9 and 0.1 respectively, keeping all other variables identical to the benchmark. Scenario S6 examines variable sensitivity by replacing fixed assets with total assets and restricting the final output to net profit alone, while maintaining the equal weight distribution. Finally, Scenarios S7, S8, and S9 assess the impact of different methodological frameworks by applying the standard SBM, BCC, and Super SBM models respectively. When evaluating the individual stage models, these three models treat cargo throughput as the output of the first stage and the input of the second stage to independently assess the efficiency of the service stage and the profitability stage.

Table 5. Configuration of scenarios for sensitivity analysis and model comparison.

NUM	Model	Input	Intermediate	Output	Weight
S1	NSBM	Fixed assets, employee, cost, berth length	Cargo throughput	Revenue, net profit	0.5/0.5
S2	NSBM	Fixed assets, employee, cost, berth length	Cargo throughput	Revenue, net profit	0.1/0.9
S3	NSBM	Fixed assets, employee, cost, berth length	Cargo throughput	Revenue, net profit	0.3/0.7
S4	NSBM	Fixed assets, employee, cost, berth length	Cargo throughput	Revenue, net profit	0.7/0.3
S5	NSBM	Fixed assets, employee, cost, berth length	Cargo throughput	Revenue, net profit	0.9/0.1
S6	NSBM	Total assets, employee, cost, berth length	Cargo throughput	Net profit	0.5/0.5
S7	SBM	Fixed assets, employee, cost, berth length	/	Cargo throughput, revenue, net profit	/
S8	BCC	Fixed assets, employee, cost, berth length	/	Cargo throughput, revenue, net profit	/
S9	Super SBM	Fixed assets, employee, cost, berth length	/	Cargo throughput, revenue, net profit	/

These last three scenarios evaluate the overall process as a single stage, directly linking the initial inputs to a combined set of outputs that include cargo throughput, operating revenue, and net profit.

5.4.1. Comparison Under Different Weights and Varying Input–Output Levels

Based on the analysis of Figure 7, in terms of OE, the differences between S1 and S2–S5 are relatively small. The OE differences between S1 and the other weight scenarios range from 0.0309 to 0.0508, indicating limited overall fluctuation. This suggests that under the NSBM framework, although the weight settings of the service stage and the profitability stage change, the OE results remain relatively stable, and the OE result of S1 has good representativeness. From the perspective of variance, the OE variance of S1 is 0.2416. Although it differs slightly from those of the other scenarios, the variances remain within a relatively close range, with no obvious abnormal fluctuation. This indicates that different weight settings do not significantly change the dispersion of OE among the sample ports, further verifying that S1 has good stability in terms of both efficiency mean and efficiency distribution. Therefore, it is reasonable to use S1, with an equal weight setting of 0.5/0.5, as the benchmark NSBM model for subsequent analysis.

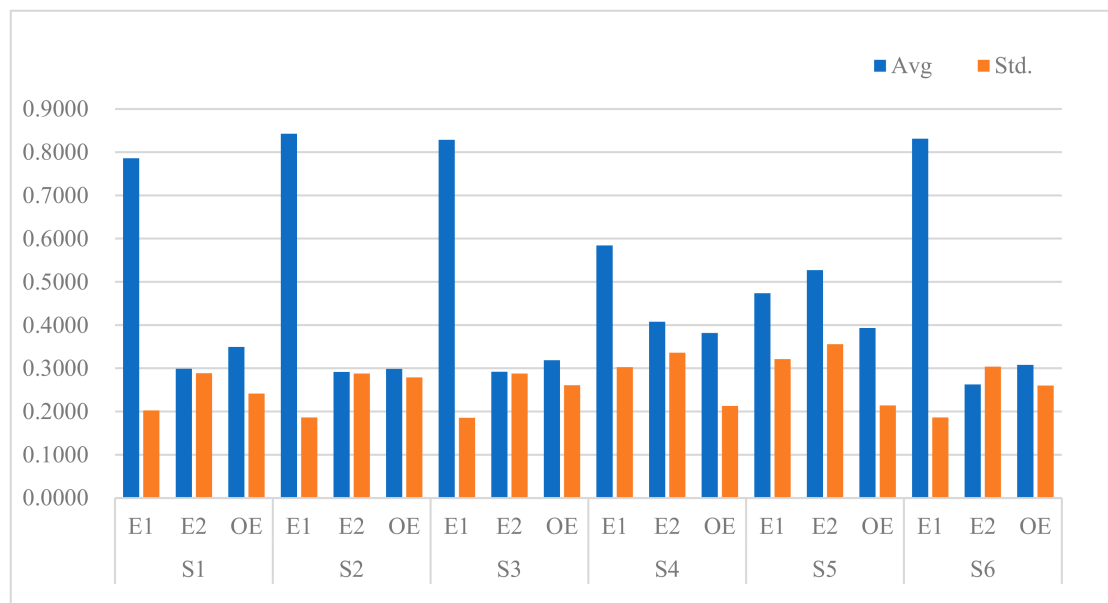


Figure 7. Comparison of results under the network SBM model with different weights and input–output configurations.

A further comparison between S1 and S6 shows that both belong to the NSBM model, but they differ in the settings of input and output variables. In terms of OE, the mean OE of S1 is 0.3494, while that of S6 is 0.3079, with a difference of 0.0415, indicating a relatively small gap. From the perspective of stage efficiency, the mean E1 of S6 is 0.8310, slightly higher than that of S1 at 0.7859, with a difference of 0.0451. However, the mean E2 of S6 is 0.2627, slightly lower than that of S1 at 0.2992, with a difference of 0.0365. Overall, whether in terms of OE or E1 and E2, the efficiency differences between S1 and S6 are relatively small. This indicates that after adjusting the capital input variable and final output variables, the model evaluation results do not deviate substantially, suggesting that the evaluation results of S1 have a certain degree of robustness.

5.4.2. Comparison Among Different Models

Based on the analysis of Figure 8, in terms of OE, the mean OE of S1 is much lower than those of S7–S9. This is due to differences in the objective functions and evaluation logic of different models. The objective function of the two-stage NSBM model in S1 is to optimize overall operational performance under the network structure while simultaneously evaluating the performance of the service stage and the profitability stage. In contrast, S7–S9 mainly conduct relatively independent evaluations of stage performance and overall performance, and their objective functions are not consistent with that of S1. In particular, S9 adopts the super-efficiency SBM model, which allows the efficiency scores of efficient decision-making units to exceed 1. Therefore, its mean OE is significantly higher than those of the other models, and its variance is also higher. This indicates that, under the comparison of multiple models, the evaluation results of S1 show a certain degree of robustness.

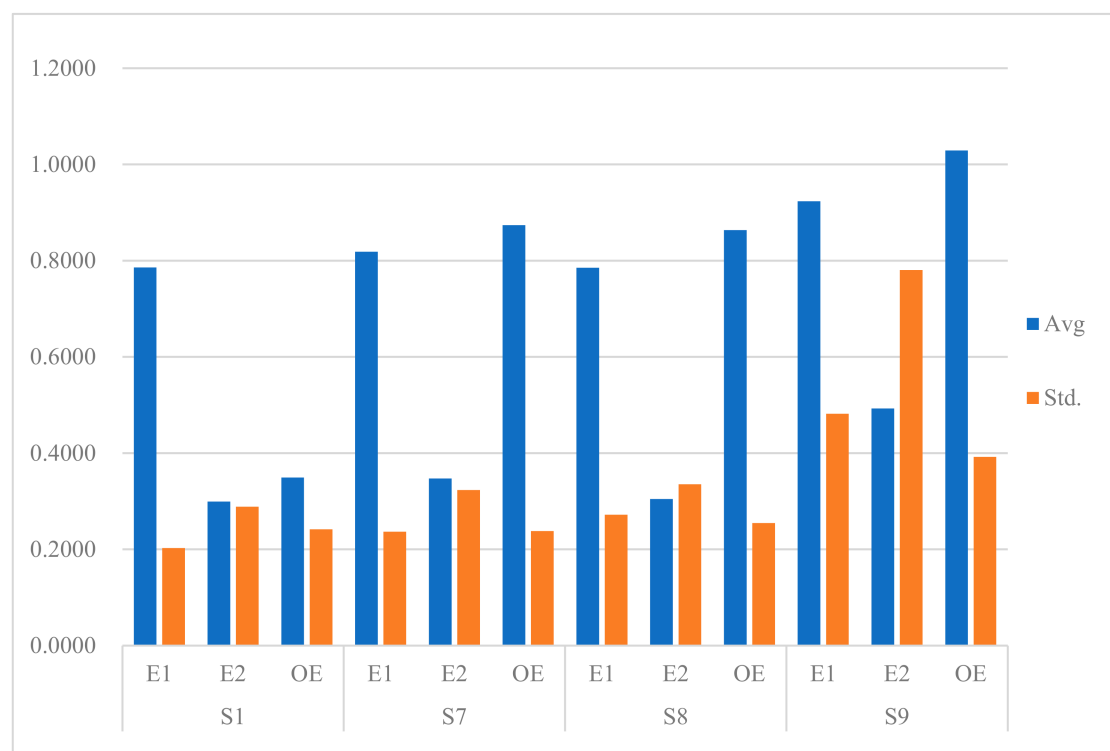


Figure 8. Comparison of results among the network SBM, BCC, SBM, and super-efficiency SBM models.

Overall, the OE mean and variance of S1 remain relatively stable under different weight scenarios. After adjusting the input and output variables, its OE, E1, and E2 results do not show obvious deviations. At the same time, compared with the BCC, SBM, and super-efficiency SBM models, S1 can better characterize the internal structure of the port operation process and identify stage-level efficiency losses. Therefore, it is reasonable to use S1 as the benchmark NSBM model for subsequent analysis in this study.

6. Discussion and Managerial Implications

6.1. General Discussion

The discrepancy between our findings and those reported by Ju et al. [36] and Wang et al. [37] may be associated with differences in sample composition and observation periods. Specifically, our dataset covers the COVID-19 pandemic period (2018–2023) and includes both coastal and inland port-listed companies, whereas previous studies mainly

focused on coastal ports and pre-pandemic conditions. These differences may influence efficiency estimates and therefore contribute to the observed variation in results. However, the present study does not explicitly isolate the individual effects of pandemic-related disruptions or sample composition. Therefore, these explanations should be interpreted as plausible rather than definitive. Future research could conduct separate analyses for coastal ports and pre-pandemic periods to further examine the sources of these discrepancies.

Furthermore, inefficiency in port companies primarily originates from the profitability stage. The results indicate that profitability-stage efficiency during the period 2018–2023 is generally lower than service-stage efficiency, indicating that improving profitability-stage efficiency should be a priority for strengthening the overall operational efficiency of port companies. This shows that although port companies perform well in the service stage, many port companies face difficulties in translating service capabilities into economic benefits. There could be two reasons for this phenomenon. On the one hand, the profit model of most ports mainly relies on traditional loading, unloading, and storage operations, which leads to intense homogenized competition and price-based competition. As a result, the tariffs for core loading and unloading services are driven down to low levels, creating a situation of increased throughput without corresponding revenue growth. On the other hand, port companies exhibit insufficient expansion of high-value-added services, such as supply chain finance and integrated logistics solutions, which can enhance customer loyalty and profit margins. This is also addressed in Zhang et al. [38], who found that among various dimensions of port efficiency, economic efficiency accounted for a substantial proportion and played a critical role in enhancing overall port operational efficiency.

In addition, the classification analysis reveals significant regional disparities in port operational efficiency, suggesting that regional advantages are reflected more strongly in profitability conversion than in basic service provision. The SCPC records the highest overall operational efficiency (0.4184), mainly because it achieves the highest profitability-stage efficiency (0.3683), despite having the lowest service-stage efficiency (0.7566). This indicates that the advantage of the SCPC lies not in generating the largest amount of basic cargo-handling services, but in converting operational services into financial returns. Ports in this region, such as CMGP, GZP, and XMG, are closely connected with export-oriented manufacturing, high-value logistics demand, and market-oriented port services, which may help them generate stronger revenue and profit from a given level of operational output. By contrast, the BRPC shows the highest service-stage efficiency (0.8198), but its profitability-stage efficiency is the lowest (0.2110), leading to the lowest overall operational efficiency (0.2963). This pattern suggests that ports such as QDP, TJP, and QHDP may have strong cargo-handling and service provision capacity, but their overall performance is constrained by weaker profit conversion, possibly due to a higher dependence on bulk cargoes, lower-margin logistics activities, and intense intra-regional competition. The YREBPC presents a more balanced but moderate pattern, with service-stage efficiency of 0.7678, profitability-stage efficiency of 0.3535, and overall operational efficiency of 0.3548. Ports such as SIPG and NBP benefit from strong hinterland economies and integrated river–sea transport networks, but the regional average still suggests that service capacity does not automatically translate into the highest profitability-stage performance. This finding partially aligns with Chen [39], who found relatively low comprehensive port technical efficiency in the Bohai Rim region. However, the stage-based results of this study further reveal a more specific mechanism: the low overall efficiency of the BRPC is mainly attributable to weak profitability-stage efficiency rather than insufficient service-stage efficiency. Therefore, the regional comparison supports the central argument of this study that the key bottleneck in port operational efficiency lies not only in service generation, but also in the ability to appropriate financial value from operational services.

From the perspective of operational scale, the results suggest that a larger scale does not automatically lead to higher efficiency in all stages. Small-scale ports achieve the highest service-stage efficiency (0.9243), which may be attributed to their simpler organizational structures, more flexible resource allocation, and lower coordination costs. For example, ports such as XMG and LYGP are relatively smaller in scale but can operate as specialized regional or feeder ports, allowing them to maintain focused and efficient service processes. However, their profitability-stage efficiency remains limited (0.2921), indicating that strong service provision does not necessarily translate into superior financial returns. Medium-scale ports exhibit the lowest profitability-stage efficiency (0.1889) and overall operational efficiency (0.2728) among the three groups. One possible explanation is that ports with relatively low efficiency may be unable to generate sufficient operational and financial returns to support further expansion. As a result, they tend to remain in the medium-scale category, whereas ports with stronger profitability and operational performance are better positioned to achieve the economies of scale necessary for growth into large-scale operations. This finding suggests that profitability generation may play an important role in determining the long-term development trajectory of port companies. In contrast, large-scale ports have the lowest service-stage efficiency (0.5036), which may reflect the coordination costs, complex management structures, and rigid resource allocation associated with large-scale operations. Nevertheless, they achieve the highest profitability-stage efficiency (0.5069) and overall operational efficiency (0.4667), suggesting that their advantages lie mainly in stronger market bargaining power, diversified logistics services, higher-value cargo structures, and economies of scale in revenue generation.

From an efficiency-persistent perspective, the results indicate that improving operational efficiency alone is not sufficient for long-term development. Instead, port companies need to ensure that efficiency gains are stable and can be sustained over time. The observed imbalance between the service stage and profitability stage suggests that short-term improvements in throughput or revenue may not necessarily translate into sustained efficiency improvement. Therefore, enhancing the coordination between operational capability and profit generation is essential for improving efficiency persistence and supporting the long-term development of port companies.

Based on Table 4, an additional observation concerns the potential impact of the COVID-19 pandemic. The increase in profitability-stage efficiency in 2020 may be associated with temporary surges in freight rates and strong cargo demand in certain sectors. By contrast, the subsequent decline during 2021–2022 may reflect the adverse effects of port congestion, labor shortages, supply-chain disruptions, and rising operating costs. The partial recovery observed in 2023 is consistent with the gradual normalization of international trade and logistics activities after the pandemic.

6.2. Managerial Implications

First, to enhance operational efficiency, port companies should focus on strengthening resource allocation and technological innovation. On the one hand, through effective resource allocation, port companies should optimize the use of labor, fixed assets, and infrastructure to improve operational efficiency. On the other hand, port companies should increase investment in technological innovation, particularly in the application of new technologies and equipment, to enhance their technical capabilities and market adaptability. Port companies should also keep pace with industry technological trends to promote service innovation and enhance market competitiveness.

Second, port companies should place greater emphasis on improving efficiency at the profitability stage. Port companies should conduct in-depth exploration of revenue sources, move beyond the traditional handling-fee model, and actively develop value-

added services. For example, ports should actively extend upstream and downstream along the supply chain and develop businesses such as bonded logistics, cold chain processing, and cross-border e-commerce logistics, as these activities typically generate higher profit margins than basic port operations. At the same time, the implementation of refined and differentiated pricing strategies is also crucial. For example, ports can adjust rates dynamically based on the value of goods, service urgency, and market peak and off-peak periods so as to maximize revenue generation.

Third, to address efficiency gaps among ports across different regions and scales, port companies should strengthen collaboration and mutual learning. As the SCPC exhibits the highest profitability-stage efficiency and overall operational efficiency, other ports can draw lessons from its effective resource allocation and market positioning to improve their profitability-stage performance. The small-scale port group, characterized by flexible resource management and optimized service processes, exhibits strong performance in the service stage and overall operational efficiency, and its flexible operational models can be adopted by other ports. Through cooperation and systematic experience sharing among ports across different regions and scales, the port industry can enhance operational efficiency, particularly in resource allocation, technological innovation, and market adaptability.

Overall, these strategies contribute not only to efficiency improvement but also to enhancing the long-term persistence and resilience of port operations.

7. Conclusions

7.1. Research Conclusion

This study divides the operational process of port companies into the service stage and the profitability stage. Employing a network SBM model, this study systematically assesses the operational efficiency of 17 Chinese port companies from 2018 to 2023. In addition, stratified analyses by region and scale are conducted to clarify differences in port operations. Our study not only pinpoints whether efficiency shortfalls arise in the service stage or the profitability stage, but also identifies benchmarkable practices and performance gaps across regions and scales, thereby providing actionable evidence for efficiency improvement.

The main findings are summarized as follows: First, the overall operational efficiency of port companies remains persistently low and stable at a suboptimal level, indicating substantial room for improvement. Second, profitability-stage efficiency lags behind service-stage efficiency, identifying the profitability stage as the priority for efficiency improvement. Third, a majority (60%) of the inefficient port companies demonstrate a negative or zero persistence score, meaning their operational persistence is at a weak level of persistence. Fourth, from a regional perspective, the southeast coastal port group records the highest service-stage efficiency and overall operational efficiency, whereas the Bohai rim port group exhibits the highest profitability-stage efficiency but the lowest overall operational efficiency. When analyzed by operational scale, the small-scale port group exhibits the highest service-stage efficiency and operational efficiency, while the medium-scale group leads in profitability-stage efficiency, and the efficiency of each stage as well as the overall efficiency of the large port group are all at a medium level.

In conclusion, this study emphasizes that achieving persistent port development requires not only improving efficiency levels but also enhancing the stability and persistence of efficiency over time.

7.2. Limitations and Future Research

Despite offering valuable managerial insights, this study is subject to several limitations that warrant consideration. First, the sample includes 17 listed port companies, which reflects the limited number of publicly listed port enterprises in China. Although the sample size is relatively small, it covers the majority of major listed port companies and provides a balanced panel spanning six years (102 observations in total). Nevertheless, the limited number of DMUs may reduce the discriminatory power of DEA models. Therefore, future research based on a larger sample would provide a more comprehensive view of port operational efficiency. Second, the influencing factors of operational efficiency are not examined in sufficient depth. Although this study classifies firms by geographical region and operational scale, it does not examine factors such as policy subsidies and market demand in detail. Third, future research could further examine the influence of pandemic-related disruptions, including port congestion, labor shortages, and freight-rate fluctuations, on port efficiency and profitability. Fourth, the present study focuses on efficiency persistence rather than environmental sustainability. Due to the limited availability and consistency of environmental disclosure data among Chinese port-listed companies, variables such as CO₂ emissions, energy consumption, and ESG indicators were not incorporated into the analysis. Future studies may extend the framework by integrating environmental and sustainability-related indicators when more comprehensive panel data become available. Finally, although several robustness analyses were conducted, a comprehensive global sensitivity analysis (GSA) was not performed [40,41]. Future research could employ variance-based sensitivity analysis and other GSA techniques to examine the effects of alternative input–output specifications, stage weights, scale assumptions, and persistence measures on efficiency rankings and managerial conclusions. Such analyses would further enhance the robustness and transparency of DEA-based port efficiency evaluation. A more comprehensive investigation of these factors can yield clearer insights into the drivers of port operational efficiency. These limitations highlight valuable directions for future research.

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