EVALUATING PORT PERFORMANCE: INSIGHTS FROM THE SHIP PERSPECTIVE

ZHANG JING

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The Hong Kong Polytechnic University

Department of Logistics and Maritime Studies

Evaluating Port Performance: Insights from the Ship Perspective

ZHANG Jing

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CERTIFICATE OF ORGINALITY

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ABSTRACT

Ports are complex systems, acting as production units of global supply chains, service providers for their users, and key drivers of the regional economy. With intense competition and the growing awareness of sustainable development, providing efficient and resilient services has become necessary for ports to remain competitive. Consequently, efficiency analyses and resilience studies have been widely applied for port operators to assess their relative performances, identify potential weaknesses and provide directions for improvement. However, an efficient port for port operators may not necessarily be efficient for port users. Additionally, while it is recognized that individual ports are vulnerable to disruptions, research has yet to adequately explore how their interactions within a regional cluster determine the collective resilience of the cluster. This thesis develops a multi-stakeholder framework for evaluating port performance, moving progressively from the efficiency of individual ports to the resilience of interconnected port clusters.

The first study reviews literature on port efficiency analyses published before the end of 2023. We found the majority of studies assessed port efficiency from the perspective of port authorities, managers, and operators. Few did it from the perspective of the users and the public. Even fewer noticed the possible conflicts between the port service level and its profitability. Frontier methods are popular in port efficiency evaluation, but publications extending or combining different methods are still very rare. Novelty classifying the studies by efficiency types and analysis perspectives, this study reveals the complex nature of port operations, the possible limitations of traditional efficiency analyses, the reason behind the lack of consensus in measuring port efficiency and the need to develop advanced approaches and incorporate different methods.

The second study assesses port efficiencies from the dual perspectives of port operators and shipping companies. Considering port heterogeneity, this study classifies the world's top 80 container ports into homogeneous groups and employs the meta-frontier Data Envelopment Analysis (DEA) method to assess their efficiency. The analysis reveals the disparities in port efficiency among different stakeholders and across different port sizes. Large ports demonstrate relatively consistent efficient performance from both perspectives, benefiting from economies of scale and efficient service delivery. In contrast, small and middle-size ports show inconsistent or even opposing efficiency performance when evaluated by port operators and shipping companies. This study provides a reference for port operators and shipping companies to enhance overall efficiency.

The third study analyzes the resilience performance of port clusters through the lens of port interactions. We first propose a method to analyze how ports can substitute for one another in managing ship calls during disruptions in a port cluster. Next, we investigate how the internal characteristics of the port cluster, such as connectivity, differences in operational efficiency, and hierarchical structures, affect its overall resilience, utilizing econometric tools. Employing a multi-source dataset that includes AIS data and satellite ship positioning data, we apply our proposed method to assess the resilience of Chinese port clusters during the COVID-19 pandemic. Our findings indicate that dense internal connectivity through ship flows is positively correlated with cluster resilience. In contrast, resilience is undermined in clusters characterized by significant efficiency disparities or a pronounced hierarchical structure dependent on a few core ports. This study suggests that the resilience of a port cluster is a function of inter-port interactions rather than merely the sum of individual port capacities.

Keywords: Port efficiency, frontier analysis, port cluster, resilience, ships' turnaround time, ship flows

PUBLICATIONS ARISING FROM THE THESIS

Zhang, J., Yang, D., & Luo, M*. (2024). Port efficiency types and perspectives: A literature review. Transport Policy, 156, 13-24.

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Chapter 1. Introduction

1.1 Research Background

Ports are critical nodes in international trade and logistics, operating in a complex environment. With different interests in port production and operation, stakeholders view port performance from various perspectives.

Efficiency analyses have been widely applied for port operators to assess their relative performances, identify potential weaknesses and provide directions for improvement. However, differing interests and objectives among stakeholders can lead to varied interpretations of port efficiency. For port operators, an efficient port should be able to maximize port outputs, such as total throughputs or revenue, or minimum inputs, such as port facilities or expenditures. While, such a port often over-emphasizes the utilization rate of terminal resources, which may result in long waiting times for the ships. This is not consistent with the desire of shipping companies in port selection, which often prefer a short turn-around time when calling the port (Rødseth et al., 2020). With intense intra-port and inter-port competition and higher emphasis on just-in-time logistics, ships' turn-around time becomes critical for the port to determine its operation policy and for shipping companies to arrange port call schedules (Suárez-Alemán et al., 2014). How to consider both the interests of port operators and shipping companies has become a critical question in evaluating port performance.

Moreover, ports are operated in a complex environment, each with unique operation conditions. Although traditional frontier methods, such as the data envelopment analysis (DEA) and stochastic frontier analysis (SFA) have been widely used in measuring port efficiency, they have certain requirements. DEA requires the ports to be homogenous and assumes that they operate using similar production technology, which refers to the combinations of physical, human, financial capital, economic infrastructure, resources and any other characteristics of the physical, social and economic environment (Chang & Tovar, 2022; Panayides et al., 2009). However, the worldwide ports operating at different scales may be subject to different technologies. This significant heterogeneity among ports may render traditional efficiency analyses less meaningful. Therefore, it is necessary to take into account ports' unique features and adopt appropriate methods when assessing port efficiency.

Additionally, the rising occurrence of unpredictable events such as natural disasters and economic fluctuations highlights the vulnerabilities of port systems and their significant impact on regional economies and world transportation (Lau et al., 2024; N. Wang et al., 2023; Zheng et al., 2022). Notably, the unexpected emergence of the COVID-19 pandemic severely disrupted the global port network, leading to economic downturns in many regions (Notteboom et al., 2021). According to the Clarkson Port Congestion Index, the ports of Los Angeles and Long Beach experienced more than double their usual congestion levels in 2021, with ships waiting up to twelve days to load and unload. This congestion led to estimated losses in U.S. export at approximately $15.7 billion, drastically undermining the competitiveness of U.S. businesses (Steinbach, 2022). Resilience analysis is crucial for ports, ships and regions to assess their performance and develop strategies.

Port clusters, characterized by regional concentration and collaboration in port-related activities (Bai & Lam, 2015; Li et al., 2023), has emerged in various geographic regions, including European countries (Gianfranco et al., 2014), the United States (De Langen & Visser, 2005), Japan (Shinohara, 2016) and China (Li et al., 2023). While individual ports exhibit varying levels of resilience, the integrated resilience of a port cluster is not a mere sum of its parts but rather emerges from the interactions among its members. In the face of disruptions impacting one or more port members, the port cluster can activate its collective resilience through the internal adaptive mechanisms. The unaffected port members within the port cluster can act as substitutes for their impacted counterparts, sustaining the port clusters' transport functions through accommodating rerouted vessels, sharing operational capacity, and reallocating cargo. This systemic perspective is corroborated by recent studies, which confirm that the availability of alternative ports within port clusters and the alternative port call behavior of ships contribute to the overall ability of port clusters and the shipping network to absorb the shocks (Li et al., 2024; Zhang et al., 2023). Such unique features of port clusters and the contribution of ship flows among ports to the resilience performance deserve a detailed examination.

This thesis aims to have a sound understanding of the efficiency of ports and the resilience of port clusters, taking into account the distinguished perspectives and significant impacts of ships.

1.2 Research Questions

Given the background above, our research is structured around three main questions:

Question 1: Efficiency has been analysed widely and interpreted differently by scholars. As a system, the port is not only a production unit but also a service provider for its users and a contributor to the regional economy. How has port efficiency been analysed in existing studies? Have the differences in port efficiency from various stakeholders' perspectives been identified?

To answer this question, the first study of this thesis conducts a systematic review of the literature on port efficiency. Classifying the studies by efficiency types and analysis perspectives, we found most studies focused on traditional port efficiencies (i.e., the technical, allocative and economic efficiency). Some extended these traditional types by considering ships' time in port and the negative environmental impacts. The majority of studies assessed port efficiency from the perspective of port authorities, managers, and operators. Few did it from the perspective of the users and the public. Even fewer noticed the possible conflicts between the port service level and its profitability. Frontier methods are popular in port efficiency evaluation, but publications extending or combining different methods are still very rare. Several issues are identified, including the consistencies between decision-making units and the selection of input/output variables, the nature of port services, the extension and combination of these methods, and the impacts of new developments and occurrences. By summarizing the relationship between the types and perspectives of the existing studies, this study identifies the need for port efficiency analysis from the perspective of different stakeholders, especially the shippers, carriers and the public.

Question 2: Due to inconsistent interests in port operations, port operators and users have differing views on port efficiency. Additionally, applying DEA to evaluate port efficiency without considering model requirements and port heterogeneities may result in inaccurate estimates. How can port efficiencies be evaluated while taking into account the diverse perspectives of port operators and users and the heterogeneity of ports?

To answer this question, the second study of this thesis classifies the world's top 80 container ports into homogeneous groups and employs the meta-frontier DEA method to assess their efficiency. Recognizing the different interests of port operators and shipping companies in the port, we incorporate relevant variables for the two stakeholders and compare the port efficiencies evaluated from the two perspectives. The findings are achieved with a dataset comprising port data collected from Lloyd's List, IHS Market, and Google Earth, alongside ships' data extracted from the Automatic Identification System (AIS). The analysis reveals the disparities in port efficiency among different stakeholders and across different port sizes.

Among the 80 container ports, only 4 achieved dual efficiency, while 17 were identified as one-sided frontier ports. Large ports demonstrate relatively consistent efficient performance from both perspectives, benefiting from economies of scale and efficient service delivery. In contrast, small and middle-size ports show inconsistent or even opposing efficiency performance when evaluated by port operators and shipping companies, with many exhibiting low levels of resource utilization or service delivery. This study provides a reference for port operators and shipping companies to enhance overall efficiency.

Question 3: While it is recognized that ports exhibit varying levels of resilience, there is a lack of research on how their interactions determine the collective resilience of port clusters. How to evaluate the resilience of port clusters with the consideration of interactions among ports? How do the internal characteristics of port clusters contribute to their resilience performance?

To answer this question, the third study of this thesis first measures the resilience of port clusters by analyzing how well member ports can substitute for one another in handling ship calls during a disruption. Subsequently, we examine how the port cluster's internal features, including its internal connectivity, operational efficiency differences, and structural hierarchy level, impact its resilience by regression models. Using a multi-source dataset that incorporates AIS data, we conducted case studies focusing on the resilience of Chinese port clusters during the COVID-19 pandemic. The results reveal that dense internal connectivity via ship flows is positively correlated with cluster resilience. Conversely, resilience is diminished in clusters with significant efficiency disparities or a pronounced hierarchical structure reliant on a few core ports. These findings lay a foundation for stakeholders of port clusters to assess their resilience performance and develop strategies to improve their ability against disruptions.

1.3 Structure of the Thesis

This thesis consists of three main studies. The first study reviews the literature on port efficiency analyses published before the end of 2023. The second study assesses the efficiencies of the global top 80 ports from the dual perspectives of port operators and shipping companies. The third study evaluates the resilience performance of port clusters and explores the relationships between the internal characteristics of port clusters and their resilience performance.

The structure of this thesis is organized as follows:

Chapter 1 is the introduction of this thesis. This chapter introduces the research background, the key research questions, and the structure of the thesis.

Chapter 2 represents the review study on port efficiency analysis. In this chapter, 301 studies on port efficiency analysis are reviewed from efficiency types and analysis perspectives. The applications and limitations of frontier methods in port efficiency analysis are also summarized. Several issues are identified, including the consistencies between decision-making units and the selection of input/output variables, the nature of port services, the extension and combination of these methods, and the impacts of new developments and occurrences.

Chapter 3 assesses the efficiencies of the global top 80 ports from the perspectives of port operators and shipping companies. Considering port heterogeneity, it classifies the world's top 80 container ports into homogenous groups and employs the meta-frontier DEA method to assess their efficiency. Recognizing the different interests of port operators and shipping companies in port, this chapter incorporates relevant variables for the two stakeholders and compares the port efficiencies evaluated from the two perspectives. The analysis reveals the disparities in port efficiency among different stakeholders and across different port sizes.

Chapter 4 proposes a method to analyze how ports can substitute for one another in managing ship calls during disruptions in a port cluster and investigates the relationship between the internal characteristics of port clusters and their resilience performance. Using a multi-source dataset that incorporates AIS data, this chapter assesses the monthly resilience of three main port clusters in China, specifically in the Yangtze River Delta (YRD), Pearl River Delta (PRD), and Bohai Rim (BR), following the outbreak of COVID-19. The results reveal that dense internal connectivity via ship flows is positively correlated with cluster resilience. Conversely, resilience is diminished in clusters with significant efficiency disparities or a pronounced hierarchical structure reliant on a few core ports.

Chapter 5 summarizes the findings and contributions of the thesis. It also discusses the limitations of the current research and suggests directions for future research.

Chapter 2. Port Efficiency Types and Perspectives: A Literature Review

2.1 Introduction

Efficiency analyses have been widely applied for ports to assess their relative performances, identify potential weaknesses and provide directions for improvement. However, as an integral part of the local economy, a port serves multiple users, such as shippers and shipping companies, in addition to the development of the local community. An efficient port from the perspective of a port operator may not be necessarily efficient from the perspective of others.

With intense inter-port competition and the increasing trend towards larger ships and alliances, providing efficient container handling service and shortening the turnaround time (TAT) of the vessels have become necessary for ports to remain competitive (Suárez-Alemán et al., 2014; Tongzon & Heng, 2005). At the same time, the growing environmental awareness requires the manager to operate the port in a more environmentally friendly manner. Weighting the economic contribution together with the negative environmental impacts of port operations is crucial in assessing its sustainability, establishing benchmarks, and setting up development strategies (Tichavska & Tovar, 2015). Port efficiency analysis is not only the means for port operators to know their weaknesses but also serves as the basis for managing ship schedules, assessing future capacity needs, and adopting public policies (Seth & Feng, 2020; Suárez-Alemán et al., 2016). Thus, understanding port efficiency from different perspectives is essential for port managers, operators, users, policymakers, and other related stakeholders.

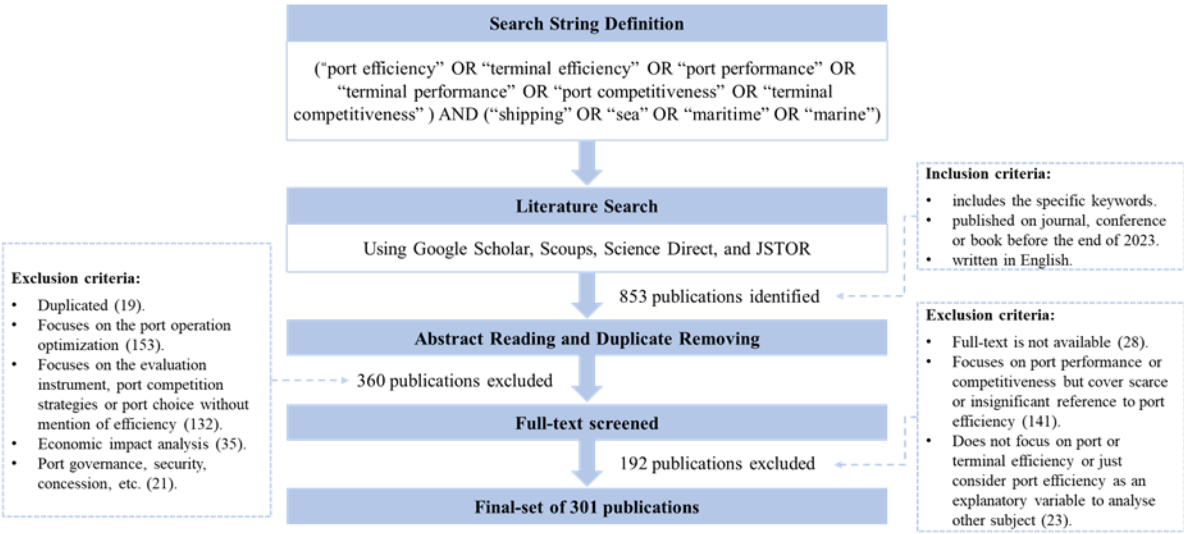
Given the importance, many scholars have conducted in-depth analyses to compare the efficiencies of ports at regional, national and global levels and identify what contributes to their performance. Most of them focused on traditional port efficiency (i.e., technical, allocative and economic efficiency) from the needs and interests of port owners, operators and managers. Not enough attention was paid to users' interests, nor offered any insights into balancing the interests of other stakeholders. Only a few recent studies considered ships' port time and the environmental impacts of ports. Very few attempted to evaluate port efficiency from the perspective of the users and the public. Regarding the research method, previous studies mainly applied frontier methods, including the parametric (e.g., SFA) and the non-parametric (e.g., DEA). The extensions and combinations of different methods in port efficiency analyses are still in their infancy.

Existing reviews on port efficiency analyses (Krmac & Mansouri Kaleibar, 2022; Merkel & Holmgren, 2017; Panayides et al., 2009; Tovar & Rodríguez-Déniz, 2015) are mainly on the application of DEA methods or factors on port efficiency. To the best of our knowledge, no existing study has classified and summarized port efficiency analysis by efficiency types, perspectives of different stakeholders, or the development of applied methods in the analysis of port efficiency. This review distinguishes itself from previous review papers by filling in this gap. A total of 301 studies published before the end of 2023 are collected and reviewed in this paper. For the first time, existing studies on port efficiency are classified according to the types of efficiency, and its link with the perspectives. The application and needs of developed frontier models in port efficiency are summarized. By emphasising the importance of different stakeholders' interests, especially the users' interests, this paper aims to highlight missing blocks in the existing studies on port efficiency and provide directions for future research.

2.2 Review Method and Literature Collection

The objective of this study is to provide a comprehensive and systematic review of relevant publications on port efficiency, thereby identifying gaps and highlighting the limits in existing research. Following the guidance of Moher et al. (2009), this paper adopts the systematic and meta-analysis (PRISMA) method to gather and explore the literature through three-stage procedures: literature searching, selecting, and reporting.

To collect the studies, we first use the keywords “port efficiency” or “terminal efficiency”. As port efficiency analysis is mainstream in port performance and competitiveness studies (Chang & Talley, 2019; Talley et al., 2014), “port performance”, “terminal performance”, “port competitiveness” or “terminal competitiveness” are added to expand the keyword search. Additionally, “shipping”, “sea”, “maritime”, or “marine” are used with logic “AND” to ensure all findings are related to maritime transportation. The searches are conducted in Google Scholar, Scopus, Science Direct, and JSTOR. A total of 853 articles published before the end of 2023 were collected initially. After reading these articles, we found some articles focus on operation optimization, port choice, competition strategies, or other aspects of port but cover scarce or insignificant references to port efficiency. These articles are considered irrelevant and excluded in this review. Finally, 301 publications are retained, including 271 journal articles, 6 book chapters, 22 conference papers, and 2 reports. The literature search and selection process are shown in Figure 2-1.



Note: Numbers in parentheses represent the number of studies excluded due to the reason.

Figure 2-1 Literature search and selection process

Among these studies, 167 were published in the following journals: *Maritime Policy and Management* (30), *Maritime Economics and Logistics* (28), *Asian Journal of Shipping and Logistics* (14), *International Journal of Shipping and Transport Logistics* (14), *Transportation Research Part A* (13), *International Journal of Transport Economics* (10), *Transport Policy* (10), *Transportation Research Part E* (7), *Research in Transportation Business and Management* (6), *Sustainability* (6), *Transport Reviews* (6), *Utilities Policy* (6), *Research in Transportation Economics* (5), *International Journal of Logistics Research and Applications* (4), *Journal of Transport Geography* (4), *Transportation Research Part D* (4). Table 2-1 shows the distribution of these studies by journals and years. It can be found that the efficiency analysis of the port sector started in 1978 and has grown in recent years.

Table 2-1 Major journal of collected studies on port efficiency analysis

Journal	**1978-1989**	**1990-1999**	**2000-2009**	**2010-2019**	**2020-2023**	**Total**	**%**
Maritime Policy and Management	2	4	4	11	9	30	10.0%
Maritime Economics and Logistics	0	0	10	11	7	28	9.3%
Asian Journal of Shipping and Logistics	0	0	0	5	9	14	4.7%
International Journal of Shipping and Transport Logistics	0	0	5	8	1	14	4.7%
Transportation Research Part A	0	1	5	6	1	13	4.3%
International Journal of Transport Economics	0	2	4	4	0	10	3.3%
Transport Policy	0	0	0	8	2	10	3.3%
Transportation Research Part E	0	0	1	5	1	7	2.3%
Research in Transportation Business and Management	0	0	0	4	2	6	2.0%
Sustainability	0	0	0	3	3	6	2.0%
Transport Reviews	0	0	1	5	0	6	2.0%
Utilities Policy	0	0	1	3	2	6	2.0%
Research in Transportation Economics	0	0	0	4	1	5	1.7%
International Journal of Logistics Research and Applications	0	0	2	1	1	4	1.3%
Journal of Transport Geography	0	0	0	0	4	4	1.3%
Transportation Research Part D	0	0	0	3	1	4	1.3%
Others	2	3	24	55	50	134	44.5%
Total	4	10	57	136	94	301	100.0%

Based on the contents, the collected publications are classified by their research method, data types, and region (Table 2-2). Empirical analyses are dominant (91.0%), while the rest are literature reviews, descriptions of indicators, or conceptual frameworks. Among the 274 empirical studies, most applied non-parametric methods (68.2%) and used panel data (60.6%). 25.2% of them focused on the ports worldwide, while 31.8% on Asia ports, 22.6% on European ports, 12.8% on American ports, and 6.6% on the Middle East and African ports.

Table 2-2 Distribution of collected studies on port efficiency

	Empirical Studies	Other Studies	Total
Methods			
Non-parametric	187	0	187
Parametric	45	0	45
Both parametric and non-parametric	20	0	20
Indicators	22	7	29
Others	0	20	20
Data types			
Panel	166	0	166
One-year	105	0	105
Others	3	27	30
Region			
Asia	87	0	87
Cross-regional (world)	69	0	69
Europe	62	0	62
America	35	0	35
Middle East and Africa	18	0	18
Australia	2	0	2
Others or N.A.	1	27	28
Total studies	274	27	301

2.3 Types of Port Efficiency

Efficiency has been interpreted differently by scholars. Technical efficiency refers to the ability of a decision-making unit (DMU) to produce the maximum level of output from given inputs or to achieve a given output at minimum inputs (Farrell, 1957). Allocative efficiency refers to optimal combinations of inputs and outputs in light of prevailing prices (Lovell, 1993). Allocative efficiency involves choosing the right combination of inputs to produce a given output at the lowest cost, while technical efficiency focuses on the production process itself and how well resources are utilized to produce goods and services. Economic efficiency is a broader concept that encompasses both technical and allocative efficiency. These three traditional efficiency types have been widely adopted in existing port efficiency studies. Based on the traditional efficiency types, some researchers extended the efficiency analysis with specific concerns: time efficiency and environmental efficiency (or eco-efficiency). In this section, we summarised the articles by the efficiency types.

2.3.1 Traditional port efficiency

Technical efficiency is the most widely used type in existing literature. Table 2-3 lists the empirical studies on port technical efficiency having the highest citations in the past years. The representative and highly cited one is Cullinane et al. (2006) who studied port technical efficiency using terminal length, terminal area, quayside gantry, and straddle carrier as inputs and container throughput as the output. Similarly, Chang et al. (2018) used the terminal area, berth length, and number of gantry cranes as inputs and container throughput as output to evaluate ports' ability to approach the production frontier. It can be found that technical efficiency is mainly used to indicate the ability of physical input-output transformation of ports.

Allocative efficiency concerns whether the combination of inputs or outputs is efficient. Since such analysis depends on the input prices, it is also called price efficiency. Banos-Pino et al. (1999) measured it using the relationship between the estimated shadow prices and the market prices of the inputs. Similarly, Zheng and Yin (2015) used the ratio between the actual cost share of every input to its optimal share to represent the allocative efficiency. Although it is important for port authorities, operators and managers to examine whether the input ratios are efficient, the studies on allocative efficiency are relatively low in number. Only 6 out of the 274 empirical studies are in this direction (shown in Table 2-4). The main difficulties may be the data unavailability in the price of inputs, exchange rates, market prices, and resource values.

Compared with technical or allocative efficiencies, economic or cost efficiencies are more general concepts. Some scholars defined economic efficiency as ports' ability to minimise the cost for a given output (Coto-Millán et al., 2000; Taliani et al., 2017). Zheng and Yin (2015) and Tovar and Wall (2017) used cost efficiency to describe the distance of the ports to the cost-minimising levels. They calculated cost efficiency as the product of technical efficiency and allocative efficiency. Meanwhile, some scholars considered “economic efficiency” as a general concept and used it in place of technical efficiency. For instance, Krmac and Mansouri Kaleibar (2022) reviewed studies on port economic efficiency but listed some studies purely on port technical efficiencies. The different understandings of economic efficiency led to varied concerns in the measurement and analysis.

Table 2-3 Representative empirical studies on port technical efficiency

Study	DMUs	Inputs and outputs	Methods	Data Types
Tongzon (2001)	4 Australian ports and 12 other international ports	Inputs: number of cranes, number of container berths, number of tugs, terminal area, delay time, and labour Output: TEU handled, ship working rate	DEA-CCR, DEA-Additive	One-year data (1996)
Cullinane et al. (2006)	57 terminals in 28 world container ports	Inputs: terminal length, terminal area, quayside gantries, yard gantries, straddle carriers. Output: container throughput	DEA-CCR, DEA-BCC, SFA	One-year data
S. Cheon et al. (2010)	98 world container ports	Inputs: berth length, terminal area, capacity of container cranes. Output: container throughput	DEA model	Panel data (1991, 2004)
Yuen et al. (2013)	21 container terminals in China	Inputs: number of berths, total berth length, land size, number of quay cranes and yard gantries Output: container throughput	DEA-CCR	Panel data (2003-2007)
Chang et al. (2018)	58 European container ports	Inputs: terminal area, berth length, number of gantry cranes Outputs: container throughput	SBM-DEA	Panel data (2000-2011)

Note: This table shows the empirical studies on port technical efficiency with the highest citation published in each of the five periods (1998-2002, 2003-2007, 2008-2012, 2013-2017, and 2018-2023). The citation records are collected from Scopus and Web of Science by February 2024. The DEA-CCR model represents the DEA model proposed by Charnes et al. (1978), considering constant return to scale. The DEA-BCC model represents the DEA model proposed by Banker et al. (1984) considering variable return to scale. The DEA-Additive model represents the DEA model proposed by Charnes et al. (1985) based on the concept of a Pareto efficient function. SBM-DEA represents the slack-based measures of DEA models.

Table 2-4 Empirical studies on port allocative efficiency

Publication	DMUs	Inputs and outputs	Methods	Data Types
Banos-Pino et al. (1999)	27 Spanish ports	Inputs: labour, energy, capital, and their respective prices. Quasi-fixed input: the number of linear meters of depth beyond 4 metres. Output: tons transferred.	SFA	Panel data (1985-1997)
Barros (2003)	6 Portuguese ports	Inputs: labour, capital, and their respective prices. Output: ships, movement of freight, gross tonnage, market share, break-bulk cargo, containerised cargo, roll-on/roll-off traffic, dry bulk, liquid bulk, and net income.	DEA-CCR, DEA-BCC	Panel data (1999-2000)
Rodríguez-Álvarez et al. (2007)	3 multipurpose terminals in the port of Las Palmas (Spain)	Inputs: ordinary port workers, special port workers, capital, intermediate consumption. Quasi-fixed input: total area Outputs: container throughput, ro-ro cargo throughput, general break-bulk cargo throughput.	SFA	Panel data (Monthly data from 1992-1997 for T1, 1991-1999 for T2, 1992-1998 for T3)
Núnez-Sánchez and Coto-Millán (2010)	27 Spanish port authorities	Inputs: labour, capital, intermediate consumption, and their respective cost shares. Quasi-fixed input: stocking surface Outputs: movements of solid and liquid bulk, movements of general cargo.	SFA	Panel data (1986-2005)
Zheng and Yin (2015)	16 listed Chinese port companies	Inputs: labour, capital assets, intermediate input, and their respective prices. Outputs: container throughput, dry bulk throughput, liquid bulk throughput.	SFA	Panel data (1998-2011)
Tovar and Wall (2017)	26 Spanish port authorities	Inputs: labour, intermediate consumption expenditures, and their respective prices. Quasi-fixed input: buildings, infrastructure, and their price. Fixed input: deposit surface. Outputs: throughput of solid bulk and general non-container cargo, liquid bulk throughput, containerised merchandise throughput, and number of passengers.	SFA	Panel data (1993-2012)

2.3.2 Extended port efficiency

With the growing awareness of environmental issues, many researchers have extended the traditional efficiencies to consider the negative impacts of port operation on the environment, which is often called environmental efficiency (EE) and eco-efficiency in literature. Among the 274 empirical studies, we found 20 publications in this category. Table 2-5 shows the most cited articles on port EE and the articles on port eco-efficiency.

Most of the port EE analyses included port-related pollution as undesirable outputs, in addition to the usual outputs. For example, an early study by Chin and Low (2010) used ship emission as the undesirable output in port efficiency analysis. Such efficiency can be considered as environmentally adjusted efficiency (EAE) as it still focuses on the output-input ratio of the port. Among the 20 publications, 2 studies considered the environmental damage or social costs of the port production process and analysed port eco-efficiency. The most cited one is Song (2014), which adopted the emission social costs per port throughput, per ship call, and per billion US$ port annual revenue to evaluate the port eco-efficiency. It should be noted that this eco-efficiency is more like eco-productivity as it reflects the level of output per unit of input but not the ability of the port to obtain the maximum output with given input or minimise the input with given output levels. The study of Quintano et al. (2020) on the eco-efficiency of 24 container ports in Europe actually examined the EAE of ports by SBM-DEA models. The different definitions of eco-efficiency led to various concerns in studies. Despite the relatively limited number of existing studies in this field, scholars suggest to use EE and eco-efficiency indicators as practical tools to monitor port environmental impacts and performance because these indicators can help to improve the sustainability of the port and the relationship of the port with the city that hosts it (Tichavska & Tovar, 2015).

Table 2-5 Representative empirical studies on port environmental efficiency and eco-efficiency

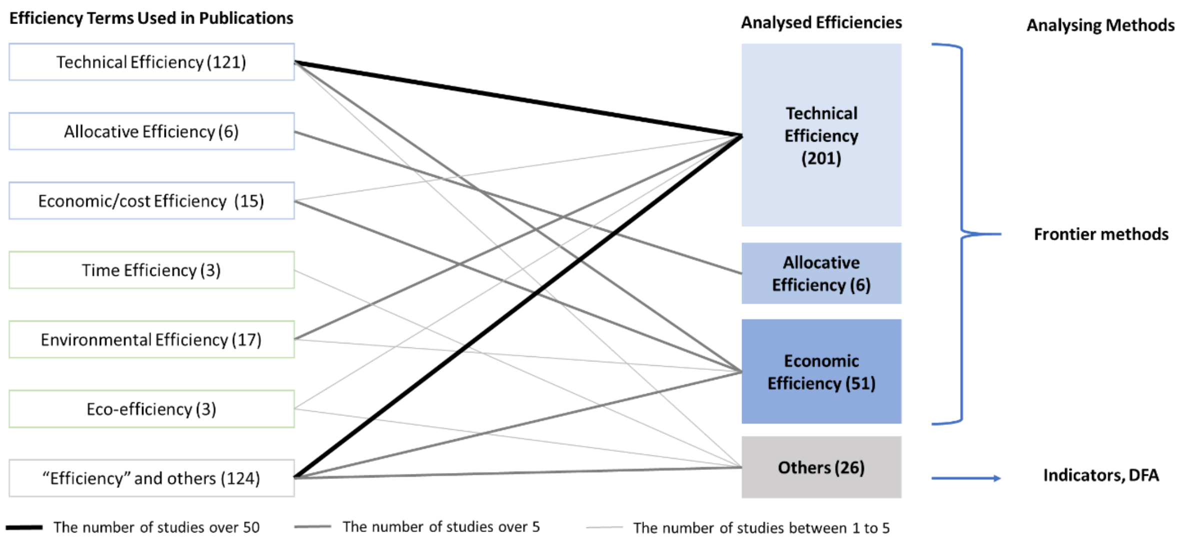
Type	Study	DMUs	Inputs and Outputs/Indicators	Methods	Data Types
Environmental Efficiency	Chang (2013)	23 Korean ports	Inputs: number of labour, quay length, terminal area, energy consumption. Desirable output: vessels, cargo handled Undesirable output: CO_2 emissions.	SBM-DEA	One-year data (2010)
	Lee et al. (2014)	11 world container port cities	Inputs: labour population in each port city. Desirable output: container throughput, RGDP Undesirable output: NO_x, SO_2, CO_2 emissions.	SBM-DEA	One-year data (2011)
	Sun et al. (2017)	17 Chinese port enterprises	Inputs: staff number, operational costs, fixed assets. Desirable output: Net profit, cargo throughput Undesirable output: NO_x emissions.	Non-radial DEA preference model	One-year data (2013)
Eco-efficiency	Song (2014)	Shanghai Yangshan Port	Emission social cost per port throughput (US$ per 1,000 TEUs handled in port), emission social cost per ship call (US$ per call), emission social cost per billion US$ port annual revenues (US$ per billion US$ revenue).	Indicators (Cost-benefit analysis, bottom-up estimation)	One-year AIS-based data (2009)
	Tichavska and Tovar (2015)	Las Palmas Port	Emission external cost per passenger (€/pax), emission external cost per ton of cargo (€/1,000 tons), emission external cost per ship call (€/call), emission external cost per port revenue (€/million euros)	Indicators (Cost-benefit analysis, bottom-up estimation)	One-year AIS-based data (2011)
	Quintano et al. (2020)	24 European ports	Inputs: number of employees, energy consumption Desirable output: total gross weight of goods handled Undesirable output: emissions.	SBM-DEA, SFA	One-year data (2016)

Note: The bottom-up approach refers to the emission estimation method based on fleet activity.

As a service provider, a port uses its facilities to serve its customers, namely cargo and ship owners. For them, the time spent in port can be an indicator for port efficiency. Sánchez et al. (2003) were the first to measure port time efficiency based on port annual congestion time, ship waiting time, general ship waiting time and the average time required for export and import processes. Ducruet et al. (2014) defined port time efficiency as the average TAT of ships. Using the data from Lloyd's List Intelligence in May 1996, 2006 and 2011, they found that a high number of vessel calls can reduce TAT, and larger ports with high vessel traffic are more time efficient than smaller ports or ports for irregular trade.

In recent years, emerging big data, such as the Automatic Identification System (AIS) data, has allowed researchers to incorporate ships' time in the analysis (Yang et al., 2019). For instance, based on AIS data, studies have used time-related indicators like ships' time in different port areas (Feng et al., 2020), the average berthing time for ships and the average number of container lifts per hour (Svanberg et al., 2021), port time of ships for different ships and call sizes (Ashley et al., 2022), and port turnover rate (Yang et al., 2023) to estimate port efficiency. The novelty of these studies is that they directly measured how efficiently a port can serve its users by time metrics. However, it should also be noted that just using time indicators as efficiency measures does not belong to the traditional understanding of economic efficiency as they do not concern port production possibilities.

Figure 2-2 summarises the terms used and efficiencies analysed in existing empirical studies. The term "technical efficiency" is frequently used by scholars. Out of the 121 studies using "technical efficiency", 8 articles should be categorized under port economic efficiency analysis as they used expenses, intermediate consumption, capital, and other costs as inputs, reflecting the ports' ability to minimize costs for a given output. 2 used the term "technical efficiency" but their analyses are on port performance using productivity indices, not using frontier methods. Among the studies on port economic efficiency, 2 studies considered "economic efficiency" as a broader concept, using it as a substitute for technical efficiency. Among the 17 studies on port environmental efficiency, 11 can be considered as EAE, which can be categorised under technical efficiency as they mainly focused on the ports' ability to approach the input-output transformation frontier. Additionally, 124 publications didn't specify the efficiency type or used terms such as "production/productive efficiency", "operation/operational efficiency", or "performance". The majority of these can be considered as studies on port technical efficiency (82 out of 124) or economic efficiency (23 out of 124).



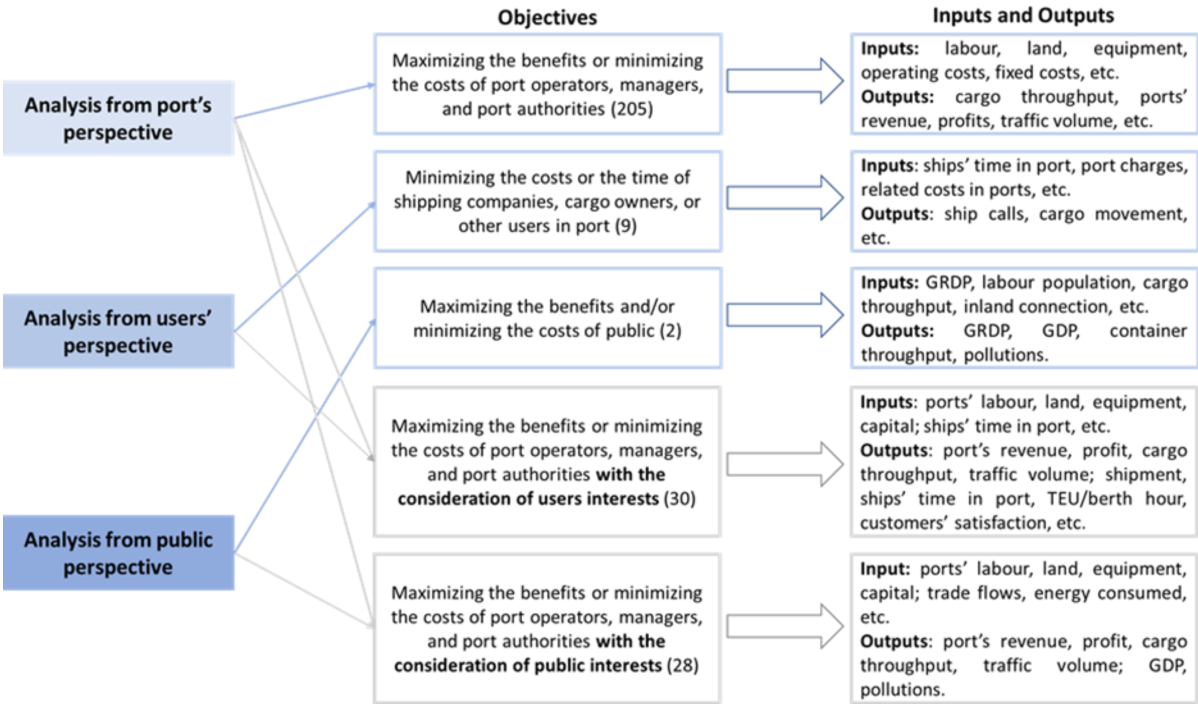
Note: Numbers in parentheses represent the number of empirical studies using the efficiency term or analysing the efficiency type. Some papers used and analysed more than one efficiency type. 2 articles used and analysed both "technical efficiency" and "allocative efficiency". 4 articles used and analysed "technical efficiency", "allocative efficiency", and "economic efficiency". 4 articles used "technical efficiency" with "environmental efficiency". 1 article used both "economic efficiency" and "environmental efficiency.

Figure 2-2 Efficiency terms used and the actual efficiency analysed by publications

However, it is important to note that productivity and efficiency are related but not synonymous. Productivity refers to the ratio between the products obtained and the factors used in its production. Efficiency is the ability to obtain the maximum amount of output by given inputs or obtain a given output level using the minimum inputs. Some scholars mixed up these two concepts, stating that they evaluate port efficiency but actually analyse port productivity or performance using output-input ratios or indicators.

2.4 Classification of Analysis Perspectives

Port is a complex system with multiple stakeholders, each has its own objectives. For authorities, port operators, and managers, the port is the production unit that uses resources, such as employees, terminal surface, cranes, or related costs, to finish cargo throughput and gain profit. For users, the port is the service unit that requires time or usage costs. For the public, the port is a component of the local economy that uses resources to contribute to international trade and the local economy, with some environmental impacts. The complex nature of port operations highlights the need to bring in the perspective of the stakeholders and the relevant objectives and variables in efficiency analysis (Merkel & Holmgren, 2017). Wang et al. (2005) summarised the various objectives of port operation, including maximising the benefits of port owners, minimising the costs to the users, maximising the economic benefits to the region or increasing local employment. Based on the objectives and the nature of inputs and outputs, we classified the 274 empirical port efficiency studies into three categories: analysis from the perspective of port managers, that of port users, and that of the public (Figure 2-3).



Note: Numbers in parentheses represent the number of empirical studies. GRDP represents the gross regional domestic product; GDP represents the gross domestic product.

Figure 2-3 Classification of existing studies by analysis perspectives.

2.4.1 From the perspective of port

Most port efficiency analyses are done to meet the needs and interests of port authorities, operators and managers. These analyses mainly use port production resources, such as labour, land, equipment, and related costs as the inputs and cargo throughputs, traffic volume, and port revenue as outputs to identify the possible measures for ports to improve efficiency. For instance, Tovar and Wall (2022) examined the efficiency of 16 Spanish ports from the view of port authorities. Using the throughput of four types of cargo and the number of passengers as the outputs, labour, intermediate consumption expenditures and the expenditures on capital asset services as inputs, they found that the improvements in port connectivity are positively associated with the output levels and port efficiency. It should be noted that some scholars used "port" to represent port authorities, terminal operators or managers without detailed clarification. Port authority is usually a public body, whose interests may not be the earnings from port operation, which is the main interest of the terminal operators. Trujillo and Tovar (2007) also pointed out that the activities of port authorities, operators, stevedores, pilotage, etc., are different. Thus, in port efficiency analysis, a clear definition of the DMU and analysis perspective is important for both the variable selection and the understanding of research results.

2.4.2 From the perspective of users

Port users, such as shipping lines, cargo owners and supply chain partners, are more concerned about their time, costs and service quality at ports. For users, an efficient port means a short turnaround time for ships and cargo. From this point of view, some scholars used ships' time or costs in port to reflect users' perceptions of port efficiency. For instance, Brooks and Schellinck (2013) used the incidence of delays, availability and capability of dockworkers, provision of adequate and on-time information, fast cargo loading/unloading, and short vessel turnaround time to measure the port effectiveness for users. Ducruet et al. (2014) and Slack et al. (2018) directly use the ships' port time in port efficiency analysis to meet the needs of users. Michaelides et al. (2019) used arrival punctuality, berth waiting time, and berth utilisation rate to reflect the port efficiency. These studies can be considered as those from users' perspectives, but they are very rare in the existing research. Besides, as we mentioned in Section 3.2, some of them differ from the traditional understanding of efficiency but use some indices to reflect port performance in terms of time or service quality.

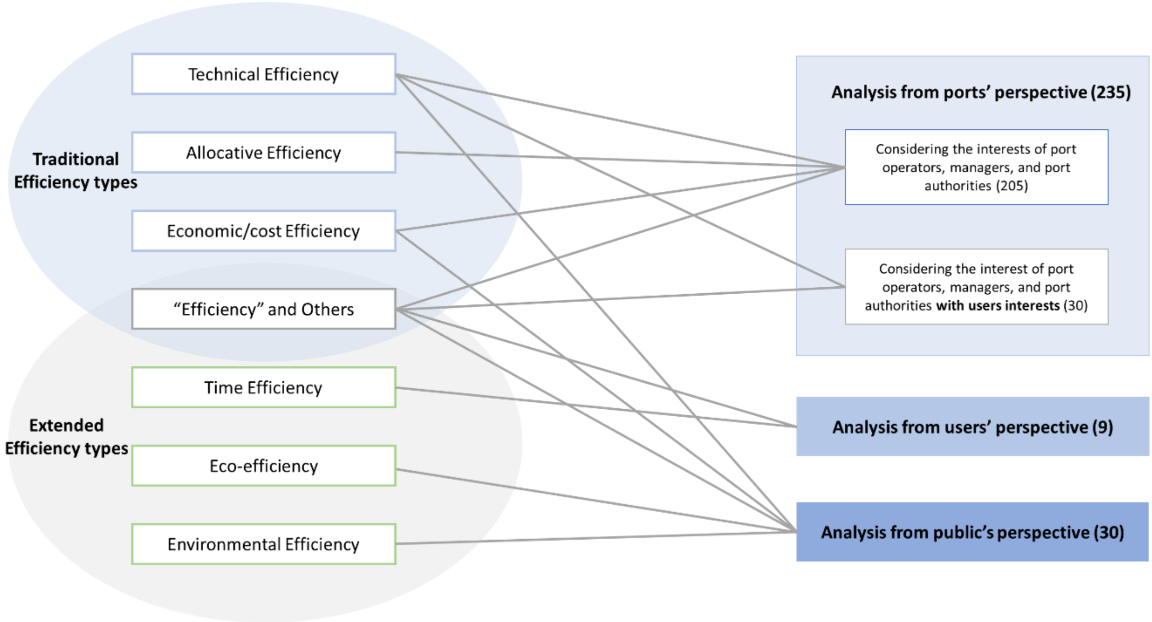
With increased port competition, some studies have noticed that using cargo throughput or revenue alone to assess port efficiency and ignoring users' interests can be highly questionable (Merkel & Holmgren, 2017; Munim, 2020; Panayides et al., 2009). Thus, scholars attempted to include users' interest in port efficiency analysis. For instance, Schøyen et al. (2018) considered the logistic service delivery performance in port efficiency analysis by combining three scaled outputs, namely timeliness, price, and reliability, with the traditional container throughputs. They found that the average technical efficiency of ports was 0.86 when using these four outputs in DEA evaluation. It decreased to 0.71 when only the container throughput was used as the output. Sun et al. (2022) used ships' total berthing time and net activity time, the number of foremen, signalmen or winchmen, and the number of riggers deployed as the input variables and the general cargo throughput and container throughput as the output variables in studying the efficiency of a multipurpose port. Although these studies included users' interest, they should be classified to the analyses from port's perspective as they still focused on the port production possibilities. In certain instances, the time ship stays in port may be viewed as an ancillary outcome of port operations. However, in nature, ship's time in port is the cost to ships or shipping companies rather than that to most ports. Including ship's time in port together with ports' inputs or outputs in port efficiency analyses without clarification of the research objective may lead to confusion in understanding the result.

2.4.3 From the perspective of the public

As ports play an essential role in the local economy, some scholars evaluate port efficiency from the public's perspective. From the view of the local economy, Amin et al. (2021) used the gross regional domestic product (GRDP) of the previous year, cargo throughput, number of port labour, inland connection, loading and unloading tariff and sea freight cost as inputs and GRDP in the study year as output to measure each port's ability to contribute the local economy. Lee et al. (2014) measured the environmental efficiency of port cities using the city's labour population as an input, the gross domestic product (GDP) and container throughput as desirable outputs and emissions as undesirable outputs. Apart from these two studies, port environmental and eco-efficiency analyses considered pollution and social costs associated with port throughputs. These studies mentioned in section 2.3.2 can be classified under the category of port efficiency from the perspective of the public.

Cullinane et al. (2004) pointed out that if the research is from the perspective of the port business operator, employment or any information on labour should be counted as inputs. However, from the perspective of the public, the objective should be to increase employment, and employment should be used as an output. As there are different levels of public opinion, the performance of the port needs to be measured with different approaches and considering different input/output relationships. And the different combinations of inputs and outputs may lead to variations in efficiency scores.

Having reviewed the efficiency types and analysis perspectives in existing literature, their relationships can be summarised in Figure 2-4. All the traditional efficiency types have been applied to analyse the port efficiency from the perspective of the port. Some environmental or eco-efficiency analyses that consider ports' contributions to local economies or the social costs of port production can be considered as those from the public perspective. Only few studies using ship's time or costs in the port technical efficiency analysis and those on the time efficiency in port can be considered from the perspective of users. Moreover, according to our knowledge, none of the existing studies balanced various stakeholders' interests in port efficiency analyses. There are opportunities for researchers to develop more comprehensive port efficiency analyses that can balance the needs of multiple stakeholders.

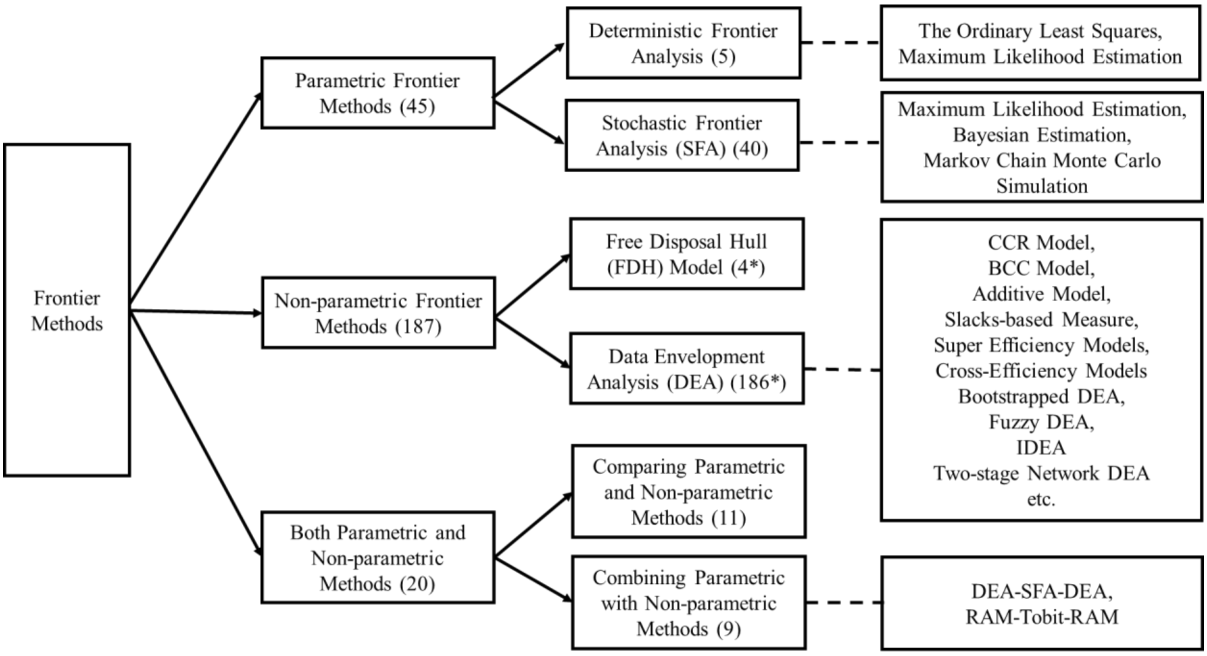


Note: Numbers in parentheses represent the number of empirical studies from the perspective.

Figure 2-4 Classification of existing studies by efficiency types and analysis perspectives

2.5 Application of Frontier Methods

Frontier methods are more popular in port efficiency analyses, which include parametric (e.g., SFA) or non-parametric (e.g., DEA). The former requires the assumption on the production function, while the latter does not. There are existing review papers on the application of these methods in the port sector, but they mainly focus on the traditional DEA models (Krmac & Mansouri Kaleibar, 2022; Panayides et al., 2009). Recently, some scholars adopted both parametric and non-parametric methods, or more advanced models in their studies, to enhance the robustness of results or to remove the bias in the efficiency scores. Figure 2-5 shows the detailed methods in port efficiency analyses extended from the basic classification from Wang et al. (2005) and Farrell (1957).



Note: Numbers in parentheses represent the number of empirical studies using the method; * represents three articles using both DEA and FDH.

Figure 2-5 Alternative methods in port efficiency analyses

2.5.1 Efficiency measurement

Many DEA-based models have been applied in port efficiency analyses. For instance, slacks-based Measures (SBM) were used to identify the over-utilised inputs, deficient outputs, and undesirable outputs in port production(Chang et al., 2018; Lee et al., 2014; Liu et al., 2021; Low, 2010; Ye et al., 2020). Super-efficiency and Cross-efficiency models were used to further differentiate the efficient ports (Barros, 2006; Lin & Tseng, 2007; Nguyen et al., 2020; Wu & Liang, 2009). Bootstrapped DEA and Fuzzy DEA were developed and applied to handle the uncertain or imprecise variables embedded in actual port production (Bray et al., 2015; Hung et al., 2010; Nguyen et al., 2016). Two-stage network DEA was used to recognise the intrinsic trade-off between two subsequent production stages of ports or terminals (Bichou, 2011; Wanke, 2013). Tiered DEA (TDEA) classifies the sampled ports into rank-ordered peer groups using DEA, removing the subjectiveness in the port selection process (Cheon, 2009). Recursive DEA(RDEA) constructs multi-layer efficiency frontiers to increase the discriminatory power of the DEA efficiency scores (Park et al., 2019). Bi-objective multiple-criteria DEA (Bio

MCDEA) uses a weighted model to improve the discrimination power, overcome weight dispersion, and find the optimal solution for all the objectives at the same time (de Andrade et al., 2019). Meta-frontier DEA provides a homogeneous boundary for all ports, which may be heterogenous, by estimating the frontiers of relatively homogeneous groups and enveloping the frontiers of the different groups (Fernández et al., 2021; Ghiara & Tei, 2021). These developments and wide applications show the popularity of the DEA approach in port efficiency measurement.

SFA considers a composed error structure with a two-sided symmetric distribution capturing the randomness and statistical noise, as well as a one-sided distribution capturing the inefficiency. Some studies compared the efficiency yielded by DEA and SFA and found that DEA scores may be less valuable than SFA scores, but the rankings are consistent (e.g., Barros & Athanassiou, 2004; Cullinane & Song, 2006; Nguyen et al., 2018). Considering the respective strength of parametric and non-parametric methods, some combines these two methods in analysing port efficiency. For instance, the three-stage DEA (also called DEA-SFA-DEA or DEA-Tobit-DEA), which uses DEA to evaluate efficiency in the first and third stages and SFA or Tobit regression model to control the role of external factors and adjust the inputs in the second stage, was adopted by some scholars (Cui, 2017; Liu, 2008). The results suggest that using both DEA and SFA/Tobit regression in port efficiency analyses can enhance the reliability of the study and accommodate the influence of environmental factors and randomness on the efficiencies. Besides, most studies focused on port static efficiency and ignored the time interdependence of production decisions and port adjustment paths over time. Incorporating the evolution of productivity, technological change, and the adjustment of inputs and outputs across multiple periods, dynamic efficiency analysis is developed and employed in various sectors. Using a directional distance function and stochastic cost frontiers, Tovar and Wall (2017) first adopted the dynamic efficiency measurement in the port sector. Based on a panel data set of 26 Spanish port authorities from 1993 to 2012, their study shows that ports could achieve long-run cost savings of over 38%, two-thirds of which could be achieved by reducing input use and the remainder by changing the input-mix used. Although the combination of DEA with SFA and the developed dynamic efficiency measurement can overcome some limitations of traditional frontier models, studies using these methods are still very rare. Researchers in this direction should be encouraged to develop more advanced methods or use multiple methods.

2.5.2 Factor measurement

In addition to evaluating efficiencies, some researchers have delved into exploring the factors for port efficiency. SFA can incorporate external variables into the model to assess their impacts in one step. For instance, Serebrisky et al. (2016) employed the translog stochastic production frontier model to examine the impacts of variables affecting port output and efficiency. In their model, the size of the economy, trade openness, liner connectivity and terminal type are included to explain the port throughput. Factors, including ownership, public sector corruption and income per capita of the country hosting the port are considered as potential determinants of technical inefficiencies. Using the 10-year data of 63 ports, their study reveals that including variables such as terminal types and liner connectivity can help explain port output in the production function, and the private section participation is significantly associated with efficiency gains.

Unlike the one-step approach in SFA models, DEA commonly employs a two-stage process: in the first stage, the efficiency scores are measured, and in the second stage, the efficiencies are explained. The Ordinary Least Squares (OLS) and Tobit Regression (TR) are frequently used in the second-stage analysis. However, the use of OLS and TR in the second stage of DEA has been criticized by Simar and Wilson (2007) because they do not solve the problem of serial correlation among the different factors and the efficiency scores, which results in inconsistencies in the second-stage regression. Chang and Tovar (2022) reviewed the studies using the two-stage DEA models in port research and recommended the bootstrap method as a solution to overcome this problem and enhance statistical reliability. Despite this, among 274 empirical studies examined, only 23 were found to employ bootstrap methods in the second-stage DEA analysis. A notable study by Le and Nguyen (2020) demonstrated that the double-bootstrap two-stage DEA method significantly enhances the precision of efficiency measurements and the analysis of contributing factors. Given its benefits in increasing both the accuracy and consistency of results, the double-bootstrap method warrants greater consideration in future research.

2.6 Discussion

Although existing studies provide valuable insights for port operation and management, there remain several issues that could potentially limit the impact of studies. This section summarises these issues and proposes possible directions for future research.

Firstly, the DMUs are not specified and the selection of variables is not explained in some studies. Port comprises a set of activities serving the vessel from arrival to departure and uses different kinds of inputs, such as pilot, tug, channels, etc. Port authorities, terminal operators, stevedore companies, etc., are responsible for various aspects of these port's activities, using the inputs under their control and focusing on their target outputs. The definition of DMUs, which are ports or terminals, operators or authorities, should be clarified before the variable selection. Besides, a clear explanation of how the selected factors or indicators relate to DMUs and contribute to port operations and productivity is essential. Without clear explanation and justification, the result may be questionable and fail to offer practical insights or policy recommendations for ports.

Secondly, the interests of the users and the public are still not adequately considered. As a system, the port is not only a production unit but also a service provider for its users and a contributor to the regional economy. Most of the existing studies analysed port efficiency from the perspective of ports, few considered the users' and public interests. In addition, only a few studies noticed that the port service level, such as the availability of berths for ship arrival, might conflict with its profitability. From the view of ports, expenditures on port services should be kept minimal for a given demand level. But for the users, the port capacity should be large enough to eliminate congestion. How to balance the interests of various stakeholders in evaluating port efficiency is a topic for further studies.

Thirdly, the unique natures of ports were not fully considered. Unlike the DMU in manufacturing activity, the port demand or the port output is derived from international trade. Some studies evaluated port efficiency using only one year's data and recommended the inefficient port adjust its capacity only based on these evaluation results. This may be problematic when the demand shrink is temporary, and the port can actually operate at its full capacity and be efficient after the demand rebounds. Thus, when analysing port efficiency, researchers or operators should distinguish ports at different development stages and consider the market situation. Furthermore, a port should not be viewed as an isolated entity but rather as a crucial node within the global supply chain. Scholars such as Suárez-Alemán et al. (2016) and Tovar and Wall (2022) have proved that the surrounding water and land transportation systems can significantly influence a port's attractiveness to cargo and its operational efficiency. With the development of multimodal transportation and the integration of resources, it becomes imperative to evaluate the efficiency of supporting infrastructures beyond the port system, so as to identify the bottlenecks and improve the overall efficiency.

Fourthly, each method in port efficiency measurement has its strengths, weaknesses and application requirements. DEA-based models can accommodate multiple inputs and outputs, but the results may be sensitive to sample size, number of inputs and outputs, statistical noises and ports' heterogeneity. SFA models considering environmental factors can distinguish port heterogeneity and statistical noise from (in)efficiency, but they are subjected to assumptions on the form of production function and error structure. This highlights the need for extending and/or combining different methods to avoid the limitations of individual methods. In addition, the requirements of the specific model have to be checked before being applied in the port efficiency analysis. For example, when applying DEA, the DMUs are required to be isotonicity and homogenous (Cochrane, 2008), but the ports included in the study may not satisfy such requirements. The consistency test on ports is helpful but ignored by many scholars. Accommodating the requirements of measurement models is an essential step in efficiency analysis.

Lastly, the impacts of new developments and occurrences warrant more attention. The automation and digitisation of ports and terminals reduce human interventions in port operations but require more capital investments, which has profound implications for efficiency and productivity (Tsolakis et al., 2021). Also, the requirement for emissions encourages ports to use alternative energies, adopt innovative technologies and pay special attention to the impact on the environment when increasing their competitiveness and productivity (Balić et al., 2022). Emerging trends in port development strategies, such as cooperation and integration, have the potential to reshape competition for cargo and alter port governance structures (Luo et al., 2022). Moreover, unforeseen events, such as the COVID-19 pandemic and the Suez Canal blockage, have posed challenges to the shipping market and affected port operations (Notteboom & Haralambides, 2020; Wan et al., 2023; Xu et al., 2021). The effects of these developments and incidents have not been thoroughly investigated in existing research. The implications of these emerging issues in port efficiency analysis merit more extensive research.

Overall, after reviewing the existing studies, we found the majority of studies have concentrated on traditional efficiency types, with less attention given to time issues and the associated negative environmental impacts. Most research evaluates port efficiency from the standpoint of port authorities, managers, and operators, with only a few studies considering the perspectives of users and the general public. The use of AIS data enables the assessment of ship emissions and turnaround times at ports, which can be considered in future studies to include environmental impacts and users' interests. Additionally, while traditional DEA and SFA models are commonly used in evaluating port efficiency, there is a scarcity of applications that either extend these models or integrate different methods in port efficiency analysis. Several critical issues remain underexplored, which can be considered in future research.

2.7 Conclusion

This study reviewed 301 literature on port efficiency analyses published before the end of 2023. Novelty classifying the studies by efficiency types and analysis perspectives, this study reveals the complex nature of port operations, the possible limitations of traditional efficiency analyses, the reason behind the lack of consensus in measuring port efficiency and the need to develop advanced approaches and incorporate different methods.

A key issue identified in this paper is the need to analyse port efficiency from the perspective of different stakeholders and balance their interests. With intense competition, ports should put more emphasis on improving service levels for users, meeting the requirement of sustainable development. Analysing port efficiency from different perspectives, especially from the users, can help ports gain competitiveness. In addition, the traditional DEA models or single methods have some limitations in port efficiency analyses. Developing advanced approaches and/or incorporating different methods can better accommodate the complex port production process and improve efficiency measurement. Furthermore, the DMUs and the selection of input/output variables must be consistent. As each DMU can only decide its own inputs and outputs, a clear definition of the DMU is important for both the researchers in selecting variables for efficiency analyses, and for the readers to understand the results. Finally, future analyses should consider the nature of port services, the impacts of new technology developments, port cooperation and integration, and the impact of unforeseen events.

The major contribution of this research lies in providing an updated and comprehensive review of existing studies on port efficiency. Emphasizing the interests of users and the environmental impacts of port operation, this study provides a multi-dimensional and sustainable view for port operators, managers, policymakers, and related stakeholders in assessing port efficiency and enhancing port competitiveness. Meanwhile, this paper underscores the potential benefits of using emerging big data and applying advanced models, and highlights the need for assessing the impacts of recent changes and events on port efficiency, which may help future researchers determine the direction for port efficiency research.

Chapter 3. Are efficient ports for port operators also those for shipping companies? A meta-frontier analysis of global top 80 container ports

3.1 Introduction

Port efficiency is an important indicator with different meanings for various stakeholders. For port operators, including terminal operators, port managers and other port-related businesses, it means higher productivity or profitability. For port users, such as shipping companies and cargo owners, it means shorter turn-around time and higher service quality. Therefore, evaluating port efficiency is not only useful for port operators to measure their performance and identify sources of inefficiency (Wang et al., 2005), but also important for sea carriers to select ports to call and manage ship schedules (Seth & Feng, 2020; Suárez-Alemán et al., 2016).

Numerous studies have conducted in-depth analyses of port efficiency at regional, national, and global levels. However, most of them are conducted from the port operators' perspectives without consideration of users' interests (J. Zhang et al., 2024). Some scholars investigated the views of different stakeholders on port performance or competitiveness and found that the important factors for port operators are not necessarily of equal importance for shipping companies (Baştuğ et al., 2022; Brooks & Schellinck, 2015). Seldom have noticed the inconsistencies between the goals of port operators with those of port users. For port operators, an efficient port should be able to maximize port outputs, such as total throughputs or revenue, or minimum inputs, such as port facilities or expenditures. However, such a port often over-emphasizes the utilization rate of terminal resources, which may result in long waiting times for the ships. This is not consistent with the desire of shipping companies in port selection, which often prefer a short turn-around time when calling the port (Rødseth et al., 2020). With intense intra-port and inter-port competition and higher emphasis on time-saving logistics, ships' turn-around time becomes critical for the port to determine its operation policy and for port users to arrange logistic schedules (Suárez-Alemán et al., 2014). Therefore, it is essential to analyze port efficiency considering both the interests of port operators and users.

Data envelopment analysis (DEA) and stochastic frontier analysis (SFA) have been widely used in measuring port efficiency. DEA, accommodating multiple inputs and outputs without prior assumptions on the production function, is more popular in existing port studies than SFA (Krmac & Mansouri Kaleibar, 2022; Merkel & Holmgren, 2017). However, some scholars pointed out that DEA requires the decision-making units (DMUs) to be isotonicity and homogenous (Cochrane, 2008), but the ports located in different socio-economic environments and development stages, may operate under different production technologies, leading to performance discrepancies (Nguyen et al., 2018). With the increasing use of large vessels, some ports have upgraded their handling technology and improved their infrastructure and facilities, existing production differences with ports serving small ships (Monios, 2017; Sáenz et al., 2023). Using DEA to evaluate port efficiency without considering model requirements and port heterogeneities may result in inaccurate estimates (Chang & Tovar, 2022; Wang et al., 2022). To address this issue, meta-frontier analysis has been used in efficiency analysis (O'Donnell et al., 2008). Recent studies on port efficiencies have demonstrated the advantages of meta-frontier methods in evaluating the efficiencies of ports across diverse regions and environments, as well as in identifying technology gaps among port groups (Chang & Tovar, 2022; Fernández et al., 2021; Martínez-Moya et al., 2024; Nguyen et al., 2018).

This study employs the meta-frontier DEA approach to assess the efficiencies of the world's top 80 container ports from the perspectives of port operators and shipping companies. We classify the global top 80 container ports into three groups based on their abilities to handle containers and accommodate ships. Port efficiencies are then estimated relative to meta-frontier and group frontier. By comparing the efficiencies evaluated from port operators' and shipping companies' perspectives, we identify the discrepancies in port efficiency perceived by these two stakeholders. This study contributes to port efficiency literature in three ways. First, this study provides a dual-perspective efficiency assessment for global ports and explores the consistency of port efficiency perceived by port operators and shipping companies. Using variables relevant to port operators and shipping companies in frontier models, this study provides evidence that the efficient ports from the port operators' perspective may not be the efficient ones for shipping companies. The result of this study provides the basis for port operators to improve the port's competitiveness and for shipping companies to arrange ships' schedules efficiently. Second, this study considers port heterogeneity and explores the discrepancies in port efficiencies across different port groups. The results highlight the need for port operators and managers to adopt varied strategies based on their specific characteristics and suggest the pathway for inefficient ports to improve their overall efficiencies. Last, this study is one of few works focused on the efficiency of global ports using port data with ships' data extracted from the latest automatic identification system (AIS) data, intended to introduce the application of big data in port efficiency studies and attract more attention to time-in logistics in the maritime industry.

3.2 Literature Review

Ports operate under varying conditions and business environments, involving multiple stakeholders. When two ports have the same level of inputs but operate in different environments with different technology, their potential maximum outputs are likely to differ. Such a difference in outputs can be interpreted as technology heterogeneity rather than efficiency difference, which requires careful consideration in efficiency assessments (Yan et al., 2009). Additionally, each stakeholder has its own view of what is an efficient port. J. Zhang et al. (2024) summarised these differing views, noting that port operators focus on maximizing port profitability or minimizing operating costs while shipping companies, cargo owners, and other port users prioritize minimizing usage costs or port time. Given the importance and complex nature of ports, their efficiency has been analysed by many scholars with various concerns using different methods.

3.2.1 Port efficiency evaluation methods

Originating from the concept of technical efficiency proposed by Farrell (1957), frontier methods, including parametric and non-parametric methods are widely applied in port efficiency analysis. Parametric methods involve estimating a cost, production, or distance frontier using a predefined functional form, which can be classified as either deterministic or stochastic depending on the characteristics of the frontier function. In contrast, non-parametric methods, such as DEA and Free Disposal Hull (FDH), do not require assumptions about the production function. Recent studies have integrated parametric and non-parametric approaches to enhance the accuracy of efficiency estimations (Cui, 2017; Huang et al., 2020). Additionally, in the broader context of productivity, scholars have employed various indicators, such as TEUs per crane, TEUs per quay length, waiting time and berthing time of ship calls, to assess port efficiency (Ashley et al., 2022; Feng et al., 2020; Laxe et al., 2021).

Each method has its strengths, weaknesses and application requirements. While indicator-based methods are straightforward and easy to comprehend, they have limitations when addressing multiple inputs and outputs in port production processes (González & Trujillo, 2008). Additionally, these indicators assess port productivity, which is the ratio of port outputs to inputs, rather than efficiency, which focuses on maximizing outputs from given inputs or minimizing inputs for a given output level. SFA models excel at distinguishing external factors and statistical noise from inefficiency, but they are limited by assumptions regarding the production function and error structure. In contrast, non-parametric methods, which are not bound by these constraints, can effectively manage multiple inputs and outputs without predefined functional forms. Notably, the DEA method is preferred for yielding more reliable results compared to the FDH method (Charisis et al., 2019; Cullinane et al., 2005). Some scholars have reviewed the use of various methods in the port sector, acknowledging that DEA is a more powerful and widely adopted approach for analysing port efficiency (Krmac & Mansouri Kaleibar, 2022; Merkel & Holmgren, 2017; Tovar & Rodríguez-Déniz, 2015; J. Zhang et al., 2024).

Among various DEA models, the model introduced by Charnes et al. (1978), which is known as the CCR model, and that introduced by Banker et al. (1984), which is known as the BCC model, are most widely applied in the field of port efficiency analysis. Roll and Hayuth (1993) first illustrated the application of the CCR model in the port sector using 20 hypothetical ports as the sample. Martinez-Budria et al. (1999) used the BCC model to assess the efficiency of 26 Spanish ports. Following them, a large number of studies adopted these two methods in the port efficiency analysis (e.g., Beuren et al., 2018; Chen et al., 2020; Huang et al., 2021; Ju & Liu, 2015; Turner et al., 2004; Wu et al., 2010). Despite their popularity, CCR and BCC models have certain requirements in analysing port efficiency. DEA requires the DMUs to be homogenous and assumes that they operate using similar production technology, which refers to the combinations of physical, human, financial capital, economic infrastructure, resources and any other characteristics of the physical, social and economic environment (Chang & Tovar, 2022; Panayides et al., 2009). However, the worldwide ports operating at different scales may be subject to different technologies.

Considering the possible technology differences among DMUs, Battese and Rao (2002), Battese et al. (2004), and O'Donnell et al. (2008) introduced the meta-frontier framework into efficiency analysis. Splitting all the DMUs into several homogenous groups, the meta-frontier model enabled the measurement of comparable technical efficiencies and estimates of technology gaps of DMUs in different groups. Nguyen et al. (2018) first used the meta-frontier analysis with DEA and SFA methods to examine the technical efficiency of 43 Vietnamese ports. Classifying the ports by region and estimating the port efficiencies with respect to meta-frontier and region frontier, they found the Northern ports in Vietnam were the most efficient group in both SFA and DEA results. Chang and Tovar (2022) measured the technical efficiency of Peruvian and Chilean terminals through a DEA model in a non-convex meta-frontier framework and found that ports with high container/bulk ratios show higher efficiency. Martínez-Moya et al. (2024) classified the ports in the Mediterranean Sea into two groups by transhipment share and used the meta-frontier DEA model to identify whether there are differences in the efficiency scores between transhipment ports and gateway/mixed ports. These studies show the advantages of meta-frontier methods in evaluating heterogeneous ports.

3.2.2 Different views on port efficiency

As a complex system, a port is not only a production unit but also a service provider for its users and a contributor to the regional economy. It has been found that most scholars analysed port efficiency from the view of port operators, authorities or managers, but few considered the interests of users (J. Zhang et al., 2024).

From the view of port operators, port managers and other port-related businesses, efficient ports are those that use minimal port resources for a given output or achieve maximum output using given port resources. For instance, Jeh et al. (2022) evaluated the efficiency of 21 global terminal operators (GTO) and compared the efficiency scores of these operators by classifying them into stevedore, carrier-based, and hybrid GTO types. They found that carrier-based GTOs were the most inefficient as their objective was to reduce the overall cost of the shipping process, while stevedore and hybrid GTOs focused on generating profits. Considering port authority as the DMU, Tovar and Wall (2022) measured the efficiency of 16 Spanish ports using port production data from the Spanish State Ports Public Body. These studies from the perspectives of port operators or authorities, mainly focused on the input-output transformation in the port production process, using port resources such as quay length, yard area, and number of cranes as inputs, cargo throughputs, ship calls and port revenues as outputs.

From the perspective of port users, an efficient port should be able to provide high-quality service at low cost. Munim (2020) defined port service level as the availability of berths upon vessel arrival and the ability to serve vessels without any waiting time. He pointed out that ports with high technical efficiency might have unreliable service levels. The facilities and infrastructure of a port can not only impact the operational efficiency of ports but also impact ships' turnaround time in port, thereby influencing shipping companies' operating costs, emissions and related externalities (Moon & Woo, 2014; Xu, Wu, et al., 2024). Given the interactive yet often conflicting interests of port operators and users, some scholars argued that it was highly debatable to use cargo throughput or revenue alone in assessing port efficiency, ignoring other indicators such as service level, time spent in port, and customer satisfaction (Merkel & Holmgren, 2017; Panayides et al., 2009). Some studies have attempted to integrate users' interests into port efficiency analysis. For example, Kamble et al. (2010) evaluated the efficiency of Indian ports by using ships' turnaround time and average throughput per ship-day as outputs, while considering port storage facilities, berths, and handling equipment as inputs. de Andrade et al. (2019) included ships' waiting and berthing time as inputs in their efficiency assessment of Brazilian ports.

With intense competition and more emphasis on time-saving logistics, using the ship's time directly to reflect users' perceptions of port efficiency has become a new trend. Current trends in digitalization, artificial intelligence, and sustainability within the shipping sector present opportunities for port operators to measure performance from different perspectives (Chen et al., 2024). The introduction of big data, especially Automatic Identification System (AIS) data, has significantly enhanced the analysis of ships' time in port and the overall assessment of port efficiency. For instance, World Bank (2023) and Ashley et al. (2022) used the ships' time extracted from AIS data to rank global port performance from the perspective of ship operators. Yang et al. (2023) assessed the handling efficiency of ten container ports by aggregating the berthing time of ships with port historical throughput. W. Chen et al. (2023) employed data mining methods to explore ships' berthing and waiting events at ports, subsequently monitoring port congestion based on AIS data. T. Zhang et al. (2024) further highlighted the importance and illustrated the methods of using ships' time in port as a critical metric for measuring port efficiency and productivity. These studies offer potential methods for measuring port efficiency from users' perspective.

Table 3-1 Port efficiency analysis from the perspective of port operators and users

	From port operators' perspective	**From port users' perspective**
Objectives	Maximizing the benefits or minimizing the costs of port operators, managers and related business.	Minimizing the costs or the time of shipping companies, cargo owners, or other users in port.
Input variables	Labour, land, equipment, operating costs, or fixed costs.	Ships' time in port, port charges, related costs in port.
Output variables	Cargo throughput, traffic volume, port revenues, port profits.	Number of ship calls, or cargo movements.

Due to the complex interests of different stakeholders in port operations, the objectives and variables considered in existing studies varied (Table 3-1). While some research has recognized the importance of users' interests, most studies have focused on port efficiency solely from the perspective of port operators. Only a limited number of studies have employed time indicators or cargo handling efficiency to evaluate port performance from the users' standpoint. Moreover, few have addressed the inconsistencies between the interests of port operators and those of port users, as well as the discrepancies in perceived port efficiency between these two stakeholders. Additionally, although CCR and BCC models are commonly used, they present limitations and challenges when applied to global port efficiency analysis. For ports in different social economic environments, development stages, and operating types, the heterogeneity may be too significant for traditional efficiency analysis to be meaningful. This study fills these gaps by using the variables relevant to port operators and shipping companies, classifying the international ports into homogeneous groups, and evaluating their efficiencies using meta-frontier DEA models from two perspectives: that of the port operators and the shipping companies.

3.3 Methods and Data Description

This paper incorporates the meta-frontier analysis with the DEA model to evaluate port efficiency. To assess port efficiencies from the perspectives of port operators and shipping companies, this study utilises a dataset that includes inputs and outputs relevant to the two stakeholders in port production. Data reflecting the inputs and outputs of port operators were collected from Lloyd's List One Hundred Ports, IHS Markit (ihsmarkit.com) and Google Earth. Data representing the interests of shipping companies were derived from 2022 AIS data and further estimated using information reported in the Container Port Performance Index (CPPI) (World Bank, 2023).

3.3.1 Meta-frontier DEA

(1) Meta-frontier analysis

According to the study of O'Donnell et al. (2008), the meta-technology set, including all ports' input-output combinations, can be defined as:

$$T = \{(x, y): x \geq 0; y \geq 0; x \; can \; produce \; y\} \tag{3.1}$$

Where $x \in \mathbb{R}_+^p$ represents a vector of inputs and $y \in \mathbb{R}_+^q$ represents a vector of outputs.

The output meta-frontier is the boundary of the output set (for any input vector). This meta-frontier for all ports can be defined as:

$$P(x) = \{y: (x, y) \in T\} \tag{3.2}$$

The output meta-distance function represents the maximum amount of output the port can produce using a given set of inputs. This function can be defined as:

$$D(x, y) = inf_\theta\{\theta > 0: (y/\theta) \in P(x)\} \tag{3.3}$$

The technical efficiency relative to the meta-frontier is defined as the real output of a port divided by the highest possible output at the meta-frontier. The port can be considered as efficient to the meta-frontier if and only if $D(x, y) = 1$.

The input-output combinations available to ports in the kth group can be represented as:

$$T^k = \{(x, y): x \geq 0; y \geq 0; x \text{ can be used by port in group } k \text{ to produce } y\} \quad (3.4)$$

The boundary of the group output sets can be regarded as group frontiers. The port group k's frontier and output distance function can be defined as:

$$P^k(x) = \{y: (x, y) \in T^k\}, \ \ k = 1,2, \dots, m \quad (3.5)$$

$$D^k(x, y) = inf_\theta\{\theta > 0: (y/\theta) \in P^k(x)\}, \qquad k = 1,2, \dots, m \quad (3.6)$$

The technical efficiency relative to the group frontier is defined as the real output of a port divided by the highest possible output at the group frontier. The port in the k group can be considered as efficient with respect to the group frontier if and only if $D^k(x, y) = 1$.

(2) DEA model

The meta-frontier and the group frontiers can be estimated by econometric models or frontier methods. As mentioned in Section 3.2.1, SFA requires assumptions concerning the error structure and the functional form, which may be restrictive given the various production conditions and complex interactions between inputs and outputs in ports worldwide. In contrast, DEA is more flexible as it can handle multiple inputs and outputs without the need for predefined assumptions about the production function. Walheer (2024) reviewed studies on meta-frontiers and pointed out that DEA estimation methods are the most powerful estimation methods in meta-frontier analysis especially when the DMUs are not only producers. Considering the advantages of DEA and the complex nature of ports, this study adopts the DEA model as the basis.

Under the DEA framework, the CCR model is applied to ports with constant return to scale, and the BCC model accommodates variable returns to scale. In terms of the model orientation, the DEA model can be categorized into two types: input-oriented model, which aims to minimize inputs while achieving at least the given output levels, and output-oriented model, which aims to maximize outputs without increasing any of the desired inputs. Wang et al. (2005) suggested that the input-oriented model is appropriate for analysing the port in a stable market, while the output-oriented model provides a better benchmark for the ports that need frequently review their capacity to ensure user satisfaction and maintain their competitive edge. Focusing on the world-scale ports in the competitive market, this study adopts the output-oriented DEA-BCC model to estimate port efficiency under meta-frontier and group-frontier.

Assuming that there are n ports to be evaluated. Each port consumes varying amounts of p inputs to produce q outputs. Specifically, $Port_j$ $(j = 1, 2, \ldots, n)$ consumes amount x_{ij} of input i $(i = 1, 2, \ldots, p)$ and produces amount y_{rj} of output r $(r = 1, 2, \ldots, q)$. Considering that technological differences exist among ports, the n ports are divided into k $(k = 1,2, \ldots, m)$ port groups.

A convex meta-frontier of all ports, which envelops all group frontiers, can be identified by the DEA-BCC model. Assuming that $\boldsymbol{\lambda^T} = (\lambda_1^T,\ \lambda_2^T, \ldots, \lambda_n^T)$ is a non-negative vector, the efficiency of $Port_o$ evaluated under the meta-frontier can be calculated using the following DEA-BCC linear programming:

$$max\varphi \tag{3.7}$$

$$s.t. \sum_{j=1}^{n} \lambda_j^T y_{rj} \geq \varphi y_{ro}, \quad r = 1,2, \ldots, q$$

$$\sum_{j=1}^{n} \lambda_j^T x_{ij} \leq x_{io}, \quad i = 1,2,\dots,p$$

$$\lambda_j^T \geq 0, \quad j = 1,2,\dots,n$$

$$\sum_{j=1}^{n} \lambda_j^T = 1$$

Assuming that $Port_o$ is divided to port group k, which includes g ports in the group, and $\boldsymbol{\lambda^k} = (\lambda_1^k,\ \lambda_2^k, \dots, \lambda_g^k)$ is a non-negative vector. The efficiency of $Port_o$ evaluated under the k group-frontier can be calculated using the following DEA-BCC linear programming:

$$max\varphi^k$$

$$s.t. \sum_{j=1}^{g} \lambda_j^k y_{rj} \geq \varphi^k y_{ro}, \quad r = 1,2,\dots,q$$

$$\sum_{j=1}^{g} \lambda_j^k x_{ij} \leq x_{io}, \quad i = 1,2,\dots,p \tag{3.8}$$

$$\lambda_j^k \geq 0, \quad j = 1,2,\dots,g$$

$$\sum_{j=1}^{g} \lambda_j^k = 1$$

Since the port group-frontier is a subset of the meta-fronter, the efficiency of the port to the meta-frontier is always less than or equal to the efficiency to the group frontier.

3.3.2 Research scope and port classification

(1) Research scope

Considering operational significance and data availability, this study focuses on global container ports characterized by significant container throughput and a significant volume of ship calls. To ensure the compilation of a reliable dataset, each included port should have its container terminal details recorded on IHS Markit (ihsmarkit.com) and historical maps accessible via Google Earth. Based on these criteria, the top 80 global container ports for the year 2022 have been chosen as the sample for this study. Table 3-2 lists the ports included in this study along with their container throughput in 2022. These ports are located at the main trade route and contribute to more than 75% of global container port throughputs.

Table 3-2 Research ports and their container throughput (million TEU)

Port	Throughput	Port	Throughput	Port	Throughput
Shanghai	47.30	Jawaharlal Nehru	5.96	Manzanillo	3.47
Singapore	37.29	Savannah	5.89	Dongguan	3.41
Ningbo-Zhoushan	33.35	Rizhao	5.80	Seattle-Tacoma	3.38
Shenzhen	30.04	Haiphong	5.63	Gioia Tauro	3.38
Qingdao	25.67	Cai Mep	5.59	Balboa	3.35
Guangzhou	24.86	Lianyungang	5.57	Tangshan	3.34
Busan	22.08	Manila	5.47	Melbourne	3.30
Tianjin	21.02	Qinzhou	5.41	Felixstowe	3.30
Hong Kong	16.69	Colon	5.10	Fuzhou	3.29
Rotterdam	14.46	Valencia	5.05	London	3.21
Dubai	13.97	Piraeus	5.00	Nanjing	3.20
Antwerp	13.50	Yingkou	5.00	Incheon	3.15
Port Klang	13.22	Santos	4.99	Chittagong	3.14
Xiamen	12.43	Jeddah	4.96	Cartagena	3.14
Tanjung Pelepas	10.51	Algeciras	4.77	Le Havre	3.10
Los Angeles	9.91	Bremen/Bremerhaven	4.57	Yokohama	2.98
New York/New Jersey	9.49	Salalah	4.50	King Abdullah	2.91
Kaohsiung	9.49	Dalian	4.46	Kobe	2.89
Long Beach	9.13	Tokyo	4.43	Marsaxlokk	2.89
Laem Chabang	8.74	Abu Dhabi	4.33	Ambarli	2.87
Hamburg	8.26	Port Said	4.25	Jiaxing	2.85
Taicang	8.03	Yantai	4.12	Sydney	2.84
Ho Chi Minh	7.91	Houston	3.97	Charleston	2.79
Tanger Med	7.60	Tanjung Perak	3.97	Nagoya	2.68
Tanjung Priok	7.23	Virginia	3.70	Durban	2.57
Colombo	6.86	Vancouver	3.56	Genoa	2.53
Mundra	6.50	Barcelona	3.52		

Data source: Lloyd’s List One Hundred Ports 2023.

(2) Port classification

Assessing the efficiency of a large group of ports could benefit from combining frontier techniques with port classification (Nguyen et al., 2018; Tovar & Rodríguez-Déniz, 2015). Most studies used subjective and predetermined grouping methods, classifying ports by geographical locations, the scale of operations (e.g., large ports or small ports), or the types of cargo handled (e.g., ports specializing in container cargo or bulk cargo). Table 3-3 summarizes the studies that adopted meta-frontier analysis in port efficiency evaluation and their respective criteria for port grouping.

Table 3-3 Port efficiency studies using meta-frontier analysis

Author	DMU	Method	Grouping Criteria
Martínez-Moya et al. (2024)	19 ports in the Mediterranean Sea	Meta-frontier DEA	Transhipment share (65%)
M. Wang et al. (2023)	23 Chinese ports	Meta-frontier D.D.F	Geography Location
Chang and Tovar (2022)	14 terminals in Peru and Chile	Meta-frontier DEA	Size and Degree of Mechanization
Ghiara and Tei (2021)	213 global ports	Meta-frontier DEA	Size (container throughput thresholds)
Fernández et al. (2021)	26 Spanish ports	Meta-frontier DEA	Size, technology, and complexity
Li et al. (2020)	16 port companies	Meta-frontier D.D.F	Size and complexity
Tovar and Wall (2019)	26 Spanish ports	Meta-frontier DEA	Size and complexity
Nguyen et al. (2018)	43 Vietnamese ports	Meta-frontier DEA and SFA	Geography Location

Note: D.D.F stands for the Directional Distance Function.

Port size, usually measured by container throughput or operational scales, is a crucial factor in the technological heterogeneity among ports. Following the method used by Tovar and Wall (2019) and Li et al. (2020), this study classifies ports based on their relative size to the evaluation set. It adopts the average container throughput of all evaluated ports (i.e., 8.06 million TEU) as the threshold for port size classification.

Furthermore, with the growing size of container vessels, some scholars noticed that ports serving large-size vessels need more container cranes, deeper water depth, larger infrastructure investments as well as advanced handling technologies and higher berthing standards (Meng et al., 2017; Monios, 2017; Sáenz et al., 2023). Feng et al. (2024) investigated variations in ship sizes across different ports, noting that major hub ports with deep-water berths mainly serve larger vessels, while feeder ports primarily handle smaller ships. These studies suggest that the ability to accommodate large-size ships can reveal underlying differences among ports in terms of channel depth, berth availability, proximity to hinterlands, and distribution networks. Building on these insights, this study uses the maximum ship size a port can accommodate as an additional criterion for classifying ports.

Ships exceeding 8,000 TEU are generally regarded as large vessels, requiring deep-sea berths and advanced handling technologies (Fan & Xie, 2023; Stopford, 2008). World Bank (2023) defines ships larger than 8,500 TEU as Neo-Panamax, which operate on major trade routes and call hub ports. Given the industry standards and the operational realities of modern shipping, this study adopts an 8,500 TEU threshold. Notably, there is a significant gap among the 80 container ports in their ability to handle large ships, and there are no differences in classification outcomes when using thresholds between 7,000 TEU and 9,000 TEU.

Therefore, considering the technology differences of container ports in terms of size and ability to handle large-size ships, we classify the 80 container ports according to two criteria:

1) ***Port size***. Whether the container throughput is larger than the average of the studied ports, which is 8.06 million TEUs.

2) ***Ability to handle big ships***. Whether the maximum ship size the port can accommodate is larger than 8500 TEUs.

Ports are categorized as large ports if their throughput exceeds 8.06 million TEUs and they can accommodate ships larger than 8,500 TEUs. Ports with a throughput less than 8.06 million TEUs but can accommodate large ships, or those with a throughput exceeding 8.06 million TEUs but cannot handle large ships are classified as middle-size ports. Ports that neither meet the throughput threshold nor the ability to handle big ships are categorized as small ports. Notably, among these 80 container ports, all the ports with throughputs of more than 8.06 million TEUs can accommodate ships larger than 8500 TEUs. The classification of ports is shown in Table 3-4.

Table 3-4 Port classification

Classification	Ports
Large Port (21)	Antwerp, Busan, Dubai, Guangzhou, Hamburg, Hong Kong, Kaohsiung, Laem Chabang, Long Beach, Los Angeles, New York/New Jersey, Ningbo-Zhoushan, Port Klang, Qingdao, Rotterdam, Shanghai, Shenzhen, Singapore, Tanjung Pelepas, Tianjin, Xiamen.
Middle-size Port (47)	Abu Dhabi, Algeciras, Ambarli, Balboa, Barcelona, Bremen/Bremerhaven, Cai Mep, Cartagena, Charleston, Colombo, Colon, Dalian, Durban, Felixstowe, Fuzhou, Genoa, Gioia Tauro, Haiphong, Houston, Incheon, Jawaharlal Nehru, Jeddah, King Abdullah, Kobe, Le Havre, Lianyungang, London, Manzanillo, Marsaxlokk, Melbourne, Mundra, Nagoya, Piraeus, Port Said, Qinzhou, Salalah, Santos, Savannah, Seattle-Tacoma, Sydney, Tanger Med, Tanjung Priok, Tokyo, Valencia, Vancouver, Virginia, Yokohama.
Small Port (12)	Chittagong, Dongguan, Ho Chi Minh, Jiaxing, Manila, Nanjing, Rizhao, Taicang, Tangshan, Tanjung Perak, Yantai, Yingkou.

Note: the number in parentheses represents the number of ports in that group. The container throughput of ports is collected from Lloyd’s List One Hundred Ports. The maximum ship size that the port can accommodate is identified by the ship calls in 2022 extracted from AIS data and Lloyd’s list intelligence.

3.3.3 Variables and data description

(1) Input and output variables

Port operators and shipping companies are two key stakeholders in the port production process. They both want the ports to be efficient. However, with different interests, the inputs and outputs used in the efficiency analysis from these two perspectives vary to some extent.

In the efficiency analysis for port operators, the variables are selected based on extant literature. Cullinane and Wang (2006) stated that container throughput is the most relevant, appropriate, and analytically tractable for port output in container port efficiency analysis. Therefore, container throughput (y_1) is used as the output in this study. Regarding the inputs, labour, land, capital and equipment are most commonly used in the port production process (Dowd & Leschine, 1990; Tongzon, 2001). Some scholars pointed out that port facilities can substitute for labour in efficiency analysis and modern ports depend on sophisticated equipment and information technology rather than relying heavily on labour (Cullinane et al., 2004; Notteboom et al., 2000). In cross-regional efficiency analysis, the complexity of port labour, which encompasses a wide range of roles and categories, complicates the acquisition of reliable data (SangHyun Cheon et al., 2010). Considering the inherent relationship between labour and port facilities, along with the lack of reliable data on labour across global ports, this study does not include labour input. The total length of container berths (x_1), number of quay cranes (x_2), the maximum water-depth of berth (x_3), and the storage area of containers (x_4) are used as the inputs.

For shipping companies, their main interest at port is to load and/or unload their containers with minimal time and/or costs. Their output should be measured by the number of containers loaded/unloaded when vessels call the port. However, such data is not available. Existing research indicates a correlation between the volume of container exchanges at ports and ship size (Martin et al., 2015; Yahalom & Guan, 2018). World Bank (2023) has compiled containership call information from 348 global ports, categorizing the distribution of container movements by ship size group (as shown in Table 3-5). For example, among the ships larger than 13500 TEUs, 0.2% will move less than 250 moves when they call a port, and the average of all ships in this range is 179 moves. This dataset illustrates the general relationship between ship size and container movements at global ports, allowing us to estimate the aggregated container movements for vessels of various sizes when the actual data on container movement for each ship's port call is not available.

Table 3-5 The distribution of container movement groups in ship size groups

			Ship size category (s, TEUs)				
	Groups	Average	1. 0-1500	2. 1501-5000	3. 5001-8500	4. 8501-13500	5. >13500
Container movements (k, moves)	1. <250	179	20.5%	6.1%	1.3%	0.8%	0.2%
	2. 251-500	381	37.2%	20.1%	6.5%	4.0%	0.9%
	3. 501-1000	736	36.9%	36.0%	20.9%	13.8%	4.6%
	4. 1001-1500	1234	5.0%	20.1%	23.1%	16.7%	7.1%
	5. 1501-2000	1732	0.2%	9.9%	18.6%	15.0%	8.7%
	6. 2001-2500	2228	0.1%	4.7%	12.0%	13.7%	9.6%
	7. 2501-3000	2735	0.0%	1.8%	7.2%	10.9%	9.5%
	8. 3001-4000	3445	0.0%	1.1%	6.8%	13.4%	18.8%
	9. 4001-6000	4785	0.0%	0.2%	2.9%	8.4%	26.5%
	10. >6000	8061	0.0%	0.0%	0.6%	3.3%	14.1%

Data Source: The Container Port Performance Index 2022 (World Bank, 2023).

This study calculated the aggregated container moves (y_2) at each port based on the number of ships (No_s) of each ship size category s called at that port (Eq 3.9).

$$y_2 = \sum_{s=1}^{5}\left(No_s \times \sum_{k=1}^{10}(Avg_{sk} \times Pct_{sk})\right) \tag{3.9}$$

Where s indicates the ship size category ($s = 1, 2, \ldots, 5$), $s = 1$ represents the ship size is smaller than or equals 1500 TEU; k is the container movement group ($k = 1, 2, \ldots, 10$), $k = 1$ represents the container movements in the group of <250. Avg_{sk} represents the average container moves of the container movement group k for the ship size group s, and Pct_{sk} represents percentage of ships in size s had container moves in group k. The data for the first variable No_{sj} is captured from AIS data, while that for the second and third variables (Avg_{sk}, Pct_{sk}) are from the CPPI 2022.

In terms of inputs, shipping companies encounter various costs, including capital costs, operating costs and voyage costs during their time at port (Stopford, 2008; Yahalom & Guan, 2018). Both operating and capital costs are associated with the ship size (Lim, 1994). Larger ships always require greater investments and a larger crew, leading to higher capital and operating costs compared to smaller vessels over the same operational duration. Additionally, the turnaround time of ships in port is non-productive for shipping companies (Johnson & Styhre, 2015). For the same size vessels, a longer turnaround time in port means higher capital and operation costs for shipping companies. To incorporate these factors, we propose a ship input variable (x_5), which is the sum of the production of ship size ($Size_i$) times the turn-around time in the port (TAT_i), to represent the costs for shipping companies during their port time (Eq 3.10).

$$x_5 = \sum_{i=1}^{N} (Size_i \times TAT_i) \tag{3.10}$$

Where $Size_i$ represents the size of ship i ($i = 1, 2, \dots, N$); TAT_i represents the turn-around time of ship i in that port, and N is the total number of ships called that port.

Regarding voyage costs, port charges represent a significant component of the voyage costs for shipping companies making port calls (Stopford, 2008). Due to the unavailability of data on the actual port fees associated with each ship call, we use the aggregate number of ship calls (x_6) at the port to represent shipping companies' costs to use the port.

(2) Data description

The data on the container ports' throughput is collected from Lloyd's List One Hundred Ports (Lloyd's List, 2023). The input data is collected from IHS Markit (ihsmarkit.com) and Google Earth. It is important to note that if the port also handles other cargo types, only the inputs and outputs related to the container operation are included. Table 3-6 shows descriptive statistics of the data used for efficiency estimation from the perspective of port operators.

Table 3-6 Statistics of variables relevant to port operators

Variables	Unit	Mean	SD	Min	Max
Container throughput (y_1)	Million TEU	8.06	8.47	2.53	47.30
Total length of berth (x_1)	,000 meter	5.91	4.29	1.45	25.29
Number of quay cranes (x_2)	Number	58.19	55.10	12.00	288.00
Maximum depth of berth (x_3)	Meter	16.35	1.79	10.50	23.00
Storage area of containers (x_4)	Million m^2	2.29	1.93	0.61	10.26

Data Source: Lloyd's List One Hundred Ports, IHS Markit (ihsmarkit.com) and Google Earth.

To collect data on the inputs and output of shipping companies, we employed the method proposed by Yang et al. (2023), extracting ship call information from AIS data across 80 container ports for the period from January 1 to December 31, 2022. The process began by matching the AIS data with vessel details obtained from the Lloyd's List Intelligence database and filtering for containerships. We then identified container port and berth boundaries using location data from IHS Markit (ihsmarket.com) and Alphaliner (alphaliner.axsmarine.com), supplemented by satellite maps via Google Earth. After that, we extracted the AIS data of containerships within the identified container port areas. The turnaround time for vessels in port was calculated as the difference between the last timestamp and the first timestamp of each ship call in the port area. To ensure data quality, we applied thresholds proposed by Yang et al. (2023), filtering out abnormal port calls that were less than 5 hours or longer than 2 weeks (336 hours).

Figure 3-1 illustrates the processing steps applied to the AIS data. A total of 238,463 port calls of 5496 containerships in the selected 80 ports in 2022 were collected. It represents 94.8% of registered container ships in the world.

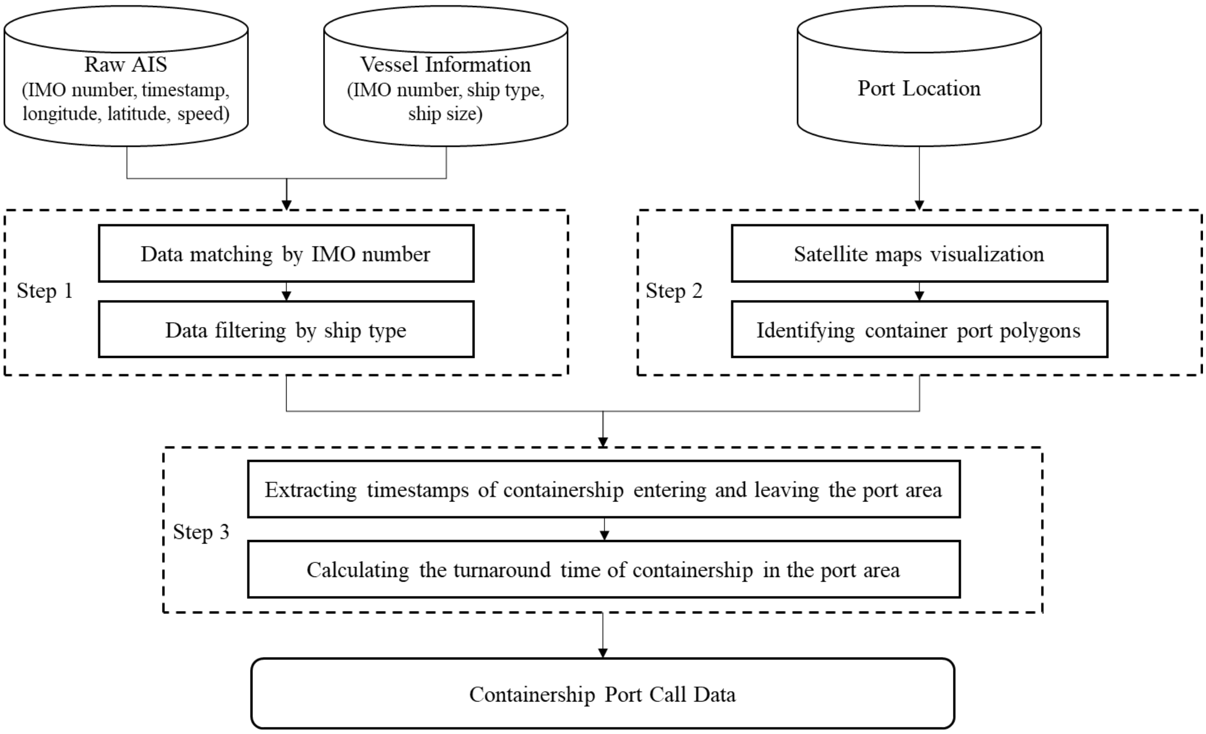


Figure 3-1 Processing steps of AIS data

Table 3-7 presents the descriptive statistics for variables pertinent to shipping companies. Ideally, if we have data for all containerships calling the ports and the details of containers in ships, the total container movements of ships in port, measured in twenty-foot equivalent units (TEU), should align with the port's throughput (y_1). However, such data is unavailable. In this study, the estimated container moves are always smaller than the container throughput (Figure 3-2). This discrepancy can be attributed to differing measurement units, as one container move can account for at least one TEU. Additionally, while we captured port call activities for 94.8% of registered container ships, there may still be some missing records in the AIS data. Given the intrinsic relationship between container movements and container throughput, we conducted a Pearson correlation analysis between these two output variables. The analysis reveals a significant correlation of 0.92, indicating that our estimation of the output for shipping companies is rational.

Table 3-7 Statistics of variables relevant to shipping companies

Variables	Unit	Mean	SD	Min	Max
Container movements (y_2)	Million moves	3.61	3.97	0.15	19.39
The sum of ship size*TAT (x_5)	K TEUs *Days	17485.13	17802.63	392.83	90832.74
Number of ship calls (x_6)	Number	2980.79	3080.12	165.00	14544.00

Data Source: AIS data, Lloyd's List Intelligence, CPPI 2022.

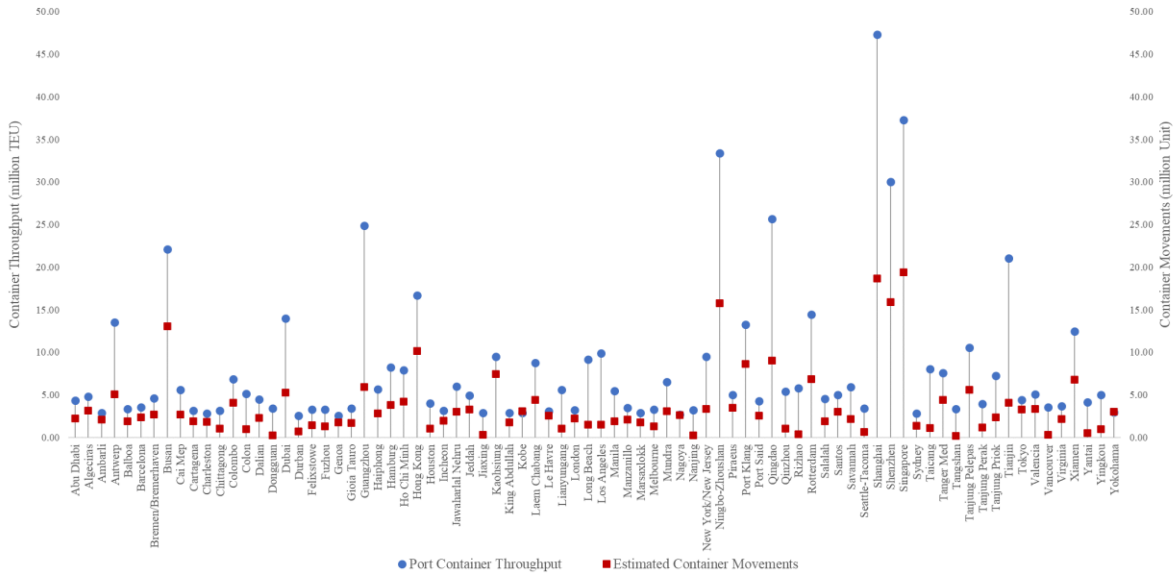


Figure 3-2 Container throughputs and estimated container movements of the top 80 container ports in 2022.

3.4 Results and Analysis

3.4.1 Port efficiency evaluation

A meta-set encompassing the input-output combinations of 80 ports is first used to conduct a meta-frontier analysis of these ports. Then, following Section 3.3.2, the 80 ports are divided into three groups by their abilities to handle containers and ships, and the efficiencies of ports within their respective groups are estimated.

(1) From the perspective of port operators

Using port operators' inputs and output, we first estimate the efficiency of the global top 80 container ports from the standpoint of port operators. Figures 3-3 to 3-5 present the efficiencies of ports to the meta-frontier and corresponding group frontier.

With respect to the meta-frontier, 12 ports, namely the ports of Chittagong, Hong Kong, Jiaxing, Manzanillo, Ningbo-Zhoushan, Qingdao, Rizhao, Salalah, Shanghai, Shenzhen, Tanjung Perak, and Yantai, are the most efficient ports to port operators, with efficiency scores equal to 1. The large and small port groups have relatively higher efficiency scores and more ports on the frontier, indicating their superior performance in the global port industry. This finding aligns with the conclusion of Ghiara and Tei (2021) that large and small ports tend to outperform medium-sized ports after assessing the efficiencies of 213 ports globally. Large ports benefit from their ability to attract more containers and ships, thereby having a higher facility utilization. Small ports provide access to small ships with fewer requirements on investments in the water depth, handling facilities and related infrastructure, which also have better efficiency (Monios, 2017).

Among the 21 ports in the large port group, there are 8 ports on the group frontier (Figure 3-3). Most of them are Asian ports and also on the meta-frontier, suggesting the leading position of the Asia hub ports. However, although Laem Chabang, New York/New Jersey, and Tanjung Pelepas are on the group frontier, they are not on the meta-frontier. These three ports may benchmark those ports on the meta-fronter and identify possible ways to enhance their efficiency. Notably, hub ports located in America, Europe, and the Middle East, such as the Port of Long Beach, Los Angeles, Hamburg, Rotterdam and Dubai, exhibit significant inefficiency, although their throughputs are high. For them, rationalizing the port operation may help to promote the efficiency level.

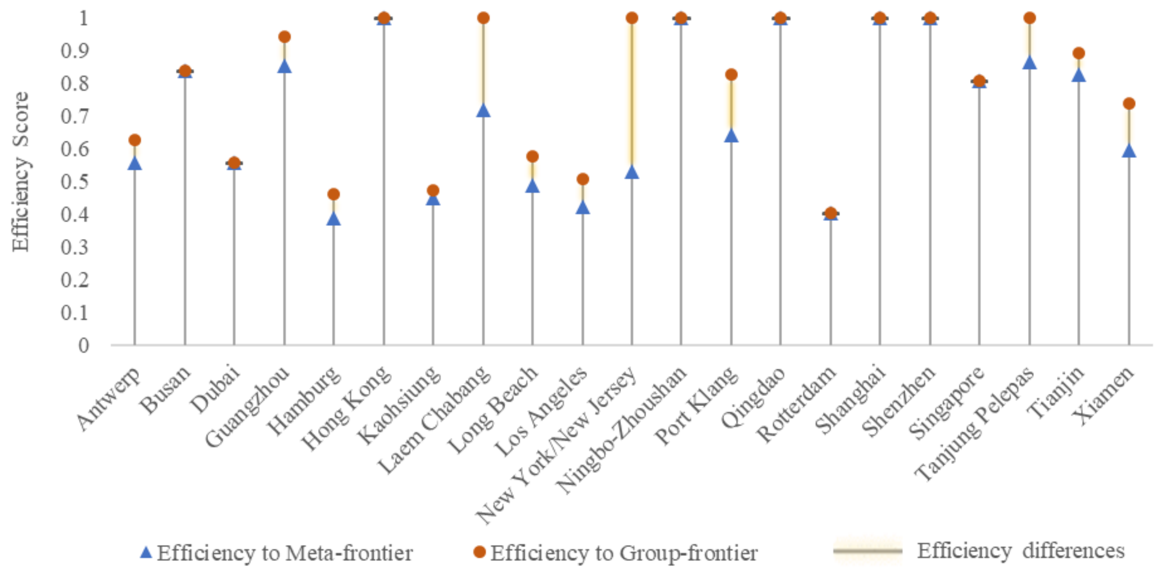


Figure 3-3 Efficiencies of large ports from port operators' perspective

Among the 47 middle-size ports (Figure 3-4), 15 ports are on the group frontier, but only 2 of these 15 ports are on the meta-frontier. The other 13 ports, although they have the capacity to accommodate large ships, do not have corresponding high demand. The large difference between the meta-efficiency scores and group ones indicates the presence of a large technology gap. Ports such as Seattle-Tacoma and Yokohama recorded low efficiencies in group assessments, indicating a need to adjust their inputs and improve resource utilization.

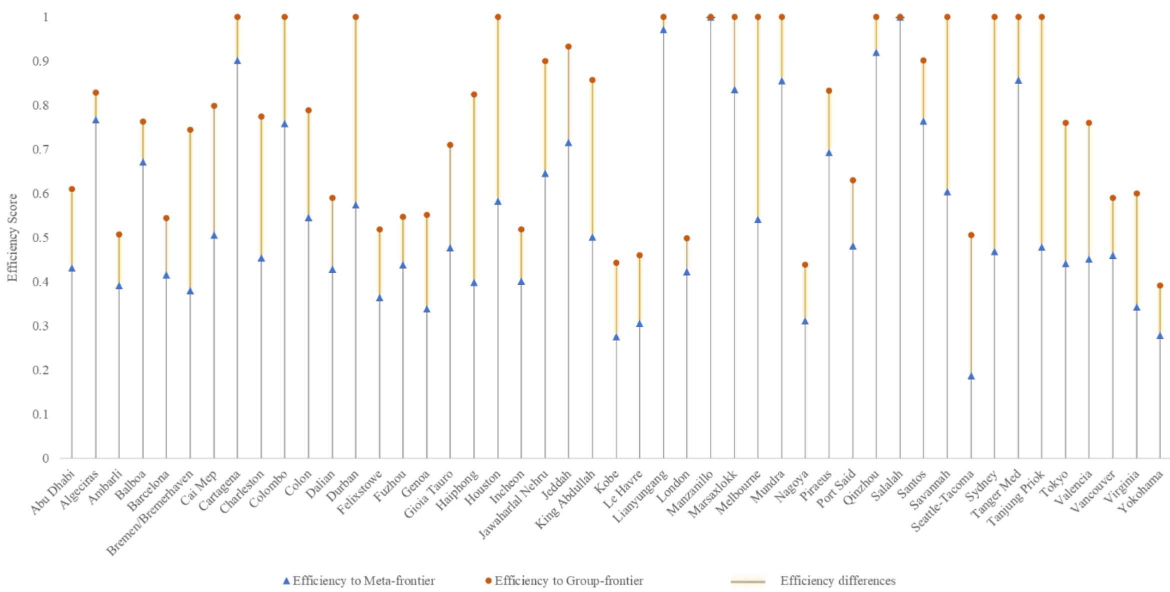


Figure 3-4 Efficiencies of middle-size ports from port operators' perspective

For port operators, the efficiencies for most small ports are high, with more than half at the group frontier and 75% with efficiency scores above 0.9 to the group frontier (Figure 3-5). However, three small ports, namely Tangshan, Nanjing, and Yingkou, demonstrate relatively low efficiency within the small port group. These less efficient ports typically serve as regional feeders, offering services to hub ports alongside many neighbouring feeder ports. For instance, Tangshan Port, located in the Bohai Rim region of China, competes with over a dozen ports, including Yantai, Yingkou, and Rizhao, for domestic market share and transhipment cargo from the hub ports. In the face of certain transportation demands, less competitive feeder ports may experience underutilization of port resources and cargo diversion.

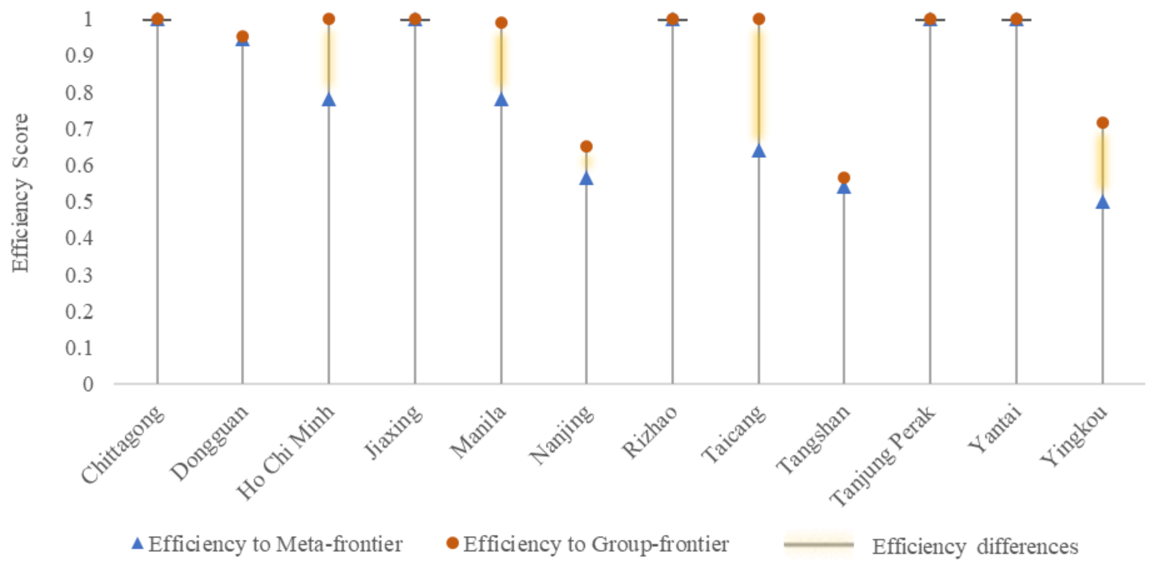


Figure 3-5 Efficiencies of small ports from port operators' perspective

(2) From the perspective of shipping companies

Port efficiencies from the perspective of shipping companies are assessed using the same method as that for port operators. The distribution of port efficiencies to the meta-frontier is shown in Figure 3-6.

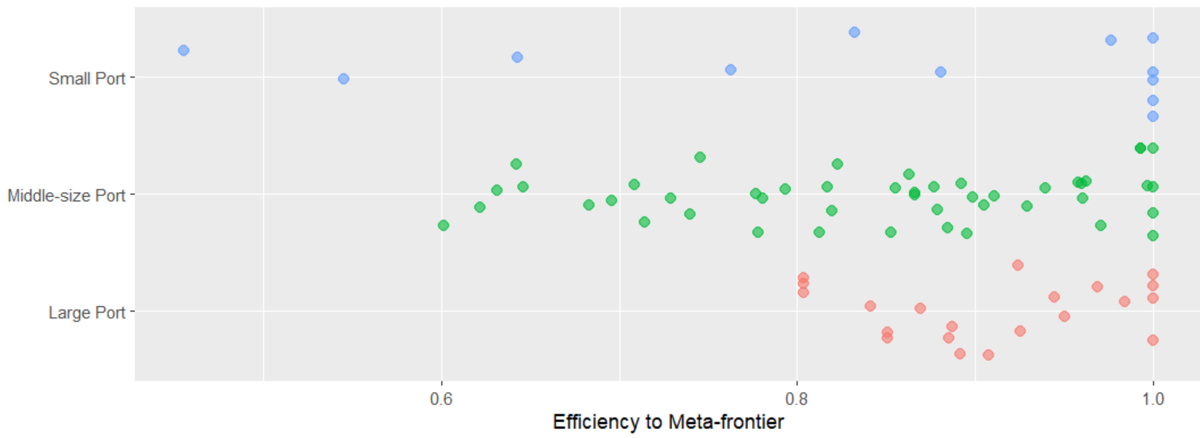


Figure 3-6 The distribution of port efficiencies to meta-frontier from shipping companies' view

With respect to the meta-frontier, most ports have efficiency scores exceeding 0.8, reflecting the relatively efficient services these ports provide to shipping companies. Among the top 80 container ports, 13 are on the meta-frontier: Cai Mep, Dongguan, Ho Chi Minh, Hong Kong, Jeddah, King Abdullah, Nanjing, Shanghai, Shenzhen, Singapore, Tangshan, Vancouver, and Yantai. All of the large ports' efficiency scores exceed 0.8, with 4 ports on the meta-frontier. In contrast, the efficiency scores of the small and middle-size ports have a large span, indicating significant differences in efficiency.

In the group frontier analysis, 10 large ports achieved their group frontier and 4 of them reached the meta-frontier (Figure 3-7). Interestingly, in the large port group, all American hub ports (LA, LB, and New York/New Jersey) are at the group frontier. Unlike other large ports, these ports have fewer calls from small vessels. Most of the ships on the trans-Pacific route are large ships that may call multiple large ports in Asia, but only one or two ports in North America. This resulted in a larger number of container movements in a smaller number of ship calls and a longer turn-around time for each ship call (Figure 3-8). This result indicates that large vessels can compensate for costs due to longer port turnaround time by reducing the number of calls and increasing the number of containers handled per ship call in these American ports. This finding also indicates that port operators can provide port charge discounts for ships experiencing longer turnaround times or speed up the handling service to attract shipping companies.

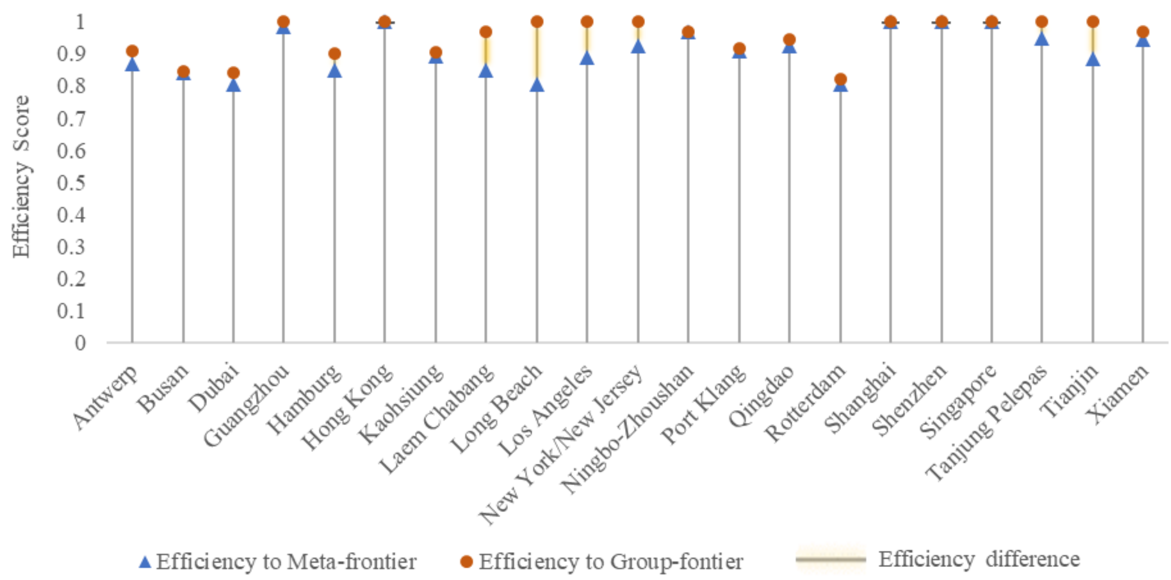


Figure 3-7 Efficiencies of large ports from shipping companies' perspective

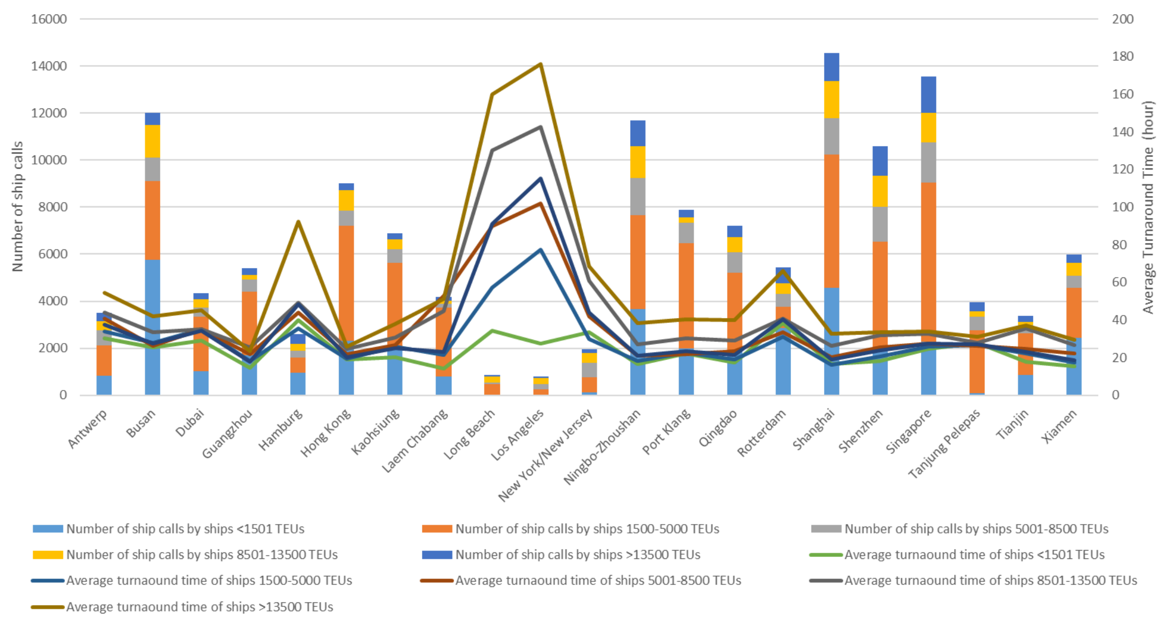


Figure 3-8 Number of ship calls and average turn-around time by ship size groups in large ports

In the middle-size port group, the efficiency scores to the meta-frontier and group frontier are similar for most ports, indicating there are no significant technology differences in serving ships between the middle-size port group and meta set (Figure 3-9). Among the 47 middle-size ports, 12 ports are on the frontier. Some ports identified as inefficient in the group-frontier analysis should consider accelerated services, lower port charges, or attract more cargo for vessels according to the slacks. For instance, the port of Valencia has significant slack in the time costs of ships. The operators of these inefficient ports can optimize the berth allocations and crane arrangement to decrease the time ships spend in port without impacting the number of container movements, therefore improving their efficiency levels for ships.

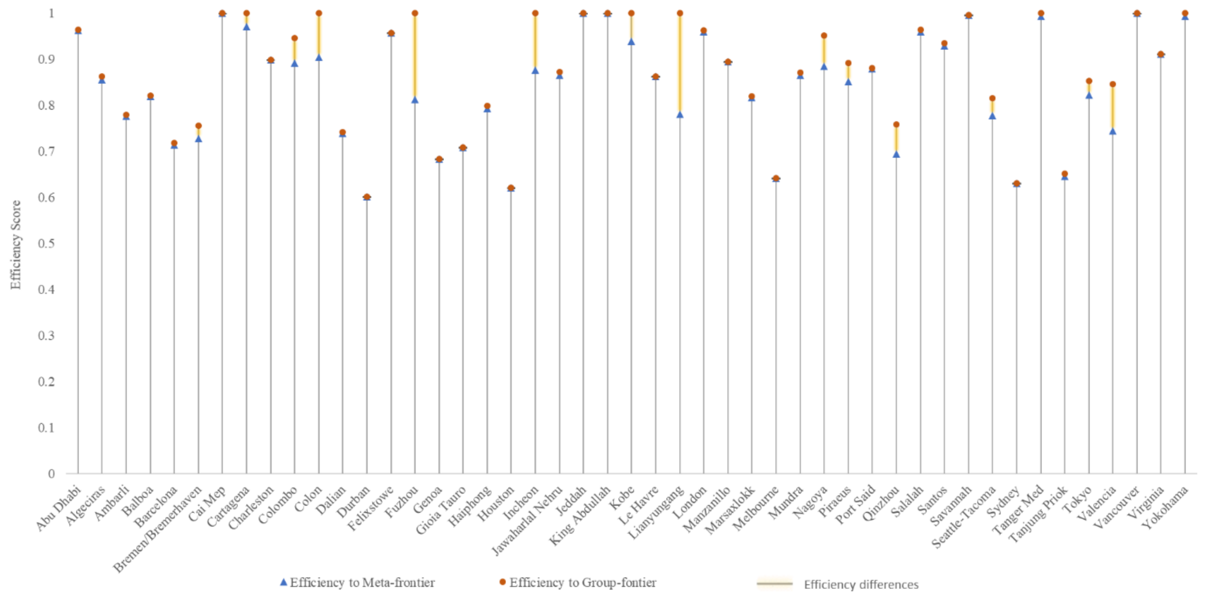


Figure 3-9 Efficiencies of middle-size ports from shipping companies' perspective

For the small ports, over half of the ports achieved their group frontier (Figure 3-10). While these ports are identified as efficient within their groups, some of them (e.g., the ports of Chittagong, Manila and Yingkou) still have the potential to improve their efficiency performance for ships by learning from the efficient ports at meta-frontier.

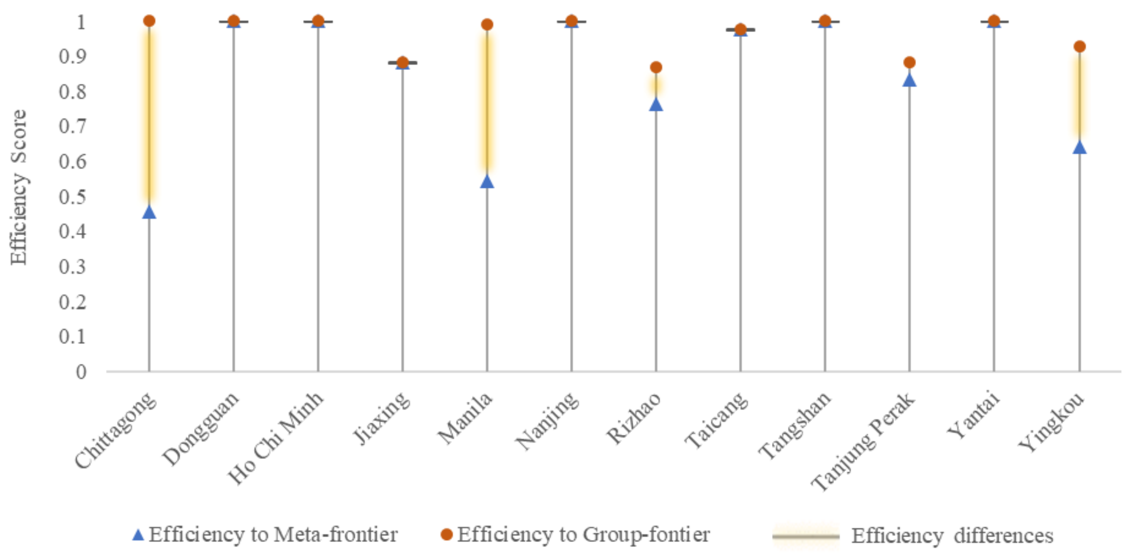


Figure 3-10 Efficiencies of small ports from shipping companies' perspective

3.4.2 Differences of port efficiencies for stakeholders

Using relevant variables, we estimated the efficiencies of the world's top 80 container ports from the perspective of port operators and shipping companies separately. To examine the relationship between the efficiencies evaluated from the perspectives of port operators and shipping companies, we conducted a correlation analysis. Table 3-8 presents the Pearson correlation coefficients and Spearman's rank correlations based on port efficiency scores evaluated from both perspectives.

Table 3-8 The correlation of port efficiencies and rankings from two perspectives

Efficiencies	Set	Efficiency Correlation	Rank Correlation
To meta-frontier	Meta-set (80 ports)	0.16	0.25*
To group-frontier	Large ports (21 ports)	0.58**	0.48*
	Middle-size ports (47 ports)	-0.20	-0.12
	Small ports (12 ports)	-0.25	-0.43

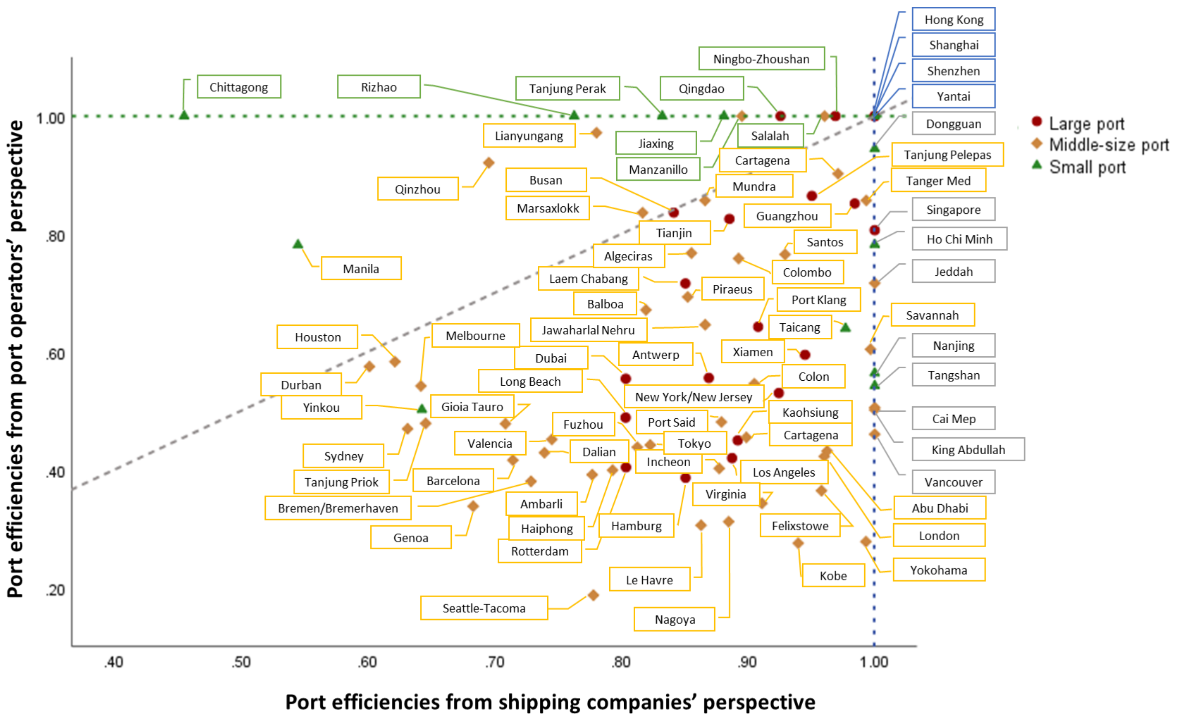
Note: * represents correlation is significant at the 0.05 level, **represents correlation is significant at the 0.01 level.

The low correlation between the efficiencies and rankings with respect to the meta-frontier, as evaluated from the two perspectives, suggests that ports deemed efficient by port operators may not necessarily be considered efficient by shipping companies.

Given the heterogeneity among ports with varying capabilities in handling containers and accommodating ships, we further analysed the correlations of port efficiencies and rankings from both perspectives to the group frontiers. The results highlight disparities among port groups. Large ports show relatively consistent efficiency performance from the viewpoints of both port operators and shipping companies, indicating that hub ports not only benefit from economies of scale in production but also recognize the importance of providing efficient services to customers. Conversely, the efficiency performance of small and medium-sized ports evaluated by port operators may differ from that assessed by shipping companies. While some small and middle-size ports offer quick services to ships, they might experience resource underutilization. Some small and middle-size ports that focus on efficient production may overlook the quality of service provided to ships.

(1) Classifying ports by efficiencies evaluated from the two perspectives

Considering the intense competition among international ports, we first use the meta-frontier efficiency scores evaluated from the two perspectives to analyze the port efficiencies. Figure 3-11 plots the meta-frontier efficiencies of the 80 container ports from port operators’ and shipping companies’ perspectives. Based on this, these ports can be divided into three categories: dual-efficient ports, one-side efficient ports, and inefficient ports.



Note: The grey dash-line represents the efficiency score from port operators' perspective equals that from shipping companies' perspective.

Figure 3-11 Port efficiencies to meta-frontier from port operators' and shipping companies' perspectives.

1) Dual efficient ports

Dual-efficient ports are the efficient ones from the views of both port operators and shipping companies. Among the top 80 container ports, only 4 ports, namely the ports of Hong Kong, Shanghai, Shenzhen, and Yantai, are on both frontiers (shown in blue boxes in Figure 3-11). These four ports are all Asian ports, with three ports serving as major regional hubs, while Yantai functions as a regional feeder port.

As major hubs in international trade routes, the ports of Hong Kong, Shanghai, and Shenzhen benefit from strategic locations that facilitate efficient transhipment and high connectivity to other major ports, ensuring steady flows of cargo and vessels. The large scale of operations and immense handling amount of containers, allow these three ports to benefit from economies of scale. Additionally, these three hubs have continuously invested in expanding their capacity and incorporating state-of-the-art terminal equipment. These investments enabled them to accommodate larger vessels, enhance operational efficiency, and reduce turnaround times. Yantai is the only small port on both frontiers. Geographically, Yantai port is closer to the Korean Peninsula and Japan and can provide shorter transit times for Northeast Asian trade routes. Meanwhile, operating under the Shandong Port Group, Yantai port collaborates with Qingdao port to provide the "Yantai-Qingdao" daily service, which enhances the scope of domestic trade and improves service frequency in the Bohai Bay area. Despite its modest size, with a quay length of approximately 1,700 meters, Yantai port handled 4.12 million TEUs, ranking as the 49th largest container port in the world by throughput. Moreover, Yantai provides quick services for ships, with an average turnaround time of 18 hours per ship call. Overall, these four ports exemplify the most efficient practices in rapid vessel service and effective resource management, setting a high standard in the port sector.

2) One-side efficient ports

One-side efficient ports are those on one frontier, but not the other. Among the top 80 container ports, 8 ports are on the frontier from the perspective of port operators (the top horizontal line in Figure 3-11), whereas 9 ports are on the frontier from that of ship operations (the right vertical line). Almost half of these one-side efficient ports are small ports that excel from one perspective at the cost of inefficiency from the other.

The 8 ports on the top horizontal line, such as Chittagong and Rizhao, may have an overemphasis on maximizing the utilization rate of their terminal facilities. This focus led to longer vessel turnaround times, resulting in inefficiency for ships. For these ports, port operators should reconsider their berth allocation and crane arrangements in the short run and increase the capacity in the long run, to provide shorter service times for ships. For the 9 ports on the right vertical line, such as Vancouver, King Abdullah, Cai Mep, Tangshan, and Nanjing, ships can enjoy short waiting times and fast services. However, this efficient service for ships might stem from fewer ship calls and lower cargo volumes, or it may come at the expense of port operators, such as idle capacity and low berth utilization. These ports may need to balance their available capacity with the demand for container trade, increase their ability to attract more cargo if there are competitors nearby, or downsize their scale if it is impossible to increase the cargo volume.

3) Inefficient ports

Apart from the ports on the frontiers, the remaining 59 ports are discussed here (shown in yellow boxes in Figure 3-11). Most of the ports that are far from both frontiers are middle-sized ports. Some large ports also fall into this category, but their main issue is production inefficiency from the perspective of port operators.

Among these ports, three ports—Lianyungang, Qinzhou, and Manila—have lower efficiency scores from the perspective of shipping companies than from that of port operators. These ports need to focus on optimizing ship-related operations, such as establishing dedicated terminals for specific shipping lines and adopting advanced cargo handling technologies. Conversely, ports, such as Kobe, Yokohama, and Seattle-Tacoma exhibit high efficiencies from shipowners' perspective but very low efficiencies from port operators. To enhance overall efficiency, these ports should focus on attracting more container throughput, optimizing resource allocations, or implementing dynamic arrangements that can adapt to changing demands. Ports like Marsaxlokk and Mundra, which have similar efficiency scores from both port operators and shipping companies, are positioned near the 45-degree line. The operators of these ports should adopt a balanced approach to enhance both port operations and shipping services.

(2) Comparing port efficiencies from the two perspectives

Given the heterogeneity of ports and the varying efficiency relationships among different port groups, we analyze ports' efficiency performance within their respective groups from the perspectives of port operators and shipping companies. Figure 3-12 shows the efficiencies of the 80 container ports relative to the group frontier from the two perspectives.

Figure 3-12 Port efficiencies to group-frontier from port operators' and shipping companies' perspectives.

In the context of group frontiers, some ports demonstrate high efficiency for port operators but low efficiency for shipping companies. For instance, within the middle-size port group, the ports of Duban and Houston achieve the group frontier from the perspective of port operators. Conversely, from the viewpoint of shipping companies, these two ports rank as the most inefficient. A similar situation is observed at ports like Rizhao, Jiaxing, and Tanjung Perak in the small port group. The inefficiencies of these ports for shipping companies can be attributed to the relatively longer turnaround times for small ships compared to other ports in their respective groups. These ports mainly serve small vessels with capacities under 8,500 TEU. However, even the smallest ships in our analysis (those under 1,500 TEU) require over 24 hours on average to complete their cargo operations at these inefficient ports.

Conversely, some ports are efficient for shipping companies but inefficient for port operators. For example, the ports of Yokohama, and Tangshan are evaluated as the most efficient ports within their respective groups from the perspective of shipping companies, but most inefficient for port operators. Yokohama is noted for its efficient service, with ship calls completed in an average of 13 hours. Tangshan achieved the container movements with fewer ship calls. However, these ports exhibit underutilization of port resources. Benefiting from extensive coastlines, these ports have sufficient handling capacity but do not have a high volume of shipping demands, leading to underutilization of their resources. The operators of these ports should consider aligning their capacity with the actual demand for container handling and enhancing their competitiveness to attract more cargo.

3.4.3 Sensitivity analysis

DEA enables the assessment of DMUs' efficiency without the need for resource prices or assumptions of weights. However, the results yielded by DEA models are sensitive to sample size and the data used for inputs and outputs (Cooper et al., 2011). To investigate the sensitivity of efficiency estimations, this study employed alternative classification methods and adjusted the data on input and output variables.

(1) Alternative port classification

In the original port classification, we used ad hoc criteria based on the average container throughput and the accommodation capacity for 8,500 TEU containerships. This classification not only defines the port groups but also affects the efficiencies of the ports.

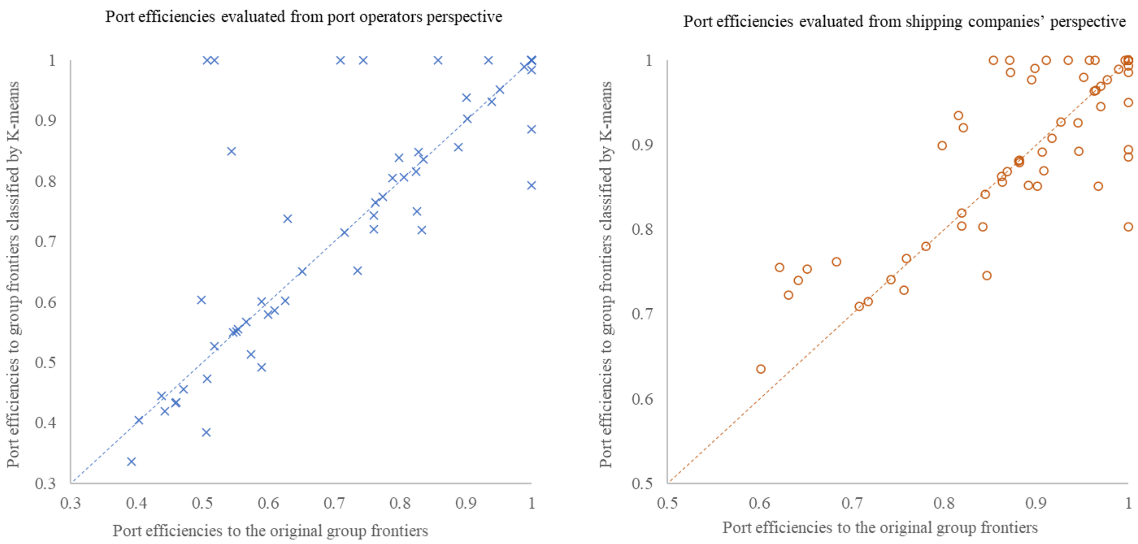
Tovar and Rodríguez-Déniz (2015) suggest that clustering methods, such as K-means and hierarchical clustering, can effectively form groups while considering unobserved heterogeneity. In sensitivity analysis, we utilized the K-means clustering method as an alternative classification approach. The results indicated that setting the number of clusters to three led to convergence and stabilization of the sum of squared errors, which suggests that classifying the 80 ports into three groups is appropriate. The K-means classification also closely aligns with our original categorization. Specifically, the third group corresponds to the small port group identified in the original classification, while several middle-sized ports were assigned to the first group, resulting in a greater number of ports in Group 1 (see Table 3-9).

Table 3-9 Port Classification by K-means

Classification	Ports
Group 1 (41)	**Abu Dhabi, Algeciras, Ambarli,** Antwerp, **Barcelona, Bremen/Bremerhaven,** Busan, **Cai Mep, Colombo, Dalian,** Dubai, **Felixstowe, Gioia Tauro,** Guangzhou, Hamburg, Hong Kong, **Jeddah,** Kaohsiung, **King Abdullah,** Laem Chabang, **Le Havre, London,** Long Beach, Los Angeles, **Marsaxlokk,** Ningbo-Zhoushan, **Piraeus,** Port Klang, **Port Said,** Qingdao, Rotterdam, **Salalah,** Shanghai, Shenzhen, Singapore, **Tanger Med,** Tanjung Pelepas, Tianjin, **Valencia,** Xiamen, **Yokohama.**
Group 2 (27)	Balboa, Cartagena, Charleston, Colon, Durban, Fuzhou, Genoa, Haiphong, Houston, Incheon, Jawaharlal Nehru, Kobe, Lianyungang, Manzanillo, Melbourne, Mundra, Nagoya, **New York/New Jersey,** Qinzhou, Santos, Savannah, Seattle-Tacoma, Sydney, Tanjung Priok, Tokyo, Vancouver, Virginia.
Group 3 (12)	Chittagong, Dongguan, Ho Chi Minh, Jiaxing, Manila, Nanjing, Rizhao, Taicang, Tangshan, Tanjung Perak, Yantai, Yingkou.

Note: the number in parentheses represents the number of ports in that group. The different classifications of ports are highlighted in bold.

Based on the groups identified through K-means clustering methods, we assessed the 80 ports' efficiencies to their respective group frontiers. Figure 3-13 displays the port efficiencies to group frontiers under the two classification methods. The results reveal that due to the similar classification outcomes, most ports achieved consistent efficiency scores, aligning closely with the 45-degree line. Nonetheless, varying the evaluation sets led to changes in frontier ports and different efficiency estimates for the affected ports. These findings suggest that while our port classification is robust, the frontiers identified by DEA are sensitive to the DMUs included in the evaluation sets.



Note: The dash-line represents the efficiency score to group frontier under original classification equals that under K-means clustering group.

Figure 3-13 Port efficiencies to group frontiers under the two classification methods

(2) Inputs and outputs adjustments

To assess the sensitivity of DEA estimates to variations in data, this study adopts the simultaneous adjustment methods for both inputs and outputs as proposed by Wu et al. (2010) and Cooper et al. (2011). For ports identified as efficient in the original analysis, their outputs will be decreased, and inputs will be increased by a predetermined percentage. In contrast, for those evaluated as inefficient in the original analysis, the adjustments will be reversed. Besides, to address the different measurement units and scales of the inputs and outputs, we employed the min-max normalization method to refine the original data.

Additionally, following the study of Gong et al. (2019) and Suárez-Alemán et al. (2014), we considered the total ship capacity shipping companies employed in the port (x_7), and the time ship spends in port (x_8) as alternative inputs in the DEA estimation. Furthermore, considering the intrinsic relationship between container movements and container throughput, we utilized the container throughputs of the ports (y_1) as an alternative output for shipping companies at the ports. Table 3-10 details the adjustments made to the inputs and outputs for the sensitivity analysis.

Table 3-10 Adjustments for inputs and outputs for sensitivity analysis

	A1		**A2**		**A3**	
	Inputs	Outputs	Inputs	Outputs	Inputs & Outputs	
Efficient DMU	+3%	-3%	+5%	-5%	$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \times 0.9 + 0.1$	
Inefficient DMU	-3%	+3%	-5%	+5%		
	A4		**A5**		**A6**	
	Inputs	Output	Inputs	Output	Inputs	Output
For shipping companies	x_7, x_8	y_2	x_5, x_6	y_1	x_7, x_8	y_1

Table 3-11 Summary of efficiency estimations to meta-frontier using different datasets

		Mean	**SD**	**Min**	**Max**	**No. of Efficient port**	**Efficiency Correlation**	**Rank Correlation**
From port operators' perspective	Original	0.63	0.23	0.19	1.00	12	1.00	1.00
	A1	0.71	0.24	0.22	1.00	19#	0.96**	0.97**
	A2	0.75	0.23	0.25	1.00	23	0.93**	0.95**
	A3	0.71	0.19	0.28	1.00	12#	0.99**	0.98**
From shipping companies' perspective	Original	0.86	0.12	0.46	1.00	13	1.00	1.00
	A1	0.90	0.12	0.50	1.00	21	-0.11	-0.21
	A2	0.90	0.11	0.51	1.00	19	-0.11	-0.20
	A3	0.92	0.07	0.71	1.00	13#	0.94**	0.95**
	A4	0.80	0.15	0.47	1.00	14	0.57**	0.65**
	A5	0.52	0.25	0.21	1.00	8	0.35**	0.37**
	A6	0.49	0.24	0.19	1.00	7	0.32**	0.36**

Note: # represents the efficient ports identified by the adjusted dataset are the same as or include all the ports assessed as efficient in the original analysis; **represents correlation is significant at the 0.01 level.

The summary of the efficiency estimates to meta-frontier under various adjustments, along with the Pearson correlation coefficients and Spearman rank correlations between the efficiencies derived from the original analysis and the adjustments, is provided in Table 3-11. When the adjustment is set under 3%, the 12 efficient ports identified in the original dataset from the perspective of port operators maintain their top-ranked status. However, when the adjustment reaches 5%, some efficient ports are replaced by those previously identified as inefficient. Notably, even minor adjustments in inputs and outputs can significantly alter the frontier and impact efficiencies evaluated from the shipping companies' perspective. This sensitivity is due to the fact that most ports show relatively similar efficiency scores and are positioned close to the frontier from the shipping companies' viewpoint. Additionally, since DEA measures relative efficiency, standardizing input and output variables may influence efficiency estimates but does not alter the identification of efficient ports or the relative rankings of these ports.

The results obtained from using alternative inputs and/or outputs for efficiency evaluation from the shipping companies' perspective show a relative consistency with those derived from the original dataset. However, when container throughput is used as an alternative output, fewer ports are classified as efficient. This decline may be due to the higher values of container throughput compared to container movements, which consequently shifts the frontier. Future research should pay close attention to the sensitivity of DEA estimates to variations in data and ensure the utilization of accurate and appropriate datasets for efficiency assessments.

3.5 Conclusion

Ports are operated in a complex environment, each with unique operation conditions and multiple stakeholders. Therefore, assessing the efficiencies of global ports has to consider their heterogeneous nature, as well as the interests of different stakeholders of the port.

This study evaluates the efficiencies of the global top 80 container ports from the perspectives of both port operators and shipping companies using the meta-frontier DEA method. Data on container port inputs and outputs of 2022 are collected from Lloyd's List, IHS Markit, and

Google Earth, and the data on the global liner shipping is extracted from 2022 AIS data, which includes ship sizes, port called, and the time spent in the port. Container moves when ships call the port are used as the output from the shipping companies' perspective, which is estimated using the available data.

The results show that from the perspective of port operators, both large and small ports exhibit relatively high efficiencies to the meta-frontier and their group frontier, whereas middle-sized ports show significant disparities in their efficiencies relative to the meta-frontier and their group frontier. Our finding suggests that both large hub ports, which benefit from network centrality and economies of scale, and small feeder ports, which thrive on operational leanness within a specialized niche, operate with high efficiency. The primary challenge lies with middle-sized ports, which are often caught in a strategic trap. This stuck in the middle problem mainly arises from a fundamental mismatch between the port's cost structure and its market position. These middle-size ports have invested in infrastructure, but their service functions and cargo volumes remain closer to those of smaller feeder ports. This disparity results in lower asset utilization and makes them less efficient than both the lean, small ports and the high-volume large ports. Moreover, a port's developmental stage is a critical factor. For small and middle-sized ports engaged in a strategy of moderately advanced construction, low efficiency scores may not signal operational failure but rather a predictable, transitional phase where investment in capacity temporarily outpaces demand growth.

From the perspective of shipping companies, most ports score above 0.8, indicating the relatively efficient service these ports provide to ships. This study also highlights inconsistencies in port efficiencies when evaluated from the perspectives of operators and shipping companies. Large hub ports show a significant positive correlation between efficiencies and rankings from both perspectives. Conversely, small and middle-sized ports exhibit weak and even negative correlations in efficiencies evaluated from the two perspectives. This finding suggests that efficient production of small and middle-size ports may be achieved at the expense of efficient service in ports, or vice versa.

The findings of this study establish a foundation for port operators and managers to improve the competitiveness of their ports in the global market. Additionally, these insights can help shipping companies optimize their scheduling of port calls and fleet arrangements. For ports that are seen as efficient within their specific group but still fall short of the meta-frontier benchmarking, port operators should consider substantial investments in production technology and advanced infrastructure to close this gap. Ports identified as inefficient in their group efficiency analysis can enhance their efficiency performance by strategically adjusting inputs, using identified slacks as a reference. Moreover, with an increased emphasis on time-in logistics, ports that are deemed efficient from the port operators' perspective but considered inefficient by shipping companies may need to adopt strategies, including attracting more cargo for each ship call, offering port charge discounts for ships with longer turn-around times, or accelerating handling services by optimizing berth allocation and crane arrangements, to enhance service efficiency for shipping companies. Given the significant impact of port operations on vessels, shipping companies, especially those operating larger ships, should prioritize calling at efficient ports that provide shorter turnaround times.

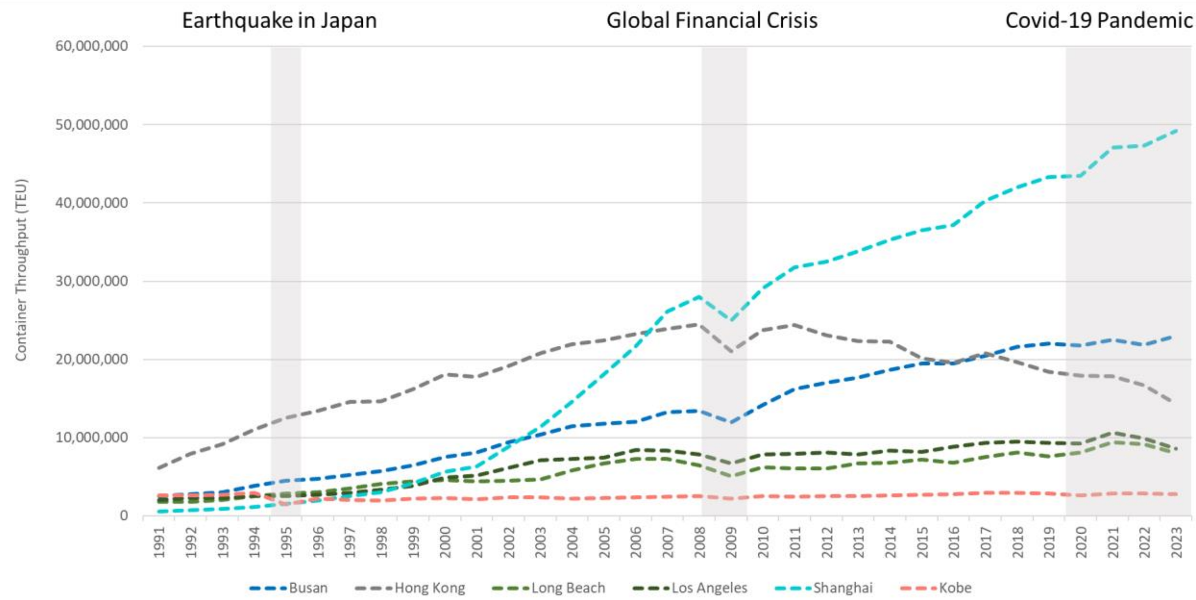
Efficient operations and rapid cargo handling are crucial for ports to remain competitive. The disparities in port efficiency among different stakeholders and across different port sizes highlight the need for port operators and managers to adopt diverse strategies based on their specific characteristics. Large ports benefit from economies of scale, yet some face challenges in providing timely and reliable transportation. For instance, the Los Angeles/Long Beach (LA/LB) port experiences longer turnaround times for vessels due to its substantial container volumes and significant trade activities. Port operators and managers could consider investing in advanced terminal equipment or deploying reserve equipment to improve container handling efficiency during peak periods. In contrast, many middle-sized and small ports struggle with insufficient cargo flows. Yantai Port sets a good example by forming cooperative alliances with surrounding hub ports and providing specialized services to these hubs, thereby increasing feeder transportation volumes and improving overall efficiency.

Chapter 4. Resilience Unveiled: How Do Port Clusters Absorb Shocks?

4.1 Introduction

As economic growth stabilizes and competition intensifies, integration and cooperation have become prevailing trends within the port industry (Guo et al., 2021; Luo et al., 2022). Port clusters, characterized by regional concentration and collaboration in port-related activities (Bai & Lam, 2015; Li et al., 2023), has emerged in various geographic regions, including European countries (Gianfranco et al., 2014), the United States (De Langen & Visser, 2005), Japan (Shinohara, 2016) and China (Li et al., 2023). Evidence from research underscores that port clusters not only improve resource utilization but also foster value creation within port networks (Ducruet, 2020; Guo et al., 2021; Haezendonck & Langenus, 2019; Haugstetter & Cahoon, 2010; Justice et al., 2016; Notteboom, 2010; Xiao et al., 2023).

The increasing frequency of unpredictable events such as natural disasters and economic instabilities underscores the vulnerability of port systems and their profound impact on regional economies and societies (Lau et al., 2024; N. Wang et al., 2023; Zheng et al., 2022). For instance, after Hanshin's earthquake in 1995, many shipping companies changed their port call from Kobe Port to Busan Port, leading to a marked decrease in Japanese container throughput and a pivotal shift in regional hub status (Chang, 2000). The financial crisis that occurred in late 2008 and the unexpected outbreak of the COVID-19 pandemic disrupted the global port network, causing recessions in most economies (Notteboom et al., 2021). According to the Clarkson Port Congestion Index, the ports of Los Angeles and Long Beach experienced more than double their usual congestion levels in 2021, with ships waiting up to twelve days to load and unload. This congestion led to estimated losses in U.S. export at approximately $15.7 billion, drastically undermining the competitiveness of U.S. businesses (Steinbach, 2022).



Data Source: Shipping Intelligence Network

Figure 4-1 Container throughput of ports suffered shocks

Considering the huge impacts of uncertain events, there is an increasing focus on studying port resilience in the face of shocks. It is recognized that individual ports exhibit varying levels of resilience, while the integrated resilience of a port cluster is not a mere sum of its parts but rather emerges from the synergistic interactions among its members. Ports serving the same region exhibit complement and substitution effects (Notteboom, 2009). In the face of disruptions impacting one or more port members, the port cluster can activate its collective resilience through the internal adaptive mechanisms. The unaffected port members within the port cluster can act as substitutes for their impacted counterparts, sustaining the port clusters' transport functions through accommodating rerouted vessels, sharing operational capacity, and reallocating cargo. This systemic perspective is corroborated by recent studies, which confirm that the availability of alternative ports within port clusters and the alternative port call behavior of ships contribute to the overall ability of port clusters and the shipping network to absorb the shocks (Li et al., 2024; Zhang et al., 2023).

Despite the acknowledged importance of these port interactions, few studies have considered port clusters as integrated entities to investigate the underlying mechanisms that shape their collective resilience. Studies on port resilience are often hindered by methodological and data limitations. Many resilience studies rely on modeling-based methods with heavy assumptions and simplifications, which may not adequately capture the complex recovery dynamics of ports during shocks or the intricate interactions among ports within the cluster (Ganguly et al., 2018; Mohsendokht et al., 2025; N. Wang et al., 2023). This issue is compounded by a dependence on low-granularity data, such as annual throughput, which fails to reflect the short-term fluctuations and intricate interactions critical to understanding the real-world resilience performance of port system (Gu et al., 2024).

This study addresses this gap by analyzing port cluster resilience through the lens of inter-port interactions. First, we assess the resilience of port clusters by quantifying the degree of ship call substitution among member ports during disruptions. Second, we employ regression analysis to investigate how this resilience is shaped by key internal characteristics, for example, shipping connectivity within a port cluster, differences in operational efficiency among member ports, and the degree of structural hierarchy. This framework is empirically applied on three representative Chinese port clusters, namely Yangtze River Delta (YRD), Pearl River Delta (PRD), and Bohai Rim (BR), during the Covid-19 pandemic, using a multi-source dataset incorporating real-time ship traffic data extracted from the Automatic Identification System (AIS) from 2016 to 2023. A key conclusion is that denser internal connectivity among ports via ship flows is a significant contributor of higher cluster resilience. In contrast, port clusters displaying large disparities in operational efficiency among member ports or those heavily reliant on a few core ports within a pronounced hierarchical structure are found to be less resilient.

This study contributes to the field in three ways. First, it advances the understanding of port system resilience by shifting the analytical unit from the individual port to the interconnected cluster. It is one of the preliminary studies that view port clusters as integrated and cohesive entities and examine their resilience considering interactions among ports. This systemic perspective enables the assessment of how ports collectively respond to disruptions, moving beyond the inherent limitations of traditional single-port analysis. Second, building on the conceptual framework, we provide empirical evidence on the specific internal characteristics of port clusters that influence their resilience. Our findings enable stakeholders to move beyond isolated, port-level interventions and develop evidence-based, regional strategies that bolster the entire system's resilience. Third, this paper employed a multi-source dataset for empirically investigating these complex port dynamics. By incorporating fine-grained AIS data with other source data, we demonstrate how newly emerged big data can be leveraged for empirical analysis of the port cluster. This approach provides a replicable framework for analyzing the resilience of real-world port systems.

4.2 Literature Review

This study is situated at the intersection of two well-established research streams: port resilience and port cluster analysis. While scholars have conducted in-depth research on port resilience, most of them focus on the resilience of individual ports but overlook how ports function collectively as a resilient system. Concurrently, studies on port clusters identify the advantages of port clusters and the importance of port interactions, but have yet to sufficiently investigate their role in shaping systemic resilience. This section reviews the studies on port resilience and port clusters to establish the foundation of this study.

4.2.1 Port resilience analysis

The concept of resilience, which originated from the fields of ecology, describes the ability to withstand external shocks, adapt to changes, maintain functionality, and recover the original state after such disturbances(Gonçalves & Ribeiro, 2020; Holling, 1973; Hosseini et al., 2016). With the increasing occurrence of unpredictable shocks impacting transportation systems, resilience analysis has emerged as a vital research focus (Gu et al., 2020; Reggiani, 2013).

In the context of the port industry, resilience is commonly conceptualized through three key dimensions: absorptive, adaptive, and restorative capabilities (Chen et al., 2017; J. Chen et al., 2023; Mohsendokht et al., 2025; Qin et al., 2023). For example, León-Mateos et al. (2021) defined the resilience of ports as their capacity to absorb and recover from a damaging event. Similarly, J. Liu et al. (2023) described port resilience as the ability of ports to adjust to a new state after a disruption. Gu et al. (2024) viewed port resilience as the ability to navigate disruption and congestion during adverse events, while Xu, Yang, et al. (2024) highlighted the importance of not only coping with external shocks and mitigating losses but also responding and adapting to these shocks. Mohsendokht et al. (2025) reviewed the studies on port resilience and summarized that the primary focus on port resilience is the ability to withstand and recover from a disruptive scenario. While foundational, these definitions consistently focus on the single port as the unit of analysis. This study extends these established definitions from the individual port to the interconnected system, defining port cluster resilience as the collective ability of its constituent ports to cope with and recover from disruptions.

Scholars have also adopted a variety of methods to study the port resilience. The main methods used in port resilience analysis are summarized in Table 4-1. One prevalent stream is the modelling-based method, which understands system behavior through analytical abstraction. For example, Folkman et al. (2021) employed simulation to analyze port operation resilience before and after a hurricane. Q. Liu et al. (2023) considered ports as nodes within a shipping network and measured their resilience by estimating the changes in their network characteristics under different attack scenarios. A larger number of researchers have favoured Bayesian networks for port resilience analysis, which allows for examining the probabilistic causal relationships between various factors and hypothetical shocks (Hossain et al., 2019; John et al., 2016; Li et al., 2025; Panahi et al., 2022; N. Wang et al., 2023). A second stream of research focuses on quantifying resilience through more direct, indicator-based assessments. These range from single-variable metrics tracking core operational data like port congestion or vessel calls (Gu et al., 2024; Xu, Yang, et al., 2024) to multi-dimensional indices that integrate structural, functional, and locational attributes into a comprehensive resilience score (J. Liu et al., 2023; Qin et al., 2023). Among studies, the most foundational metric is the recovery-to-loss ratio proposed by Henry and Ramirez-Marquez (2012). This metric serves as an indicator of a system's ability to "bounce back" and has been widely adopted in subsequent research on port resilience (Li et al., 2025; Panahi et al., 2022; Yang et al., 2025).

Table 4-1 Methods adopted in port resilience analysis

Methods		**Representative Literature**
Modelling-based	Simulations	Folkman et al. (2021); Zhou et al. (2021); Q. Liu et al. (2023)
	Bayesian networks	Hossain et al. (2019); Panahi et al. (2022); N. Wang et al. (2023)
Indicator-based	Core indicators	Verschuur et al. (2020); Gu et al. (2024); Xu, Yang, et al. (2024)
	Composite indices	León-Mateos et al. (2021); J. Liu et al. (2023); Qin et al. (2023)

These methods facilitate multi-perspective and multi-dimensional analyses of port resilience, each with its advantages and limitations. Modeling-based approaches excel in estimating causal relationships and evaluating various types of hazards, thereby effectively delineating the impacts of disruptions (N. Wang et al., 2023). However, the reliability of these methods is highly contingent upon assumptions and data quality, and numerous factors can undermine the accuracy of these estimates (Ganguly et al., 2018; Mohsendokht et al., 2025; N. Wang et al., 2023). Indicator-based measures provide insights into specific aspects of port resilience but may face challenges in determining appropriate dimensions and weights. More critically, both approaches often assume linear, short-term disruption processes (Mohsendokht et al., 2025), which may not adequately capture the complex recovery dynamics of port clusters or the interactions among ports within the cluster. The analysis of port cluster resilience necessitates the meticulous application of real-world data and a thorough understanding of the complex interactions within port systems.

4.2.2 Port cluster analysis

Port clusters are traditionally defined as regional concentrations of interrelated economic activities such as cargo handling, transportation, logistics, and trading(Bai & Lam, 2015; De Langen & Visser, 2005). Recently, this definition has broadened to include geographic regions where multiple ports are situated in close proximity (Li et al., 2023; Xiao et al., 2023). Such clusters have been established in various regions and economies around the world, including in European countries (Gianfranco et al., 2014), the United States (De Langen & Visser, 2005), Japan (Shinohara, 2016) and China (Li et al., 2023).

Research highlights the advantages of this clustered development, emphasizing its role in boosting the connectivity and competitiveness of ports within maritime networks, as well as promoting shared capacity and coordinated management (Ducruet, 2020; Guo et al., 2021; Haezendonck & Langenus, 2019; Notteboom, 2010; Xiao et al., 2023). For instance, Tagawa et al. (2022) discovered that cooperation within port clusters enhances the likelihood of connections among ports in the global shipping network and attracts new services to the cluster. Additionally, Li et al. (2022) demonstrated that port coalitions could enhance service resilience during disruptions, as they allow ports to pool resources and capacities, offering alternative solutions to shipping companies. These studies suggest the crucial role of interactions among ports within a cluster and the potential mechanisms through which port clusters can mitigate external shocks.

Motivated by the trends of port clusters and the interactions among ports within these clusters, several researchers have explored ways to assess the resilience of port clusters or port networks. A notable study conducted by Li et al. (2024) investigated the resilience of port clusters in the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) during typhoon events. Their findings suggest that strategies such as vessels' port-skipping behaviour and enhancements in port cargo handling capacities could significantly improve the resilience of port clusters. However, this study encounters limitations due to its reliance on simulation methods and hypothetical scenarios, which may not fully capture the complex dynamics of real-world port cluster operations. Additionally, some scholars have concentrated on the network resilience of ports, recognizing that ports are crucial components of various interconnected networks. Employing methodologies such as graph theory, dynamic spatial Markov chain, and system dynamics, these studies have examined the effects of disruptions on port networks and concluded that the resilience of a port is interconnected with the efficacy of other ports within the network (Chang et al., 2024; Q. Liu et al., 2023; Panahi et al., 2022; Qin et al., 2023).

While port clusters have been extensively analyzed for their economic performance and competitive dynamics, their resilience as a systemic unit remains a notable blind spot in the literature. This gap is most evident in the disconnect between the theoretical acknowledgement of port interactions and the scarcity of empirical studies that use these interactions with real-world data to quantify resilience. This highlights a need for empirical studies on port cluster resilience through the lens of port interactions.

Addressing these gaps, this paper provides an analysis framework of port cluster resilience grounded in the dynamics of port interactions. Using high-frequency AIS data, our study not only empirically measures the capacity of port clusters to withstand and recover from shocks but also uncovers the key internal mechanisms that underpin this systemic resilience.

4.3 Methodology

This section outlines our two-stage analytical framework for assessing port cluster resilience and its determinants. First, we measure the resilience of port clusters by quantifying the degree to which member ports can substitute for one another in handling ship calls during a disruption. Then, we develop an econometric model to identify the key internal characteristics that influence this substitution capability. This framework allows us to measure port cluster resilience and explain how it arises from the core internal features of the cluster.

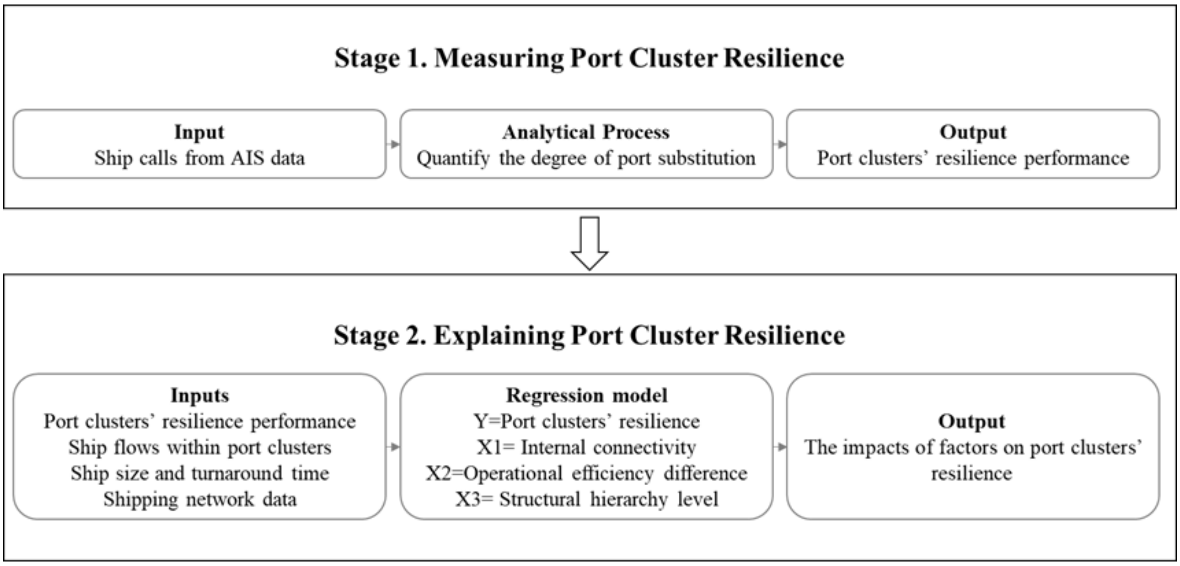
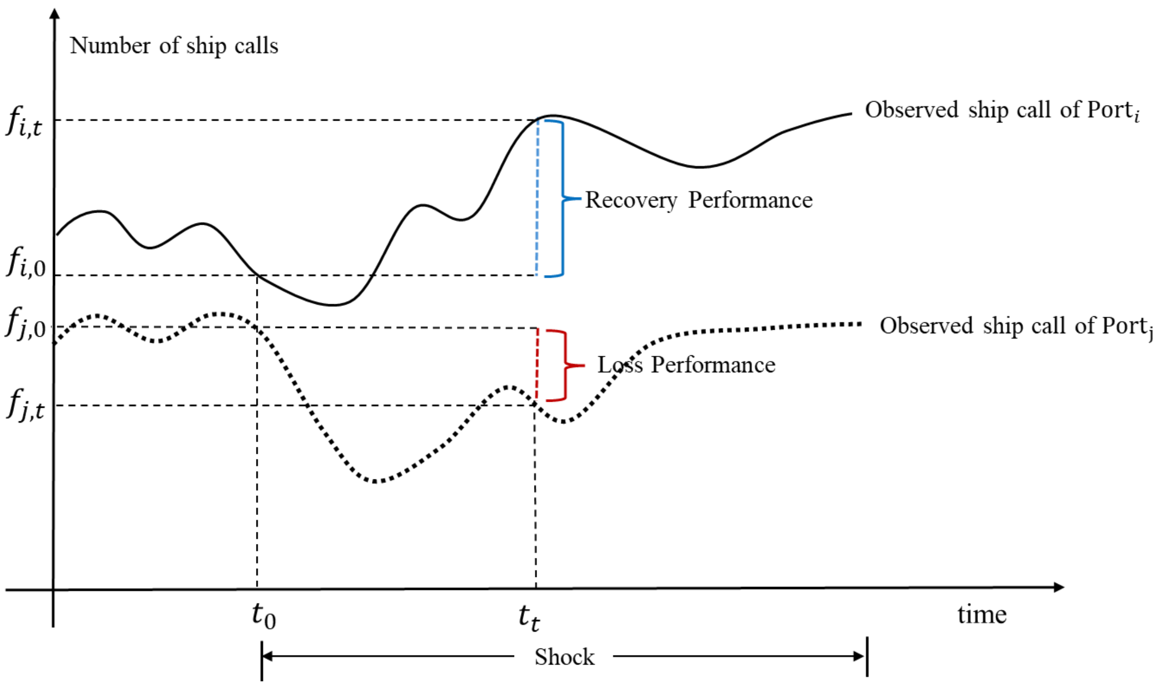


Figure 4-2 Analysis framework

4.3.1 Measuring port cluster resilience

This study adapts the foundational "recovery to loss" metric proposed by Henry and Ramirez-Marquez (2012) into a time-series analysis for port clusters. Within this framework, we identify two distinct port status at any given moment. Affected ports are those operating below their performance baseline, collectively contributing to the system's overall loss, as illustrated by $Port_j$ in Figure 3. In contrast, other unaffected ports within the same cluster may absorb the traffic diverted from affected ports, leading to performance that exceeds their pre-shock baseline, as shown with $Port_i$ in Figure 3. Crucially, these roles are not static: a port's role can switch from being affected at one moment to becoming unaffected at the next. This allows us to track the real-world process of collective adaptation and recovery.

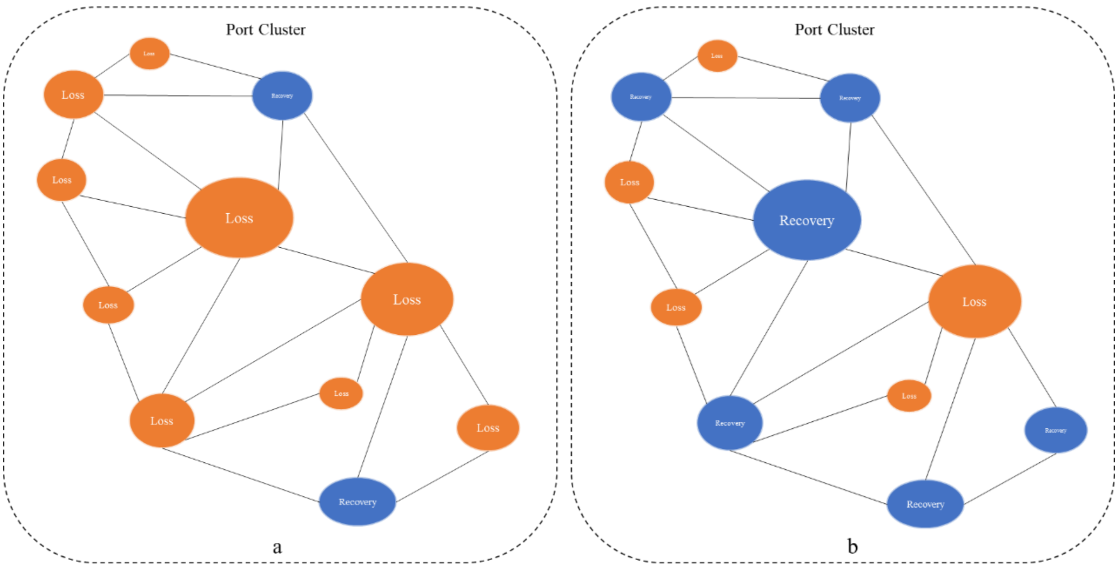


Note: t_0 represents the onset of the disruption, $f_{i,o}$ and $f_{j,0}$ denote the baseline performance levels of the respective ports before the disruption occurred.

Figure 4-3 Measurement of port cluster resilience

It is well-established that ports serving the same hinterland can function as substitutes for one another (Notteboom, 2009). The key advantage of a port cluster is the ability of its member ports to share capacity and provide alternative servicing options for ships, which helps sustain the region's overall service functionality during disruptions (Chang et al., 2024; Li et al., 2024; Li et al., 2022). Research also indicates that in response to port disruptions, ocean carriers frequently employ port skipping as a key strategy, diverting vessels to nearby alternative ports to maintain the service network (Zhang et al., 2023). Building on these insights, we assume that unaffected ports within a cluster will absorb diverted traffic, acting as effective substitutes for their affected neighbors.

However, the effectiveness of this cooperation and substitution varies significantly among clusters, leading to different levels of resilience. For instance, some clusters exhibit low resilience when disruptions affect a substantial number of ports, severely impairing their collective functionality (as illustrated in Figure 4-4a). In contrast, other clusters display superior resilience by swiftly reorganizing and utilizing unaffected ports to compensate for those that are disrupted, as depicted in Figure 4-4b.



Note: The blue bubbles represent ports where the number of ship calls surpasses the pre-disruption baseline, reflecting their recovery ability. The orange bubbles denote ports where ship call performance falls below the baseline, illustrating the loss of performance due to the disruption. The size of each bubble represents the extent of overperformance or underperformance.

Figure 4-4 Different performances of ports within the port cluster

To measure the dynamics of interactions and overall resilience performance of port clusters, we calculate the resilience of a port cluster at any given time t by the ratio of the recovery performance of the unaffected ports to the loss performance of the affected ports at time t, as shown in Eq (4.1).

$$RES_{k,t} = \frac{Recovery_{k,t}}{Loss_{k,t}} = \frac{\sum_{i\in P_{unaffected,k,t}}(f_{i,t}-f_{i,0})}{\sum_{j\in P_{affected,k,t}}(f_{j,0}-f_{j,t})} \tag{4.1}$$

where $RES_{k,t}$ reflects the resilience of port cluster k ($k \in \{1,2,\dots,m\}$) at time t . $P_{unaffected,k,t}$ and $P_{affected,k,t}$ are the sets of unaffected port i and affected port j ($i \neq j \in$ N) within port cluster k at time t. $Recovery_{k,t}$ represents the recovery performance of the port cluster k at time t, measuring the collective ability of unaffected ports ($P_{unaffected,k,t}$) to attract diverted traffic, calculated as the sum of their ship calls at time t ($f_{i,t}$) above their baseline levels ($f_{i,0}$). The denominator represents the loss performance, quantifying the total traffic deficit from affected ports ($P_{affected,k,t}$). It is calculated as the aggregate difference between the baseline ship call count before the disruption and the ship call count of the affected ports, $\sum_{j\in P_{affected,k,t}}(f_{j,0} - f_{j,t})$. The baseline ship call of port i and port j, $f_{i,0}$ and $f_{j,0}$, are established by the highest monthly ship call count during the same month over the past years, reflecting each port's optimal seasonal performance.

This method quantifies the degree to which substituting ports compensate for performance losses at affected ports, thereby reflecting the overall functionality and resilience of the port cluster. A higher resilience value signifies stronger compensatory capacity and greater overall resilience. A value exceeding 1 indicates that the cluster has not only offset its losses but has also achieved an operational capacity superior to its pre-disruption baseline.

4.3.2 Determinants of port cluster resilience

Existing research has explored the influence of various elements on port resilience, including infrastructure, the surrounding hinterland dynamics, and the connectivity of port nodes within shipping networks (Gu & Liu, 2023; León-Mateos et al., 2021; Li et al., 2025; J. Liu et al., 2023; Qin et al., 2023). In contrast to individual ports, port clusters operate as integrated units consisting of multiple ports. This study hypothesizes that interactions among port members within a cluster are determined by three key factors: internal shipping connectivity within port clusters, operational efficiency differences among port members, and the structural hierarchy level of port clusters. These factors are defined and measured in the following ways.

(1) Internal Network Density

Previous studies have underscored the importance of shipping networks, which encompass both ports and their shipping routes, as critical links within transportation systems that contribute to their resilience (Asadabadi & Miller-Hooks, 2020; Q. Liu et al., 2023; Poo & Yang, 2024). Within a port cluster, the shipping connectivity among member ports is not only the foundation for meeting transportation demands (Haugstetter & Cahoon, 2010; Justice et al., 2016) but also the pathways for port communication and coordination under disruptions (Bai et al., 2023; Li et al., 2024). Specifically, a dense network provides physical and operational pathways for port members to reroute vessels and cargo from a disrupted port to a healthy one. This connectivity also makes substitute ports a viable alternative for shipping companies (Yuan & He, 2025). Additionally, from the network perspective, dense internal connectivity contributes to the systemic reliability and redundancy (Yue & Mangan, 2024), transforming a geographic grouping of ports into a functionally integrated and resilient system. Therefore, we hypothesize that port clusters with stronger internal shipping connectivity are more resilient.

To measure this internal shipping connectivity, we use a weighted network model, which is a well-recongized approach in transport geography and network analysis (Bai et al., 2023; Newman, 2003). In this model, each port cluster can be viewed as a graph, where the individual ports within the cluster are represented as nodes. The connections, or edges, between these nodes are defined by the ship movements among them. And to capture the strength of these connections, the edges are weighted by the frequency of ship movements. This approach allows us to calculate the overall density of shipping connections within the cluster. The formula to calculate the internal connectivity of a port cluster is shown in Eq (4.2):

$$IND_{k,t} = \frac{\sum_{i \neq j \in N}^{n} w_{ij,t}}{n(n-1)} \tag{4.2}$$

Where $IND_{k,t}$ is the internal network density of port cluster k at time t, $w_{ij,t}$ is the frequency of ship flows between port i and port j ($i \neq j \in$ N) in port cluster k at time t, n is the number of port members in the port cluster k.

(2) Operational Efficiency Difference

Port efficiency and infrastructure play a vital role in the port's capacity to handle shocks (León-Mateos et al., 2021). Studies also found that port efficiency to ships can significantly influence the decisions of liner shipping companies when choosing ports (Jiannan & Zhongzhen, 2020; Martínez Moya & Feo Valero, 2017; Tongzon, 2009). Geographically proximate ports that demonstrate similar levels of efficiency and capacity can serve as feasible alternatives for shipping companies (Tang et al., 2011). While ports in a cluster are geographically proximate, they may exhibit varying levels of efficiency. These efficiency differences impact the time and costs of ships calling the port, thereby influencing the functional and economic viability of rerouting traffic (Nguyen & Kim, 2024; Strandenes, 2004). In case of disruptions at a specific port, others within the same cluster with similar service levels and capacities can serve as close substitutes, maintaining the smooth operation of the cluster. However, if there are significant differences in efficiency and service levels among the ports within the cluster, the shipping companies may find it challenging to call the alternatives in the port cluster. Given this context, this study hypothesizes that the difference in port efficiency is a vital determinant of port clusters' resilience.

Beyond using frontier methods, port efficiency to ships can be evaluated based on metrics such as ship turnaround time and cargo handling rates (Yang et al., 2023; J. Zhang et al., 2024). In this study, we measure port efficiency to ships as the ratio of container movements to the total berthing time of ships at the ports, as shown in Eq (4.3). The difference of port efficiency is measured using the coefficient of variation, which quantifies the spread of data by computing the ratio of the standard deviation to the mean (Brown, 1998). A lower coefficient of variation indicates the uniformity in efficiency levels across different ports, suggesting that ports can potentially replace each other without significant loss in operational performance. The formula for calculating the operational efficiency difference is outlined in Eq (4.4).

$$OE_{i,t} = \frac{Q_{i,t}}{\sum_{z}^{L} BT_{zi,t}} = \frac{\sum_{s=1}^{5}(No_{si,t} \times \sum_{y=1}^{10}(Avg_{sy} \times Pct_{sy})}{\sum_{z}^{L} BT_{zi,t}} \tag{4.3}$$

$$OED_{k,t} = \frac{\sigma(OE_{k,t})}{\mu(OE_{k,t})} = \frac{\frac{1}{n}\sum_{i=1}^{n} OE_{i,t}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(OE_{i,t} - \frac{1}{n}\sum_{i=1}^{n} OE_{i,t})^2}} \tag{4.4}$$

In these equations, $OE_{i,t}$ refers to the operational efficiency of port i at time t, and $OED_{k,t}$ represents the efficiency differences of ports within port cluster k at time t. $OE_{i,t}$ is calculated by the ratio of estimated container movements at port i at time t, $Q_{i,t}$, to the total berthing time of ships within the port i at time t, $\sum_{z}^{L} BT_{zi,t}$. The estimated container movements of port i at time t is calculated using the methods proposed by Zhang et al. (2025), which multiply the number of ships in each ship size category s called at that port i at time t ($No_{si.t}$) by the estimated container moves ($Avg_{sy} \times Pct_{sy}$) of ship size category s. Avg_{sy} represents the average container moves of ships in the container movement group y ($y = 1, 2, \ldots, 10$), and ship size category s ($s = 1, 2, \ldots, 5$). Pct_{sy} represents the percentage of container moves of the ship category s fall in the container movement group y. The data for $No_{si,t}$ and $BT_{zi,t}$ is captured from AIS data, while that for the Avg_{sy} and Pct_{sy} are from the Container Port Performance Index (World Bank, 2023).

(3) Structural Hierarchy Level

Port clusters are comprised of a diverse array of members, including major hub ports and smaller feeder ports. The structural hierarchy reflects the concentration of traffic and the dependency on dominant hub ports relative to smaller feeder ports (Zhao et al., 2020). A high degree of hierarchy, indicating an efficient hub-and-spoke system, simultaneously suggests a significant systemic vulnerability. This vulnerability arises because risk is concentrated in a few central ports, whose failure can trigger a cascading disruption across the entire network (Jiang et al., 2024; Qin et al., 2023; Xu et al., 2022). Besides, the feeder ports in such a system often play a complementary role to the hub (Notteboom, 2009). They may lack the scale, technology, and hinterland infrastructure to handle the large vessels or absorb the rerouted traffic from a disrupted hub, which renders them inadequate substitutes in a crisis. Thus, we hypothesize that a more balanced, low-hierarchy port cluster is more resilient, as it distributes risk and is more likely to contain multiple ports with comparable capability and substitutability.

To measure the structural hierarchy level of port clusters, this study employs the degree distribution measurement method proposed by Crespo et al. (2014). This method assesses hierarchy by analyzing the distribution of influence among nodes in a network. In this study, we use the port degree centrality, which is the number of connections a port has in the global port network, to represent the node influence. The underlying rationale is that a port with high global centrality (a major international hub) will inherently dominate its local cluster in terms of traffic volume and strategic importance. The method involves ranking all ports within a cluster by their degree centrality and then fitting this ranked distribution to a power function (as detailed in Eq. (4.5) and (4.6)). The coefficient provides a quantitative score for the hierarchy, where a steeper distribution signifies a more pronounced, hub-dominated structure of the port cluster.

$$K_{it} = C({K_{it}}^{*})^{SHL_{kt}} \tag{4.5}$$

$$\ln(K_{it}) = \ln(C) + SHL_{kt}\ln({K_{it}}^{*}) \tag{4.6}$$

Where SHL_{kt} representing the hierarchy level of port cluster k at time t, is the coefficient calculated by equations; K_{it} is the degree centrality of port i ($i \in$ N) in the global shipping network at time t, measured by the number of connections a port has within the global port network; ${K_{it}}^{*}$ is the ranking of port i in the port cluster by its degree centrality at time t, C represents the constant.

4.3.3 Econometric model

(1) Baseline model

The baseline specification of the regression model for investigating the influencing factors on the resilience of port clusters, is presented in Eq. (4.7).

$$RES_{k.t} = \beta_0 + \beta_1 IND_{k,t} + \beta_2 OED_{k,t} + \beta_3 SHL_{k,t} + \delta Control_{k,t} + \omega_k + \gamma_t + \varepsilon_{k,t} \tag{4.7}$$

The dependent variable, $RES_{k.t}$, represents the monthly resilience index of port cluster k at time t. The variables $IND_{k,t}$, $OED_{k,t}$, and $SHL_{k,t}$ denote the internal network density, operational efficiency difference, and structural hierarchy level of port cluster k at time t, respectively. $Control_{k,t}$ denotes the control variables. In this study, we control the regional economic conditions using the per capita GDP of the port cluster's hinterland, and control the size of port clusters using the sum of the maximum containership capacity of each port (TEU). Furthermore, we introduced ω_k, and γ_t, to capture the time-invariant characteristics specific to each port cluster and time-varying influences that impact all port clusters.

We take natural logs for all continuous variables to reduce the difference between variables and allow for the interpretation of the coefficients of explanatory variables as elasticities. As the resilience index, $RES_{k.t}$, includes values starting from 0, we adjust it by adding 1 before applying the logarithmic transformation. This adjustment ensures that all values are positive, making the logarithmic transformation feasible.

(2) Instrument variable (IV) approach

Our baseline model may face endogeneity issues, particularly due to potential reverse causalities between the internal network density, the operational efficiency differences and the resilience index of port clusters. Port cluster resilience, defined as a capacity to withstand and recover from disruptions and measured through ship calls, could potentially impact the internal network density. Moreover, efficiency disparities among ports within a cluster may be shaped by resilience levels, as ports with less disruption management may lead to congestion and wider efficiency gaps. These intricate interdependencies suggest the need for a robust causal inference approach.

In this study, we construct an instrumental variable (IV) for internal network density using the regional road network density. The density of the road network is determined by the ratio of the total road network length to the total land area where the port clusters are situated, according to the methodologies and data outlined by Zhang et al. (2015). The rationale for using road network density as an IV stems from that land transportation and sea transportation within a region face similar environmental conditions and play complementary roles in the regional economy. Regions with denser road networks facilitate enhanced connectivity between ports and their hinterlands, which in turn supports the growth of maritime networks (Arvis et al., 2018). Meanwhile, decisions on road infrastructure development are influenced by long-term geographical, historical, and policy considerations (Redding & Turner, 2015), which makes it exogenous to short-term changes in port resilience and maritime traffic. Therefore, we hypothesize that road network density is related to the internal shipping network density of port clusters by ship flows but remains exogenous to the resilience of port clusters.

Additionally, we employ the monthly network density of all ports in the same country, excluding those within the analyzed cluster, as another IV for internal network density. We also use the average efficiency difference of other port clusters within the same country as the IV for efficiency differences. This method is inspired by the industry-location average IV method used by Fisman and Svensson (2007) and the spatial interdependence among port clusters. Scholars have found that regional transportation development and competition/cooperation dynamics can lead to spillover effects on neighbouring regions (Cohen, 2010; Moura et al., 2019; Zhao et al., 2024). While enhancements in port infrastructure can boost production within a state, they can adversely affect neighbouring states (Cohen & Monaco, 2008). Port clusters within the same country compete for the domestic transportation market. Enhancing the internal network density of one port cluster could potentially improve its market potential, while simultaneously undermining the network strength of other regional clusters. Furthermore, a port cluster that maintains uniform operational efficiency and consistent service delivery can attract more investment and shipping demand due to scale effects or cost benefits, potentially exacerbating efficiency differences in less efficient neighbouring port clusters. Therefore, we posit that the national-level network density of other ports and the average efficiency difference among other port clusters are connected to the internal network density and operational efficiency differences of the port cluster under study, respectively, but are not directly linked to the resilience of the port cluster.

Table 4-2 presents the description of all variables and instruments.

Table 4-2 Description of variables

Types	Variable	Abbr.	Description
Dependent variable	Resilience index	RES	The ratio of recovery performance to loss performance in terms of ship calls.
Variable of Interest	Internal network density	IND	The ratio of ship movements among ports within the port cluster to the total number of possible connections in the port cluster network.
	Operation efficiency difference	OED	The coefficient of variation of ports' efficiencies within the port cluster.
	Structural hierarchy level	SHL	The slope of the degree distribution of ports within the port cluster
Control variables	Cluster Size	SIZE	The sum of the maximum size (TEU) of containership visiting the ports within the cluster.
	GDP per capita	GDP	The annual per capita GDP of the regional hinterland where the port cluster is situated.
Instruments	Road network density	RND	The road network density of the regional hinterland where the port cluster is situated.
	Country-level network density	CND	The monthly network density of all ports within the same country as the port cluster, excluding those ports that are part of the target port cluster itself.
	Average efficiency difference	AED	The average efficiency difference level of other port clusters in the same country.

4.4 Data

This study employs a multi-source dataset to capture the interaction dynamics among ports within a cluster and port activities facilitated by ship flows. This section outlines the research scope and the data processing methods.

4.4.1 Research scope

Port integration and consolidation have become the predominant trends in the global port industry (Luo et al., 2022; Ma et al., 2021). The port clusters in the Yangtze River Delta (YRD), Pearl River Delta (PRD), and Bohai Rim (BR) are particularly distinguished by their strategic importance in the international shipping network and their sophisticated operational capabilities. According to the 2024 Lloyd's List 100 ports, the ports of Shanghai and Ningbo-Zhoushan from the YRD cluster secured the first and third positions by their container throughput, the PRD's ports of Shenzhen, Guangzhou, and Hong Kong ranked fourth, sixth, and tenth, and the BR's Qingdao and Tianjin ports also placed within the top ten. Given their significant contributions to global shipping and representativeness, this study uses these three port clusters as case samples.

The ports within these clusters are chosen based on the *National Plan for the Layout of Coastal Ports* issued by the Ministry of Transport of the People's Republic of China, complemented by port information recorded on Alphaliner (alphaliner.axsmarine.com). It should be noted that the scope of this study is focused on container ports and associated containership activities. Therefore, only those ports that primarily handle container cargo are considered and included. The container ports included in each port cluster for this study are listed in Table 4-3.

Table 4-3 Analysed ports within port clusters

Port Cluster	Ports
Bohai Rim	Cangzhou, Dalian, Dandong, Huludao, Jinzhou, Panjin, Qingdao, Qinhuangdao, Rizhao, Tangshan, Tianjin, Weifang, Weihai, Yantai, Yingkou
Pearl River Delta	Dongguan, Foshan, Guangzhou, Hong Kong, Huizhou, Jiangmen, Macao, Shantou, Shenzhen, Zhongshan, Zhuhai
Yangtze River Delta	Anqing, Changshu, Changzhou, Chizhou, Jiaxing, Lianyungang, Maanshan, Nanjing, Nantong, Ningbo-Zhoushan, Shanghai, Suzhou, Taizhou (Jiangsu), Taizhou (Zhejiang), Wenzhou, Wuhu, Wuxi, Yangzhou, Zhangjiagang

The sudden outbreak of the COVID-19 pandemic and the subsequent restrictive measures have resulted in sustained impacts on the global shipping industry. Scholars have noted that COVID-19 has become the new normality, continuing to affect the port industry far longer than initially expected (Cullinane & Haralambides, 2021; J. Liu et al., 2023; Nguyen & Kim, 2024). Given this context and the AIS data availability, this study uses the months from 2016 to 2019 as the preceding period to establish a pre-pandemic operational baseline of port clusters. The months from 2020 to 2023 have been used as the research period.

4.4.2 Data processing

The data collection process involves sourcing port-related data from various databases and extracting ships' time-space trajectories to assess ship calls and network indicators of ports and port clusters. Additionally, data on the GDP per capita of port cluster regions are obtained from the National Bureau of Statistics of China (http://www.stats.gov.cn). The data on road network density is acquired from the OpenStreetMap (https://www.openstreetmap.org).

(1) Port-related data

To identify ports within each port cluster, we first gathered information from the *National Plan for the Layout of Coastal Ports*, complemented by port information recorded on Alphaliner (alphaliner.axsmarine.com) and IHS Markit (ihsmarkit.com). Utilizing vision-based techniques as described by Yang et al. (2023), we then mapped the geographic boundaries of each container terminal within the clusters using satellite maps.

(2) Ship-related data

To compile the ship-related dataset, we integrated the Automatic Identification System (AIS) data of ships with detailed vessel information from Lloyd's List Intelligence. We then matched the geographical locations of ships and terminals to identify containership port calls. The number of ship calls at each port and the maximum ship size visited each port were determined using the gathered data. The turnaround time for vessels at each port was calculated by measuring the difference between the last timestamp and the first timestamp of each ship call in the port area. Additionally, the shipping network was established by tracking the sequence of port visits for each ship. Figure 4-5 illustrates the processing steps applied to the AIS data.

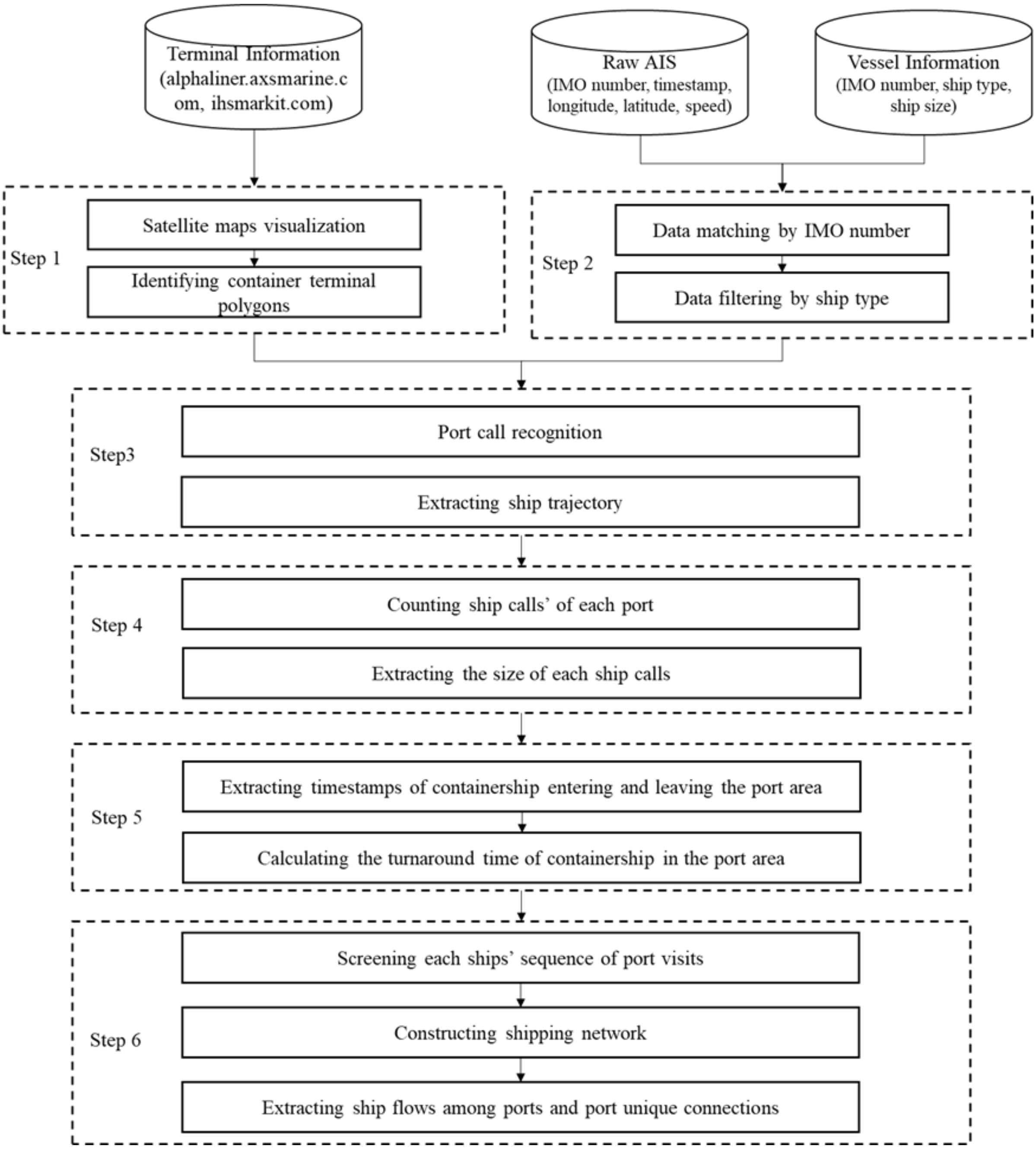


Figure 4-5 AIS data processing steps

After constructing the shipping network, we extracted ship flows among the ports under study. Each direct movement from one port to another was treated as an adjacent connection in our network analysis. Utilizing this information, we employed graph theory to quantitatively evaluate the network characteristics of ports, both within the port clusters and across the broader global shipping network. Figure 4-6 shows annual ship flows among the main container ports within the Yangtze River Delta (YRD) port cluster in 2020 and 2023.

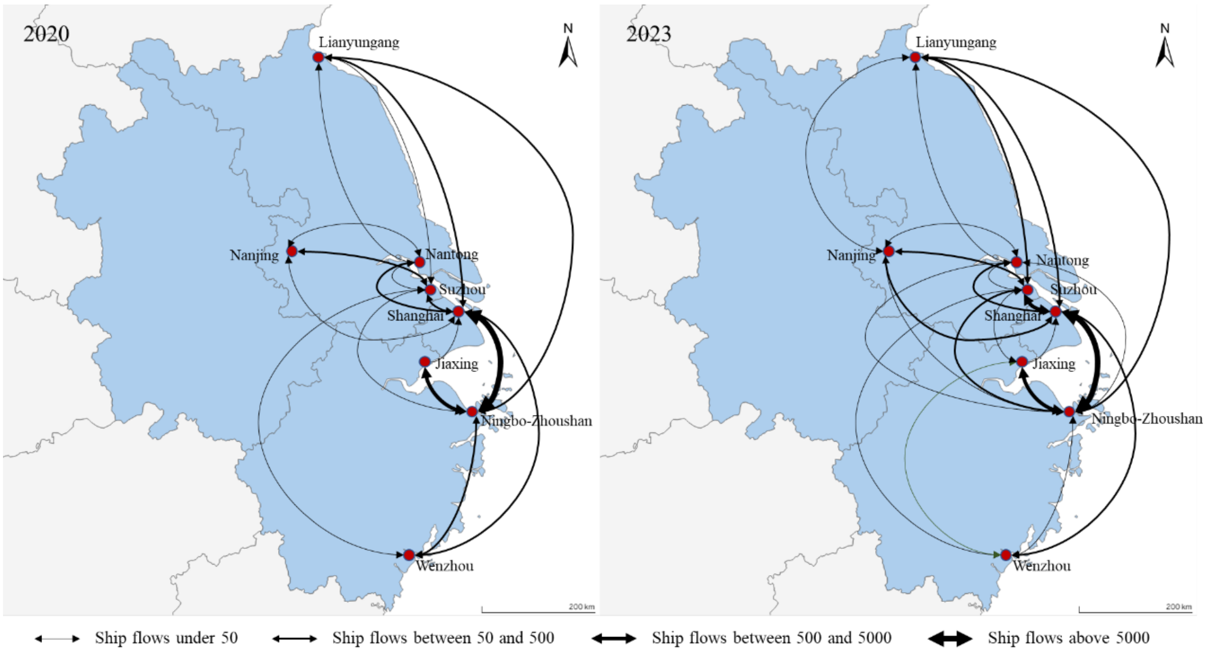


Figure 4-6 Ship flows among the main container ports in the YRD port cluster in 2020 and 2023

Our initial dataset includes 596,956 ship call records from 4,931 containerships across 57 Chinese ports, covering the period from January 1, 2016, to December 31, 2023. Excluding the 45 container ports that are identified as part of the Bohai Rim (BR), Pearl River Delta (PRD), and Yangtze River Delta (YRD) clusters, this study incorporates 12 ports from the Southeast and Southwest Coastal Port Clusters of China for the construction of instrumental variable. These ports include Beihai, Danzhou, Fangcheng, Fuzhou, Haikou, Ningde, Qinzhou, Quanzhou, Xiamen, Yangpu, Zhanjiang, and Zhangzhou. After processing the data, we derived monthly values for the variables during the period from January 2020 to December 2023. Table 4-4 provides the summary statistics of key variables utilized in this study.

Table 4- 4 Summary statistics of key variables

Variable	Abbr.	N	Mean	Std. dev.	Min	Max
Resilience index	RES	144	2.122	4.739	0.00	37.50
Internal network density	IND	144	2.812	1.277	1.250	5.288
Operational efficiency difference	OED	144	0.420	0.088	0.203	0.707
Structural hierarchy level	SHL	144	1.785	0.338	1.200	2.532
Maximal berthing size (000, TEU)	SIZE	144	89.193	11.083	66.518	111.593
GDP per capita (000, RMB)	GDP	144	105.95	22.341	63.533	131.041
Road network density (km/km2)	RND	144	1.379	0.207	1.058	1.725
Country-level network density	CND	144	1.147	0.203	0.622	1.556
Average efficiency consistency	AED	144	0.350	0.060	0.215	0.522

4.5 Results and Discussion

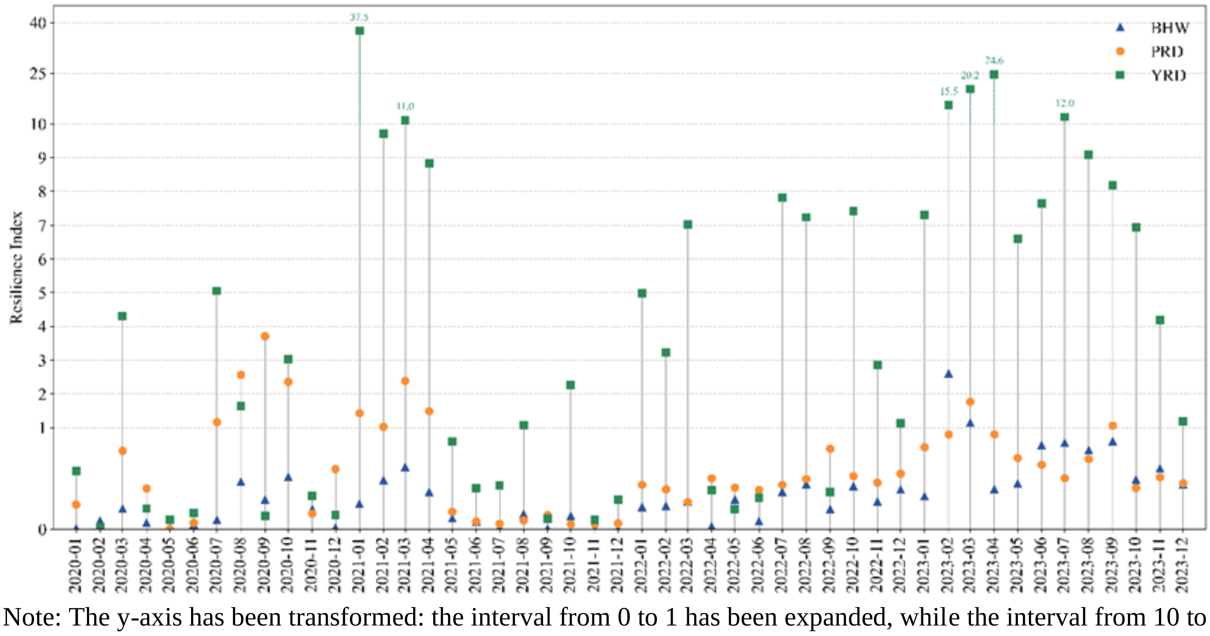
This section reports the resilience assessment outcomes for the port clusters in YRD, PRD, and BR from January 2020 to December 2023. The empirical results from our regression models are also presented and discussed in this section.

4.5.1 Resilience index

This study assesses the monthly resilience performance of the BR, PRD, and YRD port clusters following the outbreak of COVID-19. Figure 4-7 displays the resilience index for these clusters over the study period.

The result indicates that the three clusters exhibited similar patterns, facing significant challenges at the onset of the pandemic in early 2020. The resilience levels fluctuated due to the appearance of various COVID-19 variants, differing containment and mitigation strategies, and shifts in maritime trade dynamics. Despite these challenges, notable improvements in resilience were observed in these port clusters starting in early 2023. This observation aligns with the research by Gu et al. (2024), which found strong correlation between the resilience indices of ports and the impacts of the pandemic.

Among the three port clusters evaluated, the YRD port cluster displayed a higher level of resilience. In 30 of the 48 months, the decline in ship calls at affected ports in YRD port clusters was effectively offset by outstanding performances at other ports in the same port clusters, maintaining a resilience index consistently above 1. The PRD port cluster also exhibited robustness activities. After June 2020, numerous ports within this cluster managed to restart operations, returning to their foundational levels, and consequently, the overall functionality of the cluster saw a gradual improvement. Conversely, the BR port cluster exhibited less robust recovery dynamics post-pandemic compared to its pre-pandemic performance, leading to an overall tepid performance.



Note: The y-axis has been transformed: the interval from 0 to 1 has been expanded, while the interval from 10 to 40 has been compressed. Data points exceeding 10 are displayed with their values.

Figure 4-7 Resilience performance of BR, PRD and YRD port clusters from Jan 2020 to Dec 2023

4.5.2 Regression result

Our regression analysis reveals a significant positive correlation between the resilience of port clusters and their internal network density. In contrast, there is a negative correlation between the resilience of port clusters and the operational efficiency differences among the ports within these clusters. Furthermore, the structural hierarchy level of the port cluster shows a negative correlation with the resilience index, although this result is not statistically significant. Table 4-5 presents our regression results in Ordinary Least Squares (OLS) estimates.

The coefficient for internal network density is 3.276 in column (1) and significant at the 1% level, suggesting that port clusters with denser internal connections through ship flows are more resilient. The robustness of this finding concerning internal network density is further validated by the results in columns (2) and (3), which consider additional factors that may affect port cluster resilience. This finding aligns with that of Li et al. (2024), which emphasizes the critical role of vessel flexibility and adaptability in reducing the effects of disruptions on the resilience of port clusters.

The positive coefficient for internal connectivity reveals that a dense internal shipping network is not merely an operational feature but a critical strategy for bolstering a port cluster's resilience. In a port cluster with a strong internal ship flow network, even if some ports experience severe disruptions from external shocks, the dense network facilitates the quick reconfiguration of resources and rerouting of ship traffic, thereby allowing the cluster to maintain service continuity and absorb disruptions effectively. Our analysis of the PRD cluster, which demonstrated relatively resilient performance during the observed shocks, provides evidence for this result. The PRD features a remarkably dense network, averaging 4 to 5 vessel movements monthly between any given pair of its ports. This result implies that policymakers can invest in these internal links through infrastructure and policy for building regional resilience. For shipping companies, this internal connectivity can be used as a key metric in risk assessment and port selection when needed alternatives for rerouting ships and cargo.

However, our analysis reveals that operational efficiency differences among ports and the hierarchy level of the port cluster are negatively correlated with the resilience of the cluster. Specifically, the coefficient for operational efficiency differences is -0.688 and is statistically significant at the 5% level. Although the coefficient for hierarchy level is not statistically significant, its negative value (-0.876) implies that the port cluster with a more centralized configuration tends to have lower resilience.

Our analysis reveals that the significant gaps in efficiency and scale between member ports contribute to a vulnerable system where the failure of a major hub cannot be easily compensated for internally. Our comparative analysis of China's major port clusters provides empirical support. The PRD and YRD port clusters demonstrate higher resilience as they constitute a more balanced system. The YRD integrates world-class hubs like Shanghai and Ningbo-Zhoushan with a deep network of capable secondary ports (e.g., Suzhou, Jiaxing), while the PRD is anchored by a trio of global hubs (Hong Kong, Guangzhou, Shenzhen) supported by strong feeders (e.g., Dongguan, Foshan, Zhuhai). However, the BR port cluster is more vulnerable due to its port members' variations. While it contains international hubs like Qingdao, Tianjin, and Dalian, its resilience is undermined by a long tail of small feeder ports (e.g., Huludao, Jinzhou, Panjin) that lack efficient container handling ability and global connectivity to act as effective substitutes. This finding yields an insight into port governance and regional policy: resilience is not determined by the strength of the strongest port, but by the capability of the alternatives. Therefore, the development of port clusters should not only focus on the growth of hubs but also upgrade the baseline capabilities of smaller ports, transforming them from simple feeders into reliable backup options.

Table 4-5 Determinants on the resilience of port cluster

	(1)	(2)	(3)
Variable	**ln (RES+1)**	**ln (RES+1)**	**ln (RES+1)**
ln (IND)	3.276***	3.420***	3.315***
	(0.637)	(0.621)	(0.632)
ln (OED)		-0.688**	-0.660**
		(0.271)	(0.273)
ln (SHL)			-0.876
			(0.952)
ln (SIZE)	1.520**	1.470**	1.344**
	(0.674)	(0.655)	(0.670)
ln (GDP)	-0.158	0.083	0.032
	(0.381)	(0.382)	(0.386)
Constant	-19.803**	-20.387***	-18.279**
	(7.935)	(7.711)	(8.050)
Observations	144	144	144
R square	0.279	0.327	0.333
F	11.730	10.937	8.904

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

4.5.3 IV regression result

Table 4-6 presents the results of the instrumental variable regression analysis. The model convincingly passes both the Wald F statistic and the Kleibergen–Paap rk LM statistic, confirming that the instruments used are strong and effectively identify the structural relationships within our model. Additionally, the Hansen J statistic test yields a p-value greater than 0.1, suggesting the null hypothesis that all utilized instruments are valid. The empirical findings further reveal the significant relationships between the internal network density, the operational efficiency difference and the resilience of port clusters. Specifically, internal network density is positively associated with port cluster resilience, with an IV coefficient of 3.394 compared to the OLS coefficient of 3.315. This suggests that traditional OLS methods may underestimate the beneficial impact of internal network density due to unaccounted endogeneity. The IV estimate (-0.726) also indicates a stronger negative impact of differences in operational efficiency on port cluster resilience compared to the OLS estimate (-0.660). The comparison coefficients reveal that the OLS estimates are biased downwards for the coefficient of endogenous variables due to the potential reverse causality and measurement errors.

Table 4-6 2SLS regression results using IVs

	(1)			**(2)**
	2SLS			**OLS**
	1st Stage	**1st Stage**	**2nd Stage**	
Variable	**ln (IND)**	**ln (OED)**	**ln (RES+1)**	**ln (RES+1)**
ln (IND)			3.394***	3.315***
			(0.644)	(0.632)
ln (OED)			-0.726***	-0.660**
			(0.224)	(0.273)
IV: ln (RND)	1.110***	-0.644*		
	(0.373)	(0.368)		
IV: ln (CND)	-1.690***	0.015		
	(0.119)	(0.118)		
IV: ln (AED)	-0.018	-3.219***		
	(0.081)	(0.080)		
ln (SHL)	0.037	0.009	-0.834	-0.876
	(0.088)	(0.087)	(0.737)	(0.952)
Control Variables	YES	YES	YES	YES
Constant	2.720***	-3.346***	-17.702**	-18.279**
	(0.738)	(0.729)	(7.623)	(8.050)
Observations	144	144	144	144
R square	0.729	0.953	0.288	0.333
F	39.393	298.801	7.213	8.904
Kleibergen-Paap rk LM stat.			50.411	
Chi-sq(2) P-val.			0.000	
Cragg-Donald Wald F statistic			74.365	
Kleibergen-Paap rk Wald F stat.			74.834	
Hansen J stat.			1.797	
Chi-sq (1) P-val			0.180	

Note: Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The results of control variables are omitted for simplicity. The Kleibergen-Paap rk Wald F statistics (74.834) in our 2SLS model is larger than the Stock-Yogo weak ID critical value for 10% maximal IV size (13.43), rejecting the null hypothesis that the instruments are weak.

4.5.4 Robustness tests

To evaluate the robustness of the resilience index (RES) proposed in this study, we employed both the m Kendall’s tau-b and Spearman’s rho tests. These tests assess the rank correlation between our resilience index with other recognized metrics of port resilience, including the recovery-to-loss ratio (RLR) proposed by Henry and Ramirez-Marquez (2012), sensitivity index (SI) used by Xu, Yang, et al. (2024), and the loss performance during recovery index (LPR) mentioned by Gu et al. (2024). To ensure comparability, data utilized in these index calculations is the number of ship calls at ports.

The results of these correlation analyses are displayed in Table 4-7. High values in Kendall’s tau-b and Spearman’s rho indicate a strong correlation between the rankings derived from different methodologies. The correlation analyses show that our resilience index exhibits a moderate correlation with the sensitivity index, which assesses the port cluster's responsiveness to shocks compared to the global standard. Moreover, it can be found that our resilience index is highly consistent with other well-established port resilience metrics. These results indicate that our resilience index is relatively robust.

We also examined the relationships between the alternative resilience index with the internal features of port clusters. As shown in Table 4-8, the regression analyses using alternative dependent variables reveal that internal network density significantly and positively correlates with port cluster resilience. While the coefficients for operational efficiency differences and structural hierarchy levels were not statistically significant, the consistent coefficient signs of these two variables with our previous regression analysis suggest a robust relationship between these factors and port resilience.

Table 4-7 Correlation test results

		RES	RLR	SI	LPR
RES	tau-b	1.000			
	rho	1.000			
RLR	tau-b	0.755	1.000		
	rho	0.916	1.000		
SI	tau-b	0.287	0.304	1.000	
	rho	0.4155	0.4419	1.000	
LPR	tau-b	-0.524	-0.574	-0.161	1.000
	rho	-0.724	-0.752	-0.240	1.000

Note: The RLR is calculated as the ratio of the change from the port cluster's most disrupted state to its current performance, relative to the change from the most disrupted state to the port cluster's baseline performance. The SI is determined by comparing the ratio of current performance to the previous period performance of the region, relative to the same ratio on a global scale. The LRP is quantified as the ratio of the performance loss experienced during a disruption, to the peak performance level of the port cluster.

Table 4-8 Robust tests of the regressions

	(1)	(2)	(3)	(4)
Variable	**ln (RES+1)**	**ln (RLR+1)**	**ln (SI)**	**ln (LPR)**
ln (IND)	3.315***	0.807***	0.480***	-0.383***
	(0.632)	(0.098)	(0.049)	(0.038)
ln (OED)	-0.660**	-0.046*	-0.008	0.015
	(0.273)	(0.042)	(0.021)	(0.016)
ln (SHL)	-0.876	-0.020	-0.097	0.050
	(0.952)	(0.147)	(0.074)	(0.057)
ln (SIZE)	1.344**	0.212**	0.009	-0.017
	(0.670)	(0.104)	(0.052)	(0.040)
ln (GDP)	0.032	0.197***	0.069**	-0.065***
	(0.386)	(0.598)	(0.030)	(0.023)
Constant	-18.279**	-3.008**	-0.576	0.770
	(8.050)	(1.245)	(0.623)	(0.484)
Observations	144	144	144	144
R square	0.333	0.484	0.557	0.566
F	8.904	16.718	22.354	23.222

Note: Standard errors in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

4.6 Conclusion

Port clusters, characterized by regional concentration and collaborations in port-related activities, have become crucial organizational and strategic entities in the global maritime industry. However, the inherent vulnerabilities of port systems present considerable challenges, affecting not only local economies but also the broader international supply chain. This study analyzes the resilience performance of port clusters through the inter-port interaction perspective and delves into the internal mechanisms these clusters use to withstand and absorb external disturbances.

Employing a multi-source dataset, this research evaluates the monthly resilience performance of representative port clusters in China following the outbreak of COVID-19. The result reveals that the YRD port cluster exhibited proactive interactions among its ports through ship movements and maintained a relatively higher resilience level during the pandemic. Further empirical regression analysis indicates that port clusters with stronger internal connections, consistent operational efficiency, and balanced hierarchical structures tend to exhibit greater resilience to external shocks. These findings not only contribute to the understanding of port cluster dynamics but also highlight the critical role of strategic collaborations within the port cluster and the importance of port interactions in promoting sustainable development.

The significant influence of internal connectivity on resilience supports previous theoretical analysis, which argued that the interconnections among ports within a cluster enable them to bolster resilience by facilitating cooperation and providing alternative routing options to shipping companies (Li et al., 2022). These internal network connections via ship flows allow for flexible responses to disruptions, enabling the swift reallocation of resources and the rerouting of cargo flows. To maintain resilient operations across ports, it is vital for port managers and operators within a cluster to bolster their connectivity through various initiatives, such as formal agreements and cooperative frameworks. Moreover, the study underscores the importance of maintaining consistent, efficient service for ships. Ports that offer similar service levels and are geographically proximate can act as effective substitutes for shipping companies when specific ports experience disruptions. This substitutability ensures continuity in operations across port clusters and minimizes disruptions in the supply chain.

Our results reveal a tension in contemporary port development: the pursuit of individual port dominance directly versus the cultivation of collective network resilience. The conventional ‘champion hub’ strategy, while effective for boosting individual ports’ competitiveness, may bring systemic vulnerability by concentrating risk. This reality necessitates a paradigm shift in regional governance towards a polycentric model that prioritizes balanced capacity distribution. Regional policymakers need to balance port development and maintain a certain level of redundancy. On an operational level, our results suggest that neighbouring ports function within a co-opetitive framework, acting as both market rivals and partners in crisis. For port authorities and terminal operators, this duality means that long-term success hinges on establishing robust inter-port coordination and promoting flexible service arrangements for shipping companies.

Chapter 5. Conclusion and Future Work

5.1 Conclusions

This thesis concentrates on the efficiency of ports and the resilience of port clusters, taking into account the distinguished perspectives and significant impacts of ships in port operation. Using big data from ships, this thesis provides evaluation methods on ports' efficiency and port clusters' resilience performance. The empirical findings highlight the intricate relationships between ports and ships, indicating to port operators, managers, and related stakeholders the importance of considering ship activities in the analysis of port performance.

The first part of this thesis provides a comprehensive and systematic review of the literature on port efficiency. We found most studies focused on traditional port efficiencies (i.e., the technical, allocative and economic efficiency). Some extended these traditional types by considering ships' time in port and the negative environmental impacts. The majority of studies assessed port efficiency from the perspective of port authorities, managers, and operators. Few did it from the perspective of the users and the public. Even fewer noticed the possible conflicts between the port service level and its profitability. Frontier methods are popular in port efficiency evaluation, but publications extending or combining different methods are still very rare. By summarizing the relationship between the types and perspectives of the existing studies, this study identifies the need for port efficiency analysis from the perspective of different stakeholders, especially the shippers, carriers and the public.

The second study of this thesis evaluated the efficiency of global top 80 container ports with the consideration of the diverse perspectives of port operators and users and the heterogeneity of ports. Considering the different interests of port operators and shipping companies in port, we incorporate relevant variables for the two stakeholders and compare the port efficiencies evaluated from the two perspectives. To address the port heterogenous, we divided the world's top 80 container ports into homogenous groups and employed the meta-frontier DEA method to assess their efficiency. The analysis reveals the disparities in port efficiency among different stakeholders and across different port sizes. Among the 80 container ports, only 4 achieved dual efficiency, while 17 were identified as one-sided frontier ports. Large ports demonstrate relatively consistent efficient performance from both perspectives, benefiting from economies of scale and efficient service delivery. In contrast, small and middle-size ports show inconsistent or even opposing efficiency performance when evaluated by port operators and shipping companies, with many exhibiting low levels of resource utilization or service delivery.

The third study analyzes the resilience performance of port clusters through the lens of port interactions. We first measure the resilience of port clusters by analyzing how well member ports can substitute for one another in handling ship calls during a disruption. Subsequently, we examine how the port cluster's internal features, including its internal connectivity, operational efficiency differences, and structural hierarchy level, affect its resilience using econometric tools. Using a multi-source dataset that incorporates AIS data, we conducted case studies focusing on the resilience of Chinese port clusters during the COVID-19 pandemic. The results reveal that dense internal connectivity via ship flows is positively correlated with cluster resilience. Conversely, resilience is diminished in clusters with significant efficiency disparities or a pronounced hierarchical structure reliant on a few core ports. This study suggests that systemic port cluster resilience is a function of inter-port interactions, not just a summation of individual port capacities.

The aforementioned studies suggest that ships are not only direct recipients but also contributors to port performance. Ship operators and shipping companies may have differing opinions on port performance compared to those of port operators and managers. The efficient port for port operators may not be efficient for ships. Additionally, the activities of ships can contribute to port interactions, thereby impacting collaboration among ports and performance of regional port clusters. It is crucial for port operators, managers, and policymakers to emphasize services to ships and strengthen relationships with shipping companies to enhance overall port performance.

5.2 Contributions

This thesis contributes to the research on port performance in several ways.

Firstly, this thesis incorporates perspectives and insights from ships in port performance evaluation, moving beyond the traditional practice of assessing port performance solely through data and perspectives provided by port operators and managers. The first part of this thesis novelty classified the existing studies on port efficiency by the types of efficiency, and their link with the perspectives. Emphasizing the interests of users and the environmental impacts of port operation, this study provides a multi-dimensional and sustainable view for port operators, managers, policymakers, and related stakeholders in assessing port efficiency and enhancing port competitiveness. The second part of the thesis presents a dual-perspective efficiency assessment of global ports and examines whether the views on port efficiency held by port operators align with those of shipping companies. By employing variables relevant to both port operators and shipping companies in frontier models, the study demonstrates that ports deemed efficient by operators may not necessarily be viewed as efficient by shipping companies. The third part of this thesis advances the understanding of port system resilience by shifting the analytical unit from the individual port to the interconnected cluster. It is one of the few studies that examine port clusters' resilience considering interactions among ports. The empirical results reveal the critical role of port internal connections through ship flows in the resilience performance of port clusters. These analyses highlight the importance of ships in port operations and port interactions in port clusters.

Secondly, this thesis introduces the application of big data in port performance evaluation, bridging traditional approaches to port performance evaluation with innovative data-driven methods. The first part of this thesis reviews the application of big data in port efficiency analysis, highlighting both its benefits and limitations, and suggests directions for future research in this area. The second part of this thesis used port data and ship data extracted from the latest automatic identification system (AIS) data, showcasing an example of how big data can be applied to port efficiency analysis using frontier models. The third part of this thesis adopts a multi-source dataset for empirically investigating these complex port dynamics. By using fine-grained AIS data with other sources, we demonstrate how newly emerged big data can be leveraged for empirical analysis of port cluster. These applications are intended to draw greater attention to the potential of emerging big data technologies in maritime studies.

Thirdly, this thesis empirically evaluates the port performances and explores the underlying reasons, offering the basis for port stakeholders to enhance performance and respond effectively to dynamic challenges in the maritime sector. The second part of the thesis assesses the efficiencies of the top 80 global container ports in 2022 from the viewpoints of port operators and shipping companies. The findings offer a foundation for port operators and managers to tailor strategies according to their unique characteristics and outline improvement pathways for less efficient ports. The third part evaluates the monthly resilience of three representative port clusters in China following the COVID-19 outbreak and explores how the resilience of these port clusters correlates with their internal features. The results show that port clusters with denser internal networks through ship flows, more consistent efficiency, and a more balanced structure exhibit greater resilience to external disturbances. These insights provide a basis for stakeholders to evaluate and enhance port performance through strategic adjustments.

5.3 Limitations and Future Studies

This thesis aims to deepen understanding and improve the evaluation of port performance by integrating the perspectives and impacts of ships, with a particular focus on two crucial dimensions: efficiency and resilience. It comprises three studies, each of which, despite substantial effort, has certain limitations. Future research should address these limitations and further enhance the analysis of port performance.

The first study reviews the studies on port efficiency. However, port performance is a closely related concept with broader implications than efficiency alone. Future research could expand the scope to include comprehensive studies on port performance. Furthermore, despite employing a scientific and systematic review process, there is still a possibility of selection bias or omissions. The focus of this paper was primarily on the cargo-handling efficiency of the port, leaving out studies on other aspects such as inland transportation. Future research could broaden the scope of port efficiency analysis to include land-side operations by incorporating a wider range of keywords. Additionally, this review may not encompass every nuanced aspect of port efficiency. It concentrated on types of efficiency, analysis perspectives, and evaluation techniques. The critical factors influencing efficiency, which are vital for providing valuable insights to policymakers and operators, were not exhaustively examined. Future studies could delve deeper into these areas for a more comprehensive analysis.

The second study used the estimated container movements as the output to evaluate the efficiency from the shipping companies' perspective. This estimated data may neglect the variations in the container movements for each ship size calling different ports. However, this is a feasible estimation when actual container movement data is unavailable. Future research could benefit from incorporating actual container movement data or employing advanced estimation techniques to produce more nuanced efficiency assessments. Moreover, this study is limited by its reliance on a static dataset. A time-series analysis using more years of data can help to identify the trends and shifts in port efficiency due to significant events, such as the COVID-19 pandemic. Future studies could focus on developing standardized data collection methods or integrating additional data sources to facilitate a robust time-series analysis. Additionally, this study focused on the ports with certain container throughputs and ship calls. Small ports and developing ports that fall outside the top 80 in global rankings were not included. Future research could broaden the scope to encompass all ports worldwide, thereby allowing for a comprehensive assessment of their efficiencies and heterogeneities.

For the resilience analysis of port clusters, the third study focuses on the container ports and associated container ship activities within the cluster. Future research could broaden this study and consider different types of ports and their complex relationships within the clusters. Besides, the focus on Chinese port clusters may not fully capture the resilience dynamics of port clusters in other regions. Future studies can conduct large-scale, multi-regional comparative studies and use long-term panel data to better understand the resilience dynamics of port system.

REFERENCES

Amin, C., Mulyati, H., Anggraini, E., & Kusumastanto, T. (2021). Impact of maritime logistics on archipelagic economic development in eastern Indonesia. *Asian Journal of Shipping and Logistics*, *37*(2), 157-164. https://doi.org/10.1016/j.ajsl.2021.01.004

Arvis, J.-F., Vesin, V., Carruthers, R., & Ducruet, C. (2018). *Maritime networks, port efficiency, and hinterland connectivity in the Mediterranean*. World Bank Publications.

Asadabadi, A., & Miller-Hooks, E. (2020). Maritime port network resiliency and reliability through co-opetition. *Transportation Research Part E: Logistics and Transportation Review*, *137*, 101916.

Ashley, G., Guillot, D., Lane, A., Humphreys, R. M., & Mooney, T. (2022). Container port performance assessment: a nonnegative matrix factorization approach. *Maritime Economics and Logistics*. https://doi.org/10.1057/s41278-022-00248-4

Bai, X., & Lam, J. S. L. (2015). Dynamic regional port cluster development: case of the ports across Taiwan Strait. *GeoJournal*, *80*, 619-636.

Bai, X., Ma, Z., & Zhou, Y. (2023). Data-driven static and dynamic resilience assessment of the global liner shipping network. *Transportation Research Part E: Logistics and Transportation Review*, *170*, 103016.

Balić, K., Žgaljić, D., Ukić Boljat, H., & Slišković, M. (2022). The port system in addressing sustainability issues—a systematic review of research. *Journal of Marine Science and Engineering*, *10*(8), 1048.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, *30*(9), 1078-1092.

Banos-Pino, J., Coto-Millan, P., & Rodriguez-Alvarez, A. (1999). Allocative efficiency and over-capitalization: An application. *International Journal of Transport Economics*, *26*(2), 181-199.

Barros, C. P. (2003). Incentive regulation and efficiency of Portuguese Port authorities. *Maritime Economics and Logistics*, *5*(1), 55-69. https://doi.org/10.1057/palgrave.mel.9100060

Barros, C. P. (2006). A Benchmark Analysis of Italian Seaports Using Data Envelopment Analysis. *Maritime Economics and Logistics*, *8*(4), 347-365. https://doi.org/10.1057/palgrave.mel.9100163

Barros, C. P., & Athanassiou, M. (2004). Efficiency in European seaports with DEA: Evidence from Greece and Portugal. *Maritime Economics and Logistics*, *6*(2), 122-140. https://doi.org/10.1057/palgrave.mel.9100099

Baştuğ, S., Haralambides, H., Esmer, S., & Eminoğlu, E. (2022). Port competitiveness: Do container terminal operators and liner shipping companies see eye to eye? *Marine Policy*, *135*, 104866.

Battese, G. E., & Rao, D. P. (2002). Technology gap, efficiency, and a stochastic metafrontier function. *international Journal of Business and Economics*, *1*(2), 87.

Battese, G. E., Rao, D. P., & O'donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis*, *21*, 91-103.

Beuren, M. M., Andriotti, R., Vieira, G. B. B., Ribeiro, J. L. D., & Neto, F. J. K. (2018). On measuring the efficiency of Brazilian ports and their management models oa. *Maritime Economics and Logistics*, *20*(1), 149-168. https://doi.org/10.1057/mel.2016.15

Bichou, K. (2011). A two-stage supply chain DEA model for measuring container-terminal efficiency. *International Journal of Shipping and Transport Logistics*, *3*(1), 6-26. https://doi.org/10.1504/IJSTL.2011.037817

Bray, S., Caggiani, L., & Ottomanelli, M. (2015). Measuring Transport Systems Efficiency Under Uncertainty by Fuzzy Sets Theory Based Data Envelopment Analysis: Theoretical and Practical Comparison with Traditional DEA Model. *Transportation Research Procedia*, *5*, 186-200. https://doi.org/https://doi.org/10.1016/j.trpro.2015.01.005

Brooks, M. R., & Schellinck, T. (2013). Measuring port effectiveness in user service delivery: What really determines users' evaluations of port service delivery? *Research in Transportation Business and Management*, *8*, 87-96. https://doi.org/10.1016/j.rtbm.2013.04.001

Brooks, M. R., & Schellinck, T. (2015). Measuring port effectiveness: what really determines cargo interests' evaluations of port service delivery? *Maritime Policy and Management*, *42*(7), 699-711. https://doi.org/10.1080/03088839.2015.1077282

Brown, C. E. (1998). Coefficient of variation. In *Applied multivariate statistics in geohydrology and related sciences* (pp. 155-157). Springer.

Chang, S. E. (2000). Disasters and transport systems: loss, recovery and competition at the Port of Kobe after the 1995 earthquake. *Journal of Transport Geography*, *8*(1), 53-65.

Chang, V., & Tovar, B. (2022). Efficiency drivers for the South Pacific West coast port terminals: a two-stage non-convex metafrontier dea approach. *Operational Research*, *22*(3), 2667-2701. https://doi.org/10.1007/s12351-021-00626-5

Chang, W., Li, N., & Zhao, Y. (2024). Resilience of regional container port network: based on projection correlation and dynamic spatial Markov Chain. *Maritime Policy & Management*, 1-17.

Chang, Y.-T., Park, H., Lee, S., & Kim, E. (2018). Have Emission Control Areas (ECAs) harmed port efficiency in Europe? *Transportation Research Part D: Transport and Environment*, *58*, 39-53. https://doi.org/https://doi.org/10.1016/j.trd.2017.10.018

Chang, Y.-T., & Talley, W. K. (2019). Port competitiveness, efficiency, and supply chains: a literature review. *Transportation Journal*, *58*(1), 1-20.

Chang, Y. T. (2013). Environmental efficiency of ports: A Data Envelopment Analysis approach. *Maritime Policy and Management*, *40*(5), 467-478. https://doi.org/10.1080/03088839.2013.797119

Charisis, A., Manta, S., Kaisar, E. I., & Al-Ghandour, M. (2019). Estimation of container port efficiency using data envelopment analysis and free disposal hull approaches: The case of the caribbean. International Conference on Transportation and Development 2019: Smarter and Safer Mobility and Cities, ICTD 2019,

Charnes, A., Cooper, W. W., Golany, B., Seiford, L., & Stutz, J. (1985). Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. *Journal of econometrics*, *30*(1-2), 91-107.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429-444.

Chen, H., Cullinane, K., & Liu, N. (2017). Developing a model for measuring the resilience of a port-hinterland container transportation network. *Transportation Research Part E: Logistics and Transportation Review*, *97*, 282-301.

Chen, J., Liu, X., Zhou, S., & Kang, J. (2023). Knowledge mapping analysis of resilient shipping network using CiteSpace. *Ocean & Coastal Management*, *244*, 106775.

Chen, J., Zhang, X., Xu, L., & Xu, J. (2024). Trends of digitalization, intelligence and greening of global shipping industry based on CiteSpace Knowledge Graph. *Ocean & Coastal Management*, *255*, 107206.

Chen, W., Chen, J., Geng, J., Ye, J., Yan, T., Shi, J., & Xu, J. (2023). Monitoring and evaluation of ship operation congestion status at container ports based on AIS data. *Ocean & Coastal Management*, *245*, 106836.

Chen, Y., Yang, D., Lian, P., Wan, Z., & Yang, Y. (2020). Will structure-environment-fit result in better port performance? —An empirical test on the validity of Matching Framework Theory. *Transport Policy*, *86*, 23-33. https://doi.org/https://doi.org/10.1016/j.tranpol.2019.12.003

Cheon, S. (2009). Impact of global terminal operators on port efficiency: A tiered data envelopment analysis approach. *International Journal of Logistics Research and Applications*, *12*(2), 85-101. https://doi.org/10.1080/13675560902749324

Cheon, S., Dowall, D. E., & Song, D.-W. (2010). Evaluating impacts of institutional reforms on port efficiency changes: Ownership, corporate structure, and total factor productivity changes of world container ports. *Transportation Research Part E: Logistics and Transportation Review*, *46*(4), 546-561.

Cheon, S., Dowall, D. E., & Song, D. W. (2010). Evaluating impacts of institutional reforms on port efficiency changes: Ownership, corporate structure, and total factor productivity changes of world container ports. *Transportation Research Part E: Logistics and Transportation Review*, *46*(4), 546-561. https://doi.org/10.1016/j.tre.2009.04.001

Chin, A. T. H., & Low, J. M. W. (2010). Port performance in Asia: Does production efficiency imply environmental efficiency? *Transportation Research Part D: Transport and Environment*, *15*(8), 483-488. https://doi.org/10.1016/j.trd.2010.06.003

Cochrane, R. A. (2008). The effects of market differences on the throughput of large container terminals with similar levels of efficiency. *Maritime Economics and Logistics*, *10*(1-2), 35-52. https://doi.org/10.1057/palgrave.mel.9100190

Cohen, J., & Monaco, K. (2008). Ports and highways infrastructure: An analysis of intra-and interstate spillovers. *International Regional Science Review*, *31*(3), 257-274.

Cohen, J. P. (2010). The broader effects of transportation infrastructure: Spatial econometrics and productivity approaches. *Transportation Research Part E: Logistics and Transportation Review*, *46*(3), 317-326.

Cooper, W. W., Seiford, L. M., & Zhu, J. (2011). Handbook on data envelopment analysis.

Coto-Millán, P., Baños-Pino, J., & Rodríguez-Álvarez, A. (2000). Economic efficiency in Spanish ports: Some empirical evidence. *Maritime Policy and Management*, *27*(2), 169-174. https://doi.org/10.1080/030888300286581

Crespo, J., Suire, R., & Vicente, J. (2014). Lock-in or lock-out? How structural properties of knowledge networks affect regional resilience. *Journal of Economic Geography*, *14*(1), 199-219.

Cui, Q. (2017). Environmental efficiency measures for ports: an application of RAM-Tobit-RAM with undesirable outputs. *Maritime Policy and Management*, *44*(5), 551-564. https://doi.org/10.1080/03088839.2017.1319982

Cullinane, K., & Haralambides, H. (2021). Global trends in maritime and port economics: the COVID-19 pandemic and beyond. *Maritime Economics & Logistics*, *23*(3), 369.

Cullinane, K., & Song, D. W. (2006). Estimating the Relative Efficiency of European Container Ports: A Stochastic Frontier Analysis. *Research in Transportation Economics*, *16*, 85-115. https://doi.org/https://doi.org/10.1016/S0739-8859(06)16005-9

Cullinane, K., Song, D. W., Ji, P., & Wang, T. F. (2004). An application of DEA windows analysis to container port production efficiency. *Review of network Economics*, *3*(2).

Cullinane, K., Song, D. W., & Wang, T. F. (2005). The application of mathematical programming approaches to estimating container port production efficiency. *Journal of Productivity Analysis*, *24*(1), 73-92. https://doi.org/10.1007/s11123-005-3041-9

Cullinane, K., & Wang, T. F. (2006). Chapter 23 Data Envelopment Analysis (DEA) and Improving Container Port Efficiency. *Research in Transportation Economics*, *17*, 517-566. https://doi.org/https://doi.org/10.1016/S0739-8859(06)17023-7

Cullinane, K., Wang, T. F., Song, D. W., & Ji, P. (2006). The technical efficiency of container ports: Comparing data envelopment analysis and stochastic frontier analysis. *Transportation Research Part A: Policy and Practice*, *40*(4), 354-374. https://doi.org/10.1016/j.tra.2005.07.003

de Andrade, R. M., Lee, S., Lee, P. T. W., Kwon, O. K., & Chung, H. M. (2019). Port efficiency incorporating service measurement variables by the BiO-MCDEA: Brazilian case. *Sustainability (Switzerland)*, *11*(16), Article 4340. https://doi.org/10.3390/su11164340

De Langen, P. W., & Visser, E.-J. (2005). Collective action regimes in seaport clusters: the case of the Lower Mississippi port cluster. *Journal of Transport Geography*, *13*(2), 173-186.

Dowd, T. J., & Leschine, T. M. (1990). Container terminal productivity: a perspective. *Maritime Policy and Management*, *17*(2), 107-112.

Ducruet, C. (2020). The geography of maritime networks: A critical review. *Journal of Transport Geography*, *88*, 102824.

Ducruet, C., Itoh, H., & Merk, O. (2014). *Time efficiency at world container ports* International Transport Forum, Paris.

Fan, L., & Xie, J. (2023). Identify determinants of container ship size investment choice. *Maritime Policy & Management*, *50*(2), 219-234.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, *120*(3), 253-281.

Feng, H., Lin, Q., Zhang, X., Lam, J. S. L., & Yap, W. Y. (2024). Port selection by container ships: A big AIS data analytics approach. *Research in Transportation Business & Management*, *52*, 101066.

Feng, M., Shaw, S. L., Peng, G., & Fang, Z. (2020). Time efficiency assessment of ship movements in maritime ports: A case study of two ports based on AIS data. *Journal of Transport Geography*, *86*, 102741. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2020.102741

Fernández, X. L., Hidalgo-Gallego, S., Pérez-Urbaneja, S., & Coto-Millán, P. (2021). When container specialisation makes a difference: an efficiency analysis of the Spanish port authorities. *Maritime Policy and Management*, *48*(5), 629-650. https://doi.org/10.1080/03088839.2021.1903596

Fisman, R., & Svensson, J. (2007). Are corruption and taxation really harmful to growth? Firm level evidence. *Journal of development economics*, *83*(1), 63-75.

Folkman, D., Gharehgozli, A., Mileski, J., & Galvao, C. B. (2021). Port resiliency and the effects of hurricanes on port operations. *International Journal of Advanced Operations Management*, *13*(4), 409-430.

Ganguly, A. R., Bhatia, U., & Flynn, S. E. (2018). *Critical infrastructures resilience: Policy and engineering principles*. Routledge.

Ghiara, H., & Tei, A. (2021). Port activity and technical efficiency: determinants and external factors. *Maritime Policy and Management*, *48*(5), 711-724. https://doi.org/10.1080/03088839.2021.1872807

Gianfranco, F., Claudia, P., Patrizia, S., & Paolo, F. (2014). Port cooperation policies in the Mediterranean Basin: An experimental approach using cluster analysis. *Transportation Research Procedia*, *3*, 700-709.

Gonçalves, L., & Ribeiro, P. (2020). Resilience of urban transportation systems. Concept, characteristics, and methods. *Journal of Transport Geography*, *85*, 102727.

Gong, X., Wu, X., & Luo, M. (2019). Company performance and environmental efficiency: A case study for shipping enterprises. *Transport Policy*, *82*, 96-106.

González, M. M., & Trujillo, L. (2008). Reforms and infrastructure efficiency in Spain's container ports. *Transportation Research Part A: Policy and Practice*, *42*(1), 243-257. https://doi.org/10.1016/j.tra.2007.08.006

Gu, B., & Liu, J. (2023). Port resilience analysis based on the HHM-FCM approach under COVID-19. *Ocean & Coastal Management*, *243*, 106741.

Gu, B., Liu, J., Ye, X., Gong, Y., & Chen, J. (2024). Data-driven approach for port resilience evaluation. *Transportation Research Part E: Logistics and Transportation Review*, *186*, 103570.

Gu, Y., Fu, X., Liu, Z., Xu, X., & Chen, A. (2020). Performance of transportation network under perturbations: Reliability, vulnerability, and resilience. *Transportation Research Part E: Logistics and Transportation Review*, *133*, 101809.

Guo, L., Ng, A. K., Jiang, C., & Long, J. (2021). Stepwise capacity integration in port cluster under uncertainty and congestion. *Transport Policy*, *112*, 94-113.

Haezendonck, E., & Langenus, M. (2019). Integrated ports clusters and competitive advantage in an extended resource pool for the Antwerp Seaport. *Maritime Policy & Management*, *46*(1), 74-91.

Haugstetter, H., & Cahoon, S. (2010). Strategic intent: Guiding port authorities to their new world? *Research in Transportation Economics*, *27*(1), 30-36.

Henry, D., & Ramirez-Marquez, J. E. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. *Reliability Engineering & System Safety*, *99*, 114-122.

Holling, C. S. (1973). Resilience and stability of ecological systems.

Hossain, N. U. I., Nur, F., Hosseini, S., Jaradat, R., Marufuzzaman, M., & Puryear, S. M. (2019). A Bayesian network based approach for modeling and assessing resilience: A case study of a full service deep water port. *Reliability Engineering & System Safety*, *189*, 378-396.

Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety*, *145*, 47-61.

Huang, T., Chen, Z., Wang, S., & Jiang, D. (2021). Efficiency evaluation of key ports along the 21st-Century Maritime Silk Road based on the DEA–SCOR model. *Maritime Policy and Management*, *48*(3), 378-390. https://doi.org/10.1080/03088839.2020.1773558

Huang, X., Wang, Y., Dai, X., Luo, J. X., & Chen, J. (2020). Evaluation of port efficiency in Shanghai port and Busan port based on three-stage dea model with environmental concerns. *Transport*, *35*(5), 454-461. https://doi.org/10.3846/transport.2019.11465

Hung, S. W., Lu, W. M., & Wang, T. P. (2010). Benchmarking the operating efficiency of Asia container ports. *European Journal of Operational Research*, *203*(3), 706-713. https://doi.org/10.1016/j.ejor.2009.09.005

Jeh, J., Nam, J., Sim, M., Kim, Y., & Shin, Y. (2022). A Study on the Efficiency Analysis of Global Terminal Operators Based on the Operation Characteristics. *Sustainability (Switzerland)*, *14*(1), Article 536. https://doi.org/10.3390/su14010536

Jiang, L., Wang, G., Feng, X., Yu, T., & Lei, Z. (2024). Study on cascading failure vulnerability of the 21st-century Maritime Silk Road container shipping network. *Journal of Transport Geography*, *117*, 103891.

Jiannan, C., & Zhongzhen, Y. (2020). Impacts of the choice habits of port users on the effects and efficiencies of port investment. *Transport Policy*, *99*, 203-214.

John, A., Yang, Z., Riahi, R., & Wang, J. (2016). A risk assessment approach to improve the resilience of a seaport system using Bayesian networks. *Ocean Engineering*, *111*, 136-147.

Johnson, H., & Styhre, L. (2015). Increased energy efficiency in short sea shipping through decreased time in port. *Transportation Research Part A: Policy and Practice*, *71*, 167-178.

Ju, S. M., & Liu, N. (2015). Efficiency and its influencing factors in port enterprises: empirical evidence from Chinese port-listed companies. *Maritime Policy and Management*, *42*(6), 571-590. https://doi.org/10.1080/03088839.2014.996621

Justice, V., Bhaskar, P., Pateman, H., Cain, P., & Cahoon, S. (2016). US container port resilience in a complex and dynamic world. *Maritime Policy & Management*, *43*(2), 179-191.

Kamble, S. S., Raoot, A. D., & Khanapuri, V. B. (2010). Improving port efficiency: A comparative study of selected ports in India. *International Journal of Shipping and Transport Logistics*, *2*(4), 444-470. https://doi.org/10.1504/IJSTL.2010.035504

Krmac, E., & Mansouri Kaleibar, M. (2022). A comprehensive review of data envelopment analysis (DEA) methodology in port efficiency evaluation. *Maritime Economics and Logistics*. https://doi.org/10.1057/s41278-022-00239-5

Lau, Y.-y., Chen, Q., Poo, M. C.-P., Ng, A. K., & Ying, C. C. (2024). Maritime transport resilience: A systematic literature review on the current state of the art, research agenda and future research directions. *Ocean & Coastal Management*, *251*, 107086.

Laxe, F. G., Bermúdez, F. M., & Prado Domínguez, A. J. (2021). Are Spanish ports efficient and profitable? A quantitative analysis. *Utilities Policy*, *70*, 101195. https://doi.org/https://doi.org/10.1016/j.jup.2021.101195

Le, P. T., & Nguyen, H. O. (2020). Influence of policy, operational and market conditions on seaport efficiency in newly emerging economies: the case of Vietnam. *Applied Economics*, *52*(43), 4698-4710. https://doi.org/10.1080/00036846.2020.1740159

Lee, T., Yeo, G. T., & Thai, V. V. (2014). Environmental efficiency analysis of port cities: Slacks-based measure data envelopment analysis approach. *Transport Policy*, *33*, 82-88. https://doi.org/10.1016/j.tranpol.2014.02.009

León-Mateos, F., Sartal, A., López-Manuel, L., & Quintás, M. A. (2021). Adapting our sea ports to the challenges of climate change: Development and validation of a Port Resilience Index. *Marine Policy, 130*, 104573.

Li, C., Yang, X., & Yang, D. (2025). Port vulnerability to natural disasters: An integrated view from hinterland to seaside. *Transportation Research Part D: Transport and Environment*, *139*, 104563.

Li, D., Xin, X., & Zhou, S. (2023). Integrated governance of the Yangtze River Delta port cluster using niche theory: A case study of Shanghai Port and Ningbo-Zhoushan Port. *Ocean & Coastal Management*, *234*, 106474.

Li, L., Wei, C., Liu, J., Chen, J., & Yuan, H. (2024). Assessing port cluster resilience: Integrating hypergraph-based modeling and agent-based simulation. *Transportation Research Part D: Transport and Environment*, *136*, 104459.

Li, W., Asadabadi, A., & Miller-Hooks, E. (2022). Enhancing resilience through port coalitions in maritime freight networks. *Transportation Research Part A: Policy and Practice*, *157*, 1-23.

Li, Y., Li, J., Gong, Y., Wei, F., & Huang, Q. (2020). CO2 emission performance evaluation of Chinese port enterprises: A modified meta-frontier non-radial directional distance function approach. *Transportation Research Part D: Transport and Environment*, *89*, 102605.

Lim, S.-M. (1994). Economies of container ship size: a new evaluation. *Maritime Policy and Management*, *21*(2), 149-160.

Lin, L. C., & Tseng, C. C. (2007). Operational performance evaluation of major container ports in the Asia-Pacific region. *Maritime Policy and Management*, *34*(6), 535-551. https://doi.org/10.1080/03088830701695248

Liu, C. C. (2008). Evaluating the operational efficiency of major ports in the Asia-Pacific region using data envelopment analysis. *Applied Economics*, *40*(13), 1737-1743. https://doi.org/10.1080/00036840600905126

Liu, J., Qi, Y., & Lyu, W. (2023). Port resilience in the post-COVID-19 era. *Ocean & Coastal Management*, *238*, 106565.

Liu, J., Wang, X., & Guo, J. (2021). Port efficiency and its influencing factors in the context of Pilot Free Trade Zones. *Transport Policy*, *105*, 67-79. https://doi.org/10.1016/j.tranpol.2021.02.011

Liu, Q., Yang, Y., Ng, A. K., & Jiang, C. (2023). An analysis on the resilience of the European port network. *Transportation Research Part A: Policy and Practice*, *175*, 103778.

Lloyd's List. (2023). *One Hundred Ports 2023* (R. Meade, Ed.). Informa UK Ltd. https://lloydslist-com.ezproxy.lb.polyu.edu.hk/one-hundred-container-ports-2023

Lovell, C. K. (1993). Production frontiers and productive efficiency. *The measurement of productive efficiency: techniques and applications*, *3*, 67.

Low, J. M. W. (2010). Capacity investment and efficiency cost estimations in major East Asian ports. *Maritime Economics and Logistics*, *12*(4), 370-391. https://doi.org/10.1057/mel.2010.13

Luo, M., Chen, F., & Zhang, J. (2022). Relationships among port competition, cooperation and competitiveness: A literature review. *Transport Policy*, *118*, 1-9.

Ma, Q., Jia, P., She, X., Haralambides, H., & Kuang, H. (2021). Port integration and regional economic development: Lessons from China. *Transport Policy*, *110*, 430-439.

Martin, J., Martin, S., & Pettit, S. (2015). Container ship size and the implications on port call workload. *International Journal of Shipping and Transport Logistics*, *7*(5), 553-569.

Martinez-Budria, E., Diaz-Armas, R., Navarro-Ibanez, M., & Ravelo-Mesa, T. (1999). A study of the efficiency of Spanish Port Authorities using Data Envelopment Analysis. *International Journal of Transport Economics*, *26*(2), 237-253.

https://www.scopus.com/inward/record.uri?eid=2-s2.0-0032720540&partnerID=40&md5=3158ea3458a300f8673897a375e65f0f

Martínez-Moya, J., Mestre-Alcover, A., Sala-Garrido, R., & Furió-Pruñonosa, S. (2024). Are transhipment ports more efficient in the Mediterranean Sea? Analysing the role of time at ports using DEA metafrontier approach. *Journal of Transport Geography*, *116*, 103866.

Martínez Moya, J., & Feo Valero, M. (2017). Port choice in container market: a literature review. *Transport Reviews*, *37*(3), 300-321.

Meng, Q., Weng, J., & Suyi, L. (2017). Impact analysis of mega vessels on container terminal operations. *Transportation Research Procedia*, *25*, 187-204.

Merkel, A., & Holmgren, J. (2017). Dredging the depths of knowledge: Efficiency analysis in the maritime port sector. *Transport Policy*, *60*, 63-74. https://doi.org/10.1016/j.tranpol.2017.08.010

Michaelides, M. P., Herodotou, H., Lind, M., & Watson, R. T. (2019). Port-2-port communication enhancing short sea shipping performance: The case study of cyprus and the Eastern Mediterranean. *Sustainability (Switzerland)*, *11*(7), Article 1912. https://doi.org/10.3390/su11071912

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group*, t. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Annals of internal medicine*, *151*(4), 264-269.

Mohsendokht, M., Kontovas, C., Chang, C.-H., Qu, Z., Li, H., & Yang, Z. (2025). Resilience analysis of seaports: a critical review of development and research directions. *Maritime Policy & Management*, 1-36.

Monios, J. (2017). Cascading feeder vessels and the rationalisation of small container ports. *Journal of Transport Geography*, *59*, 88-99.

Moon, D. S.-H., & Woo, J. K. (2014). The impact of port operations on efficient ship operation from both economic and environmental perspectives. *Maritime Policy & Management*, *41*(5), 444-461.

Moura, T. G. Z., Chen, Z., & Garcia-Alonso, L. (2019). Spatial interaction effects on inland distribution of maritime flows. *Transportation Research Part A: Policy and Practice*, *128*, 1-10.

Munim, Z. H. (2020). Does higher technical efficiency induce a higher service level? A paradox association in the context of port operations. *Asian Journal of Shipping and Logistics*, *36*(4), 157-168. https://doi.org/10.1016/j.ajsl.2020.02.001

Newman, M. E. (2003). The structure and function of complex networks. *SIAM review*, *45*(2), 167-256.

Nguyen, H. O., Nghiem, H. S., & Chang, Y. T. (2018). A regional perspective of port performance using metafrontier analysis: The case study of Vietnamese ports. *Maritime Economics and Logistics*, *20*(1), 112-130. https://doi.org/10.1057/s41278-017-0061-0

Nguyen, H. O., Nguyen, H. V., Chang, Y. T., Chin, A. T. H., & Tongzon, J. (2016). Measuring port efficiency using bootstrapped DEA: the case of Vietnamese ports. *Maritime Policy and Management*, *43*(5), 644-659. https://doi.org/10.1080/03088839.2015.1107922

Nguyen, P.-N., & Kim, H. (2024). The effects of the COVID-19 pandemic on connectivity, operational efficiency, and resilience of major container ports in Southeast Asia. *Journal of Transport Geography*, *116*, 103835.

Nguyen, P. N., Woo, S. H., Beresford, A., & Pettit, S. (2020). Competition, market concentration, and relative efficiency of major container ports in Southeast Asia. *Journal of Transport Geography*, *83*, Article 102653. https://doi.org/10.1016/j.jtrangeo.2020.102653

Notteboom, T., Coeck, C., & Van Den Broeck, J. (2000). Measuring and Explaining the Relative Efficiency of Container Terminals by Means of Bayesian Stochastic Frontier Models. *International journal of maritime economics*, *2*(2), 83-106. https://doi.org/10.1057/ijme.2000.9

Notteboom, T., Pallis, T., & Rodrigue, J. P. (2021). Disruptions and resilience in global container shipping and ports: the COVID-19 pandemic versus the 2008-2009 financial crisis. *Maritime Economics & Logistics*, *23*(2), 179-210. https://doi.org/10.1057/s41278-020-00180-5

Notteboom, T. E. (2009). Complementarity and substitutability among adjacent gateway ports. *Environment and Planning A*, *41*(3), 743-762.

Notteboom, T. E. (2010). Concentration and the formation of multi-port gateway regions in the European container port system: an update. *Journal of Transport Geography*, *18*(4), 567-583.

Notteboom, T. E., & Haralambides, H. E. (2020). Port management and governance in a post-COVID-19 era: quo vadis? *Maritime Economics and Logistics*, *22*, 329-352.

Núnez-Sánchez, R., & Coto-Millán, P. (2010). Excess capacity, economic efficiency and technical change in a public-owned port system: an application to the infrastructure services of Spanish Ports. In *Essays on Port Economics* (pp. 269-285). Springer.

O'Donnell, C. J., Rao, D. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical economics*, *34*, 231-255.

Panahi, R., Gargari, N. S., Lau, Y.-y., & Ng, A. K. (2022). Developing a resilience assessment model for critical infrastructures: The case of port in tackling the impacts posed by the Covid-19 pandemic. *Ocean & Coastal Management*, *226*, 106240.

Panayides, P. M., Maxoulis, C. N., Wang, T. F., & Ng, K. Y. A. (2009). A critical analysis of DEA applications to seaport economic efficiency measurement. *Transport Reviews*, *29*(2), 183-206. https://doi.org/10.1080/01441640802260354

Park, Y. S., Mohamed Abdul Ghani, N. M. A., Gebremikael, F., & Egilmez, G. (2019). Benchmarking environmental efficiency of ports using data mining and RDEA: the case of a U.S. container ports. *International Journal of Logistics Research and Applications*, *22*(2), 172-187. https://doi.org/10.1080/13675567.2018.1504903

Poo, M. C.-P., & Yang, Z. (2024). Optimising the resilience of shipping networks to climate vulnerability. *Maritime Policy & Management*, *51*(1), 15-34.

Qin, Y., Guo, J., Liang, M., & Feng, T. (2023). Resilience characteristics of port nodes from the perspective of shipping network: Empirical evidence from China. *Ocean & Coastal Management*, *237*, 106531.

Quintano, C., Mazzocchi, P., & Rocca, A. (2020). Examining eco-efficiency in the port sector via non-radial data envelopment analysis and the response based procedure for detecting unit segments. *Journal of Cleaner Production*, *259*, 120979. https://doi.org/https://doi.org/10.1016/j.jclepro.2020.120979

Redding, S. J., & Turner, M. A. (2015). Transportation costs and the spatial organization of economic activity. *Handbook of regional and urban economics*, *5*, 1339-1398.

Reggiani, A. (2013). Network resilience for transport security: Some methodological considerations. *Transport Policy*, *28*, 63-68.

Rodríguez-Álvarez, A., Tovar, B., & Trujillo, L. (2007). Firm and time varying technical and allocative efficiency: An application to port cargo handling firms. *International Journal of Production Economics*, *109*(1), 149-161. https://doi.org/https://doi.org/10.1016/j.ijpe.2006.12.048

Rødseth, K. L., Wangsness, P. B., Schøyen, H., & Førsund, F. R. (2020). Port efficiency and emissions from ships at berth: application to the Norwegian port sector. *Maritime Economics and Logistics*, *22*(4), 585-609. https://doi.org/10.1057/s41278-019-00146-2

Roll, Y., & Hayuth, Y. (1993). Port performance comparison applying data envelopment analysis (DEA). *Maritime Policy and Management*, *20*(2), 153-161. https://doi.org/10.1080/03088839300000025

Sáenz, S. S., Diaz-Hernandez, G., Schweter, L., & Nordbeck, P. (2023). Analysis of the mooring effects of future ultra-large container vessels (ULCV) on port infrastructures. *Journal of Marine Science and Engineering*, *11*(4), 856.

Sánchez, R. J., Hoffmann, J., Micco, A., Pizzolitto, G. V., Sgut, M., & Wilmsmeier, G. (2003). Port efficiency and international trade: Port efficiency as a determinant of maritime transport costs. *Maritime Economics and Logistics*, *5*(2), 199-218. https://doi.org/10.1057/palgrave.mel.9100073

Schøyen, H., Bjorbæk, C. T., Steger-Jensen, K., Bouhmala, N., Burki, U., Jensen, T. E., & Berg, Ø. (2018). Measuring the contribution of logistics service delivery performance outcomes and deep-sea container liner connectivity on port efficiency. *Research in Transportation Business and Management*, *28*, 66-76. https://doi.org/10.1016/j.rtbm.2018.03.002

Serebrisky, T., Sarriera, J. M., Suárez-Alemán, A., Araya, G., Briceño-Garmendía, C., & Schwartz, J. (2016). Exploring the drivers of port efficiency in Latin America and the Caribbean. *Transport Policy*, *45*, 31-45. https://doi.org/10.1016/j.tranpol.2015.09.004

Seth, S., & Feng, Q. (2020). Assessment of port efficiency using stepwise selection and window analysis in data envelopment analysis. *Maritime Economics and Logistics*, *22*(4), 536-561. https://doi.org/10.1057/s41278-020-00155-6

Shinohara, M. (2016). Port competition paradigms and Japanese port clusters. In *Ports in Proximity* (pp. 237-246). Routledge.

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of econometrics*, *136*(1), 31-64.

Slack, B., Comtois, C., Wiegmans, B., & Witte, P. (2018). Ships time in port. *International Journal of Shipping and Transport Logistics*, *10*(1), 45-62. https://doi.org/10.1504/IJSTL.2018.088322

Song, S. (2014). Ship emissions inventory, social cost and eco-efficiency in Shanghai Yangshan port. *Atmospheric Environment*, *82*, 288-297. https://doi.org/10.1016/j.atmosenv.2013.10.006

Steinbach, S. (2022). Port congestion, container shortages, and US foreign trade. *Economics Letters*, *213*, 110392.

Stopford, M. (2008). *Maritime economics 3e*. Routledge.

Strandenes, S. P. (2004). Port pricing structures and ship efficiency. *Review of network Economics*, *3*(2).

Suárez-Alemán, A., Morales Sarriera, J., Serebrisky, T., & Trujillo, L. (2016). When it comes to container port efficiency, are all developing regions equal? *Transportation Research Part A: Policy and Practice*, *86*, 56-77. https://doi.org/10.1016/j.tra.2016.01.018

Suárez-Alemán, A., Trujillo, L., & Cullinane, K. P. (2014). Time at ports in short sea shipping: When timing is crucial. *Maritime Economics & Logistics*, *16*(4), 399-417.

Sun, J., Yuan, Y., Yang, R., Ji, X., & Wu, J. (2017). Performance evaluation of Chinese port enterprises under significant environmental concerns: An extended DEA-based analysis. *Transport Policy*, *60*, 75-86. https://doi.org/10.1016/j.tranpol.2017.09.001

Sun, Q., Chen, L., & Meng, Q. (2022). Evaluating port efficiency dynamics: A risk-based approach [Article]. *Transportation Research Part B: Methodological*, *166*, 333-347. https://doi.org/10.1016/j.trb.2022.10.002

Svanberg, M., Holm, H., & Cullinane, K. (2021). Assessing the impact of disruptive events on port performance and choice: the case of Gothenburg. *Journal of Marine Science and Engineering*, *9*(2), 145.

Tagawa, H., Kawasaki, T., & Hanaoka, S. (2022). Evaluation of international maritime network configuration and impact of port cooperation on port hierarchy. *Transport Policy*, *123*, 14-24.

Taliani, E. C., Escobar, S. G., & Silva Da Rosa, F. (2017). Environmental disclosure and economic efficiency: A correlational evaluation of Spanish ports authorities. *Intangible Capital*, *13*(4), 745-780. https://doi.org/10.3926/ic.937

Talley, W. K., Ng, M., & Marsillac, E. (2014). Port service chains and port performance evaluation. *Transportation Research Part E: Logistics and Transportation Review*, *69*, 236-247.

Tang, L. C., Low, J. M., & Lam, S. W. (2011). Understanding port choice behavior—a network perspective. *Networks and Spatial Economics*, *11*, 65-82.

Tichavska, M., & Tovar, B. (2015). Environmental cost and eco-efficiency from vessel emissions in Las Palmas Port. *Transportation Research Part E: Logistics and Transportation Review*, *83*, 126-140. https://doi.org/10.1016/j.tre.2015.09.002

Tongzon, J. (2001). Efficiency measurement of selected Australian and other international ports using data envelopment analysis. *Transportation Research Part A: Policy and Practice*, *35*(2), 107-122. https://doi.org/10.1016/S0965-8564(99)00049-X

Tongzon, J., & Heng, W. (2005). Port privatization, efficiency and competitiveness: Some empirical evidence from container ports (terminals). *Transportation Research Part A: Policy and Practice*, *39*(5), 405-424. https://doi.org/10.1016/j.tra.2005.02.001

Tongzon, J. L. (2009). Port choice and freight forwarders. *Transportation Research Part E: Logistics and Transportation Review*, *45*(1), 186-195.

Tovar, B., & Rodríguez-Déniz, H. (2015). Classifying Ports for Efficiency Benchmarking: A Review and a Frontier-based Clustering Approach. *Transport Reviews*, *35*(3), 378-400. https://doi.org/10.1080/01441647.2015.1016473

Tovar, B., & Wall, A. (2017). Dynamic cost efficiency in port infrastructure using a directional distance function: Accounting for the adjustment of quasi-fixed inputs over time. *Transportation Science*, *51*(1), 296-304. https://doi.org/10.1287/trsc.2016.0684

Tovar, B., & Wall, A. (2019). Are larger and more complex port more productive? An analysis of Spanish port authorities. *Transportation Research Part A: Policy and Practice*, *121*, 265-276.

Tovar, B., & Wall, A. (2022). The relationship between port-level maritime connectivity and efficiency. *Journal of Transport Geography*, *98*, Article 103213. https://doi.org/10.1016/j.jtrangeo.2021.103213

Trujillo, L., & Tovar, B. (2007). The European port industry: An analysis of its economic efficiency. *Maritime Economics and Logistics*, *9*(2), 148-171. https://doi.org/10.1057/palgrave.mel.9100177

Tsolakis, N., Zissis, D., Papaefthimiou, S., & Korfiatis, N. (2021). Towards AI driven environmental sustainability: an application of automated logistics in container port terminals. *International Journal of Production Research*, *60*(14), 4508-4528. https://doi.org/10.1080/00207543.2021.1914355

Turner, H., Windle, R., & Dresner, M. (2004). North American containerport productivity: 1984–1997. *Transportation Research Part E: Logistics and Transportation Review*, *40*(4), 339-356. https://doi.org/https://doi.org/10.1016/j.tre.2003.06.001

Verschuur, J., Koks, E., & Hall, J. (2020). Port disruptions due to natural disasters: Insights into port and logistics resilience. *Transportation Research Part D: Transport and Environment*, *85*, 102393.

Walheer, B. (2024). Meta-frontier: literature review and toolkit. *Operational Research*, *24*(2), 1-28.

Wan, Z., Su, Y., Li, Z., Zhang, X., Zhang, Q., & Chen, J. (2023). Analysis of the impact of Suez Canal blockage on the global shipping network. *Ocean & Coastal Management*, *245*, 106868.

Wang, M., Wu, X.-f., Xie, Y.-h., & Chiu, Y.-h. (2023). Comparative analysis of port efficiency in Yangtze River Delta and Pearl River Delta: a meta Dynamic DDF approach. *Economic Research-Ekonomska Istrazivanja*, *36*(2).

Wang, M., Wu, X. F., Xie, Y. H., & Chiu, Y. H. (2022). Comparative analysis of port efficiency in Yangtze River Delta and Pearl River Delta: a meta Dynamic D.D.F. approach. *Economic Research-Ekonomska Istrazivanja*. https://doi.org/10.1080/1331677X.2022.2129405

Wang, N., Wu, M., & Yuen, K. F. (2023). Assessment of port resilience using Bayesian network: A study of strategies to enhance readiness and response capacities. *Reliability Engineering & System Safety*, *237*, 109394.

Wang, T. F., Cullinane, K., & Song, D. W. (2005). *Container port production and economic efficiency*. Palgrave Macmillan. https://doi.org/10.1057/9780230505971

Wanke, P. F. (2013). Physical infrastructure and shipment consolidation efficiency drivers in Brazilian ports: A two-stage network-DEA approach. *Transport Policy*, *29*, 145-153. https://doi.org/10.1016/j.tranpol.2013.05.004

World Bank. (2023). *The Container Port Performance Index 2022: A Comparable Assessment of Performance based on Vessel Time in Port.*

Wu, J., & Liang, L. (2009). Performances and benchmarks of container ports using data envelopment analysis. *International Journal of Shipping and Transport Logistics*, *1*(3), 295-310. https://doi.org/10.1504/IJSTL.2009.027536

Wu, J., Yan, H., & Liu, J. (2010). DEA models for identifying sensitive performance measures in container port evaluation. *Maritime Economics and Logistics*, *12*(3), 215-236. https://doi.org/10.1057/mel.2010.6

Xiao, R., Liu, S., Wu, L., Luo, M., Ma, R., & Li, J. (2023). Regional classification and competitiveness of port cluster: a case study of China's coastal ports. *International Journal of Logistics Research and Applications*, 1-18.

Xu, L., Wu, J., Zhao, Q., Chen, J., Liu, J., Gao, F., Liu, X., & Xu, J. (2024). Spatial-temporal characteristics of port infrastructures on sulfur-oxide concentrations of coastal port in China. *Ocean & Coastal Management*, *258*, 107399.

Xu, L., Yang, S., Chen, J., & Shi, J. (2021). The effect of COVID-19 pandemic on port performance: Evidence from China. *Ocean & Coastal Management*, *209*, 105660.

Xu, L., Yang, Z., Chen, J., & Zou, Z. (2024). Spatial-temporal heterogeneity of global ports resilience under Pandemic: a case study of COVID-19. *Maritime Policy & Management*, *51*(8), 1655-1668.

Xu, X., Zhu, Y., Xu, M., Deng, W., & Zuo, Y. (2022). Vulnerability analysis of the global liner shipping network: from static structure to cascading failure dynamics. *Ocean & Coastal Management*, *229*, 106325.

Yahalom, S., & Guan, C. (2018). Containership port time: The bay time factor. *Maritime Economics & Logistics*, *20*, 211-227.

Yan, J., Sun, X., & Liu, J. J. (2009). Assessing container operator efficiency with heterogeneous and time-varying production frontiers. *Transportation Research Part B: Methodological*, *43*(1), 172-185.

Yang, D., Liao, S., Lun, Y. V., & Bai, X. (2023). Towards sustainable port management: Data-driven global container ports turnover rate assessment. *Transportation Research Part E: Logistics and Transportation Review*, *175*, 103169.

Yang, D., Wu, L., Wang, S., Jia, H., & Li, K. X. (2019). How big data enriches maritime research–a critical review of automatic identification system (AIS) data applications. *Transport Reviews*, *39*(6), 755-773.

Yang, Z., Lau, Y.-y., Poo, M. C.-P., Yin, J., & Yang, Z. (2025). Port resilience to climate change in the Greater Bay Area. *Transportation research part D: transport and environment*, *142*, 104681.

Ye, S., Qi, X., & Xu, Y. (2020). Analyzing the relative efficiency of China's Yangtze River port system. *Maritime Economics and Logistics*, *22*(4), 640-660. https://doi.org/10.1057/s41278-020-00148-5

Yuan, X., & He, X. (2025). Enhancement Strategy for Port Resilience: Shipping Route Optimization Methods Based on Network Characteristics of Ports. *Journal of Marine Science & Engineering*, *13*(2).

Yue, Z., & Mangan, J. (2024). A framework for understanding reliability in container shipping networks. *Maritime Economics & Logistics*, *26*(3), 523-544.

Yuen, A. C. L., Zhang, A., & Cheung, W. (2013). Foreign participation and competition: A way to improve the container port efficiency in China? *Transportation Research Part A: Policy and Practice*, *49*, 220-231. https://doi.org/10.1016/j.tra.2013.01.026

Zhang, J., Luo, M., & Yang, D. (2025). Are efficient ports for port operators also those for shipping companies? A meta-frontier analysis of global top 80 container ports. *Ocean & Coastal Management*, *263*, 107616.

Zhang, J., Yang, D., & Luo, M. F. (2024). Port efficiency types and perspectives: A literature review. *Transport Policy*, *156*, 13-24. https://doi.org/10.1016/j.tranpol.2024.07.014

Zhang, L., Yang, D., Bai, X., & Lai, K.-h. (2023). How liner shipping heals schedule disruption: A data-driven framework to uncover the strategic behavior of port-skipping. *Transportation Research Part E: Logistics and Transportation Review*, *176*, 103229.

Zhang, T., Yin, J., Wang, X., & Min, J. (2024). Prediction of container port congestion status and its impact on ship's time in port based on AIS data. *Maritime Policy & Management*, *51*(5), 669-697.

Zhang, Y., Li, X., Wang, A., Bao, T., & Tian, S. (2015). Density and diversity of OpenStreetMap road networks in China. *Journal of Urban Management*, *4*(2), 135-146.

Zhao, D., Dongmei, X., & Wei, D. (2024). Research on Port-Industry-City Integration and its Spatial Spillover Effects: Empirical Evidence from the Bohai Sea Rim Region. *Applied Spatial Analysis and Policy*, *17*(4), 1653-1679.

Zhao, D., Zhen-fu, L., Yu-tao, Z., Xiao, C., & Shan-shan, L. (2020). Measurement and spatial spillover effects of port comprehensive strength: Empirical evidence from China. *Transport Policy*, *99*, 288-298.

Zheng, S., Wang, K., Fu, X., Zhang, A., & Ge, Y.-E. (2022). The effects of information publicity and government subsidy on port climate change adaptation: Strategy and social welfare analysis. *Transportation Research Part B: Methodological*, *166*, 284-312.

Zheng, S., & Yin, C. (2015). Technical, allocative and cost efficiencies of Chinese ports. *Maritime Policy & Management*, *42*(8), 746-758.

Zhou, C., Xu, J., Miller-Hooks, E., Zhou, W., Chen, C.-H., Lee, L. H., Chew, E. P., & Li, H. (2021). Analytics with digital-twinning: A decision support system for maintaining a resilient port. *Decision Support Systems*, *143*, 113496.