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Posted Date: 23 September 2024

doi: 10.20944/preprints202409.1742.v1

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Evaluating the Sustainable Performances of Ocean Carriers in the Global Shipping Market: A Longitudinal Study

Jin-Hee Ma [1], Hokey Min [2,*] and Young-Hyo Ahn [3,*]

[1] Small Enterprise Policy Research Center, Small Enterprise and Market Service
[2] James R. Good Chair in Global Supply Chain Strategy, Allen W. and Carol M. Schmidthorst College of Business, Bowling Green State University, USA
[3] Division of International Trade, Institute of Digital Economy, Incheon National University, Republic of Korea
* Correspondence: hmin@bgsu.edu (H.M.); yhahn@inu.ac.krhmin@bgsu.edu (Y.-H.A.)

Abstract: Reeling from the global supply chain crisis created by the COVID-19 pandemic, the maritime industry still faces multifaceted challenges for its sustainable survival. Those challenges include shifts in trade routes, congestion at major seaports, container shortages, volatility in fuel prices, the scarcity of skilled maritime labor, and potential technical glitches stemming from digitized maritime operations. To help the maritime industry handle these challenges, this paper identifies major drivers and deterrents that affect the efficiency of ocean carriers' performances over time using two different versions of data envelopment analysis (DEA) models and the Malmquist Productivity Index (MPI). After evaluating the operating efficiencies of multinational ocean carriers across the globe over extended periods (pre- and post-pandemic periods), we developed a benchmark standard that can guide best-in-class sustainable maritime practices.

Keywords: ocean carrier performance; benchmarking; data envelopment analysis; Malmquist productivity index; cluster analysis; longitudinal study

1. Introduction

Unprecedented black swan events, such as the COVID-19 pandemic, the ongoing war between Russia and Ukraine, and geopolitical trade tensions between the United States (U.S.) and China, have transformed worldwide consumer behaviors and global supply chain dynamics. This transformation poses a myriad of challenges for the maritime industry. These challenges include industry-wide shockwaves (e.g., shipping lane changes, delayed shipments, trade flow disruptions, skilled labor/crew shortages) emanating from the COVID-19 ripple effects, mounting cost burden from fuel price hikes, shipping capacity constraints caused by container shortages, and compliance with complex international shipping rules and regulations (e.g., wood packing material regulations. ocean container certification, transportation security administration measures). To elaborate, exports from the 27 member states of the European Union (EU27) to the rest of the world via sea transport have decreased since the beginning of the pandemic and still show a sluggish recovery, as evidenced by the fact that sea-borne exports in 2023 were 17% lower than pre-pandemic levels in 2020 [1]. A decline in sea-borne exports along with ongoing regional military conflicts (e.g., the war between Israel and Hamas, the war between Ukraine and Russia) affected traditional shipping routes. For example, 25% of global shipping capacity was diverted from the Red Sea as of 2024, and many carriers rerouted their ships from the Black Sea and the Suez Canal [2]. Changes in conventional shipping routes tended to extend shipping distances and transit times, thereby increasing shipping and carrier operating costs. These shipping cost increases were compounded by recent fuel price hikes. As a result, the latest ocean freight rate (as of July 2024) has more than doubled since January 2024 [3].

 doi:10.20944/preprints202409.1742.v

Another serious challenge facing the maritime industry is a severe shortage of qualified labor (e.g., seafarers) that reached an all-time high in 2023 due to a lingering COVID impact constraining employee retention and training opportunities [4].

The failure to deal with the challenges mentioned above can jeopardize the survival of ocean carriers. To make matters more difficult, tightening monetary policy coupled with potential government budget deficits resulting from COVID-induced financial incentives introduced by the advanced economy (e.g., the U.S. and Western Europe) may trigger another worldwide financial crisis far worse than the 2008 Great Recession and a create unbearable financial burden for already struggling ocean carriers [5,6].

To overcome these hurdles, ocean carriers must pivot from their conventional wisdom of conducting business as usual to a more innovative way of managing their available resources. Recognizing such need, this paper first identifies any room for improving ocean carriers' operating efficiencies by assessing their financial performances over extended periods (pre- versus post-pandemic periods) and determining the main drivers crucial for their market success. Specifically, the primary objectives of this paper are to:

(1) measure the financial performances of global ocean carriers over time (during 2014-2023)
(2) compare the pre- versus post-pandemic performances
(3) identify key drivers for sustaining ocean carriers' financial efficiencies
(4) develop best-in-class practices for ocean carriers
(5) propose proactive strategic action plans for ocean carriers.

To achieve the above objectives, we collected and analyzed multi-year (ten-year) financial performance data of 134 ocean carriers operating in the Asia-Pacific and Europe regions.

2. Relevant Literature

After hitting a record operating profit of $208 billion in 2022, the global container shipping industry registered a record loss of $1.4 billion in 2023, indicating a significant drop in operating profits [7]. Case in point, the Ocean Network Express (ONE), a Japanese container line, posted revenue of $14.5 billion, a 50% reduction in 2022, while Earnings Before Interest and Taxes (EBIT) dropped nearly 100% from $15 billion in 2022 to $392 million in 2023 [8]. All major shipping lines suffered from sharp year-over-year revenue drops in the third quarter of 2023 [9]. These revenue and profit declines were primarily due to the freight rate decline in 2023 since shipping volumes actually rose from the previous year [8]. Although the freight rate is expected to rebound with a growing shipping demand in 2024 reported by DHL [10], many ocean carriers need to pay more attention to their financial health and reassess their business strategies, including the potential shift in their shipping (trade) lanes for greater profits. To successfully deploy those strategies, ocean carriers should evaluate their financial performances and identify operating weaknesses undermining their financial health. Also, from a shipper's perspective, the shipper may be interested in the carrier's financial performance to gauge its financial stability (or solvency) before choosing a particular carrier. Therefore, the ocean carrier's financial performance is of great interest to both the carrier and the shipper.

Despite such interest, the published literature on maritime logistics rarely studied the subject of ocean carrier performances. Nevertheless, there exist some prior studies that can be a good conceptual foundation for evaluating ocean carrier performance. For example, Lin et al. [11] were first credited with the evaluation of the operating efficiency of shipping companies. They measured the operating efficiencies of 14 Taiwanese shipping companies with respect to their four financial ratios: assets, stockholders' equity, operating revenue, and net income using data envelopment analysis (DEA). Judging from the DEA results, they identified four efficient carriers and ten inefficient carriers. Focusing on non-financial measures, Saldanha et al. [12] examined the impact of trade lanes on the ocean carrier's transit time speed and reliability in an effort to evaluate the carrier's performance and provide guidance for the shipper's carrier selection. They found significant differences in transit time performance among ocean carriers on particular lanes and across trade lanes using the analysis of the covariance (ANCOVA) model. Kannan [13] adopted the analytic

 doi:10.20944/preprints202409.1742.v1

hierarchy process (AHP) to evaluate the Indian container carriers with respect to seven performance criteria: customer service, operations, reputation, infrastructure, scheduling, and information technology orientation and communication. These criteria were identified based on the unstructured survey results obtained from the telephone interviews of 15 shippers. They experimented with the proposed AHP model to make the hypothetical carrier selection decision instead of applying it to actual decision environments.

Based on the questionnaire survey of 14 Greek tanker shipping companies, Konsta and Plomaritou [14] identified key performance indicators (KPIs) for those companies. Those KPIs include safety, customer satisfaction, and employee/crew performance. However, they did not specify any financial performance measures. Wang [15] evaluated the financial performances of three Taiwanese container shipping companies using the fuzzy multi-criteria decision-making (FMCDM) method. He used four financial measures: financial structure (e.g., asset, equity), solvency (e.g., current asset/current liabilities), turnover (e.g., operation cost/accounts payable, operation cost/accounts receivable), and profitability (e.g., operating income). Yoon et al. [16] proposed the fuzzy AHP determined the best container shipping companies in Vietnam among five Vietnamese container shipping companies in terms of five performance criteria: service (e.g., shipping agency service), operation (e.g., fleet size, tonnage), cost (e.g., shipping cost, loading/unloading fees, port charges), counterparty (e.g., market share, reputation, customer satisfaction), and financial ratio (e.g., return on asset, return on equity). Their model was presented as guidance for selecting the container shipping company. Chao et al. [17] presented the dynamic network DEA (DNDEA) to evaluate the operating efficiencies of 13 global container shipping companies from 2013 to 2015. Their performance criteria consisted of fleet capacity, expenses, workforce (employee) size, and revenue. Their proposed DNDEA enabled them to capture the fluctuating trends of container shipping companies' performances during the three-year span.

From a different angle from the abovementioned extant studies, Kuroda and Sugimoto [18] investigated how shipping routes and weather conditions (including winds and waves) affected ship performance through case studies of a 6,500TEU container ship and capsize bulker. They observed that shipping routes and weather conditions could affect ship performance since they influenced the carrier's fuel consumption and subsequent operating costs. Wang et al. [19] proposed spherical fuzzy AHP (AHP-SF) and DEA to measure the efficiencies of 14 publicly traded container shipping companies. Extending an earlier study conducted by Yoon et al. [16], they used four non-financial performance criteria that included counterparty (e.g., reputation, partnership), worker social and environmental equity (e.g., worker safety, internal green practices), service level (e.g., on-time delivery, flexibility), and operation (e.g., market orientation, scheduling). Their model considered ecoefficiency but did not explicitly consider the carrier's financial performance. More recently, Ergin and Alkan [21] employed the analytic network process (ANP) to evaluate the performances of ocean carriers as a way to select the most desirable ocean carrier. In evaluating ocean carriers, they used nine criteria: Transportation cost (e.g., freight rate, inland cost), transit time (e.g., speed, reliability), service frequency, customer satisfaction (e.g., service quality, documentation, invoicing), reliability (brand, reputation), special facilities and equipment, equipment availability, operation performance, and service network (e.g., geographical coverage) based on the input from Turkish shippers. They used their proposed ANP model to select the best carrier from four alternative carriers in Turkey.

As this literature review reveals, most of the prior literature on ocean carrier performances focused on the single-period assessment of carrier performances. That is to say, the extant literature on ocean carrier performances tends to overlook that the carrier's operating efficiency or financial health can change over time depending on freight rate fluctuations, demand volatility, and shifts in institutional regulations and rules. In addition, many prior studies on ocean carrier performances focused on the development of performance criteria to select the most desirable carriers rather than identifying the sources of inefficiencies and finding room for improvement in carrier performances. Furthermore, it should be noted that many prior studies focused on the performances of regional carriers operating in a particular country, such as Taiwan, Vietnam, and Turkey. To fill these research gaps, our proposed research utilizes the DEA and Malmquist Productivity Index (MPI) to measure

 doi:10.20944/preprints202409.1742.v

fluctuating carrier efficiencies over time and then identify the best-in-class carrier practices using actual secondary data available from multiple data sources, including the World Bank data.

3. Research Methodology

In this study, we propose multiple research tools comprised of the DEA, MPI, and statistical data analysis to quantitively measure the performances of 134 ocean carriers operating over ten years. Herein, DEA is referred to as a linear programming (nonparametric) technique that converts multiple incommensurable inputs and outputs of each decision-making unit (DMU) into a scalar measure of operational efficiency relative to its competing DMUs such as a business entity and a host country for offshoring [6,21]. Generally, the greater the output to the input, the more efficient the DMU is in managing input [21,22]. By analogy, the greater the efficiency score, the lower the risk of offshoring in DMU (a host country in our case). Unlike other OR tools, such as conventional mathematical programming techniques, DEA creates a relative measure in the form of efficiency scores and thus enables the decision-maker to compare efficient scores among many different DMUs with multiple inputs and outputs simultaneously. Another popular scoring method, such as AHP and its variations, could only allow us to compare up to nine different alternatives simultaneously [6,23]. In addition, DEA is nonparametric and thus does not require an assumption of an explicit functional form relating inputs to outputs, while Inputs and outputs can have very different units [6,24–26]. In other words, DEA identifies the efficient DMUs, quantifies the inefficiency of each of the remaining DMUs, and thus differentiates good performers (e.g., best-practice firms, innovators) from poor performers (e.g., laggards). That is to say, DEA is designed to identify the best-performing DMU without a priori knowledge of which inputs and outputs are most important in determining an efficiency measure (i.e., score) and assessing the extent of inefficiency for all other DMUs that are not regarded as the best practice DMUs [6,22]. Furthermore, the DEA efficient score was known to be robust in measuring the DMU performance [27–29]. Considering these distinguished features, the DEA models proposed by this paper enable us to quantify and evaluate the financial efficiencies of 134 global carriers in multiple continents, including Asia-Pacific, Europe, and North America.

To strengthen the DEA further, we employed the Malmquist Productivity Index (MPI) to trace changes in the degree of risk (DEA scores) over time. The proposed MPI enables carrier management to capture changing performance patterns in multiple time horizons. This paper is the first of its kind to perform longitudinal analyses or carrier performances using the novel MPI.

3.1. Baseline DEA Models

The DEA model can take various forms depending on its assumptions and orientations [28,30–33]. To elaborate, the CCR model that Charnes et al. [22] developed assumes constant returns to scale (CRS). Its objective is to maximize multiple outputs given a set of multiple inputs [22,33,34]. On the other hand, the BCC model assumes variable returns to scale (VRS). Although efficiency scores based on variable returns to scale tend to raise or inflate the scores, as observed by Garcia-Sanchez [36], we experimented with both CCR and BCC models based on the actual data of 153 ocean carriers worldwide.

The CCR scores were calculated using the following equation (see, e.g., [22]):

$$Max\ \frac{\sum_{r=1}^{n}(u_{rb})(y_{rb})}{\sum_{k=1}^{m}(v_{kb})(x_{kb})}$$

Subject to:

$$\frac{\sum_{r=1}^{n}(u_{rb})(y_{rj})}{\sum_{k=1}^{m}(v_{kb})(x_{kj})} \leq 1 \quad \text{for all } j$$

$u_{rb}, v_{kb} \geq \varepsilon$ for all r, k

y_{rj} = the vector of output r produced by unit j

x_{kj} = the vector of input k used by unit j

u_{rb} = the weight given to output r by the base unit b

v_{kb} = the weight given to input k by the base unit b

j = 1, 2, 3 ..., p

r = 1, 2, 3 ..., n

k = 1, 2, 3 ..., m

ε = a very small positive number

The BCC scores were calculated using the following equation (see, e.g., [32]):

$$\underset{u,v,\omega}{Max}\ \theta_b = \sum_{r=1}^{s} u_r(y_{rjb}) + \omega$$

Subject to:

$$\sum_{i=1}^{m} v_i(x_{ijb}) = 1$$

$$\sum_{r=1}^{s} u_r(y_{rj}) - \sum_{i=1}^{m} v_i(x_{ij}) + \omega \leq 0$$

$u_r \geq \varepsilon$

$v_i \geq \varepsilon$

r = 1, 2, 3 ..., s,

i = 1, 2, 3 ..., m,

j = 1, 2, 3 ..., N,

ω = free.

Although CCR and BCC efficiency scores do not necessarily match, they tend to correlate with each other, as summarized in Table 1. Scale efficiency (S.E.) scores are calculated using the following equation.

$$\text{S.E.} = \frac{\theta^*_{CCR}}{\theta^*_{BCC}} \qquad (1)$$

where the CCR score θ^*_{CCR} represents Technical Efficiency (T.E.), while the BCC score θ^*_{BCC} represents Pure Technical Efficiency (PTE). From Equation (9), Technical Efficiency (T.E.) is a combination of Pure Technical Efficiency (PTE) and Scale Efficiency (S.E.). That is to say, T.E. = PTE × S.E. In a nutshell, T.E. reflects how well resources (inputs) are utilized in improving the outcome (outputs), while PTE measures T.E. without the scale effect. Super-efficiency scores are computed to discriminate among multiple DMUs (five carriers highlighted in yellow in Table 1) with a full efficiency status (an efficiency score of 1) and then rank them by assigning an efficiency score greater than 1 [37,38]. In other words, since both CCR and BCC scores show so many ties among some carriers, we used the super-efficiency scores to determine the final ranking of each carrier's performance [38].

Although CCR and BCC efficiency scores do not necessarily match each other, they correlate with each other. More importantly, efficiency scores obtained from these two conventional DEA models can produce too many efficient DMUs due to their dichotomous classification (either efficient

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or inefficient) of DMU performances. To discriminate among many DMUs (ocean carriers) with a full efficiency status (efficiency score of 1), we computed super efficiency scores proposed by Anderson and Peterson [39]. Super efficiency is intended to discern truly efficient DMUs and then rank them by assigning an efficiency score greater than 1 [28,31,37,38,40]. In other words, the super-efficiency score enables us to distinguish among many high-performing carriers. To see if there is room for improving carrier performance and identifying factors that significantly affect the financial health of ocean carriers worldwide, we ran both CCR and BCC versions of the DEA models proposed earlier.

Table 1. Performance Ratings of Ocean Carriers Under Evaluation (2023).

Rank	DMU (Ocean Carrier)	CCR[1]	BCC[2]	Scale efficiency	Super efficiency	Country
1	Clasquin	1.000	1.000	1.000	1.918	France
2	AIT	1.000	1.000	1.000	1.308	Japan
3	Pakistan National Shipping	1.000	1.000	1.000	1.209	Pakistan
4	Naigai Trans Line	1.000	1.000	1.000	1.180	Japan
5	EA Technique	1.000	1.000	1.000	1.111	Malaysia
6	Pelayaran Nelly Dwi Putri	1.000	1.000	1.000	1.074	Indonesia
7	Dampskibsselskabet Norden	0.784	1.000	0.784	0.755	Denmark
8	PT Temas	0.823	0.824	0.999	0.730	Indonesia
9	Harbour-Link Group	0.693	0.695	0.997	0.677	Malaysia
10	Saigon Shipping	0.484	1.000	0.484	0.617	Vietnam
11	Phoenix Shipping Wuhan	0.623	0.633	0.985	0.616	China
12	Euroseas	0.880	0.896	0.982	0.611	Greece
13	SITC International Holdings	0.656	1.000	0.656	0.606	Hong Kong
14	Eimskipafelag Islands	0.614	0.746	0.823	0.604	Iceland
15	Tradia	0.634	0.653	0.972	0.581	Japan
16	Vinafreight	0.601	0.642	0.936	0.572	Vietnam
17	Mitra Investindo	0.568	0.758	0.750	0.560	Indonesia
18	Lorenzo Shipping	0.696	0.749	0.928	0.556	Philippines
19	Reach Subsea	0.704	0.706	0.998	0.551	Norway
20	Belships	0.753	0.933	0.807	0.550	Norway
21	Wallenius Wilhelmsen	0.681	1.000	0.681	0.527	Norway
22	Aspo Oyj	0.571	0.592	0.963	0.518	Finland
23	Braemar PLC	0.530	0.534	0.993	0.508	UK
24	Trans Power Marine	0.519	0.527	0.985	0.505	Indonesia
25	Viet Nam Ocean Shipping	0.529	0.539	0.982	0.504	Vietnam
26	Essar Shipping	0.000	1.000	0.000	0.501	India
27	SLOMAN NEPTUN Schiffahrts	0.571	0.572	0.998	0.498	Germany

28	Maybulk	0.805	1.000	0.805	0.479	Malaysia
29	Daito Koun	0.496	0.509	0.976	0.472	Japan
30	Hyoki Kaiun Kaisha	0.494	0.509	0.970	0.447	Japan
31	Marco Polo Marine	0.443	0.458	0.969	0.443	Singapore
32	Clarkson	0.469	0.581	0.808	0.439	UK
33	Sical Logistics	0.019	0.203	0.094	0.438	India
34	Samudera Indonesia	0.442	0.556	0.794	0.436	Indonesia
35	Pacific Basin Shipping	0.432	1.000	0.432	0.430	Hong Kong
36	Stolt-Nielsen	0.535	0.809	0.661	0.424	UK
37	Azuma Shipping	0.454	0.456	0.994	0.419	Japan
38	Global Ship Lease	0.631	0.924	0.684	0.418	UK
39	Shin Yang Group	0.415	0.416	0.997	0.412	Malaysia
40	Danaos	0.410	1.000	0.410	0.408	Greece
41	T3EX Global Holdings	0.403	0.426	0.947	0.402	Taiwan
42	Nippon Concept	0.448	0.452	0.990	0.402	Japan
43	Shahi Shipping	0.000	1.000	0.000	0.400	India
44	Navarino	0.713	0.828	0.861	0.398	Chile
45	Samudera Shipping Line	0.437	0.483	0.906	0.390	Singapore
46	Grupo Empresas Navieras	0.391	0.531	0.736	0.381	Chile
47	N.S. United Kaiun Kaisha	0.404	0.497	0.813	0.380	Japan
48	DFDS	0.376	0.775	0.485	0.369	Denmark
49	James Fisher and Sons	0.384	0.393	0.979	0.365	UK
50	Pangaea Logistics Solutions	0.379	0.392	0.967	0.364	USA
51	Matson	0.383	0.504	0.761	0.352	USA
52	Meiji Shipping Group	0.463	0.563	0.823	0.329	Japan
53	Egyptian Transport	0.152	0.360	0.422	0.325	Egypt
54	South Logistics	0.329	0.359	0.915	0.314	Vietnam
55	China Merchants Energy Shipping	0.322	0.670	0.481	0.287	China
56	Trada Alam Minera	0.288	0.290	0.992	0.287	Indonesia
57	Iino Kaiun Kaisha	0.295	0.389	0.758	0.286	Japan
58	Tamai Steamship	0.313	0.328	0.954	0.281	Japan
59	Chu Kong Shipping	0.283	0.283	0.999	0.279	Hong Kong
60	KSS Line	0.393	0.434	0.906	0.279	S. Korea
61	Tokai Kisen	0.295	0.310	0.951	0.279	Japan
62	Heung-A Shipping	0.296	0.300	0.987	0.278	S. Korea
63	AP Moeller-Maersk	0.286	1.000	0.286	0.272	Denmark
64	Attica Holdings	0.286	0.337	0.848	0.272	Greece
65	Ancom Logistics	0.000	0.260	0.000	0.272	Malaysia

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66	Navios Maritime Partners	0.377	0.582	0.649	0.268	Monaco
67	Top Ships	0.402	0.404	0.995	0.263	Greece
68	Jadroagent	0.299	0.356	0.839	0.262	Croatia
69	GSD Holding	0.286	0.288	0.993	0.262	Turkey
70	Hubline	0.276	0.294	0.939	0.262	Malaysia
71	Kirby	0.284	0.374	0.759	0.261	USA
72	Courage Investment Group	0.264	0.890	0.297	0.259	Hong Kong
73	Kuribayashi Steamship	0.286	0.287	0.996	0.259	Japan
74	Orient Overseas	0.270	0.913	0.296	0.258	Hong Kong
75	Algoma Central	0.276	0.301	0.918	0.252	Canada
76	Wintermar Offshore Marine	0.246	0.262	0.938	0.244	Indonesia
77	Pan Ocean	0.266	0.424	0.629	0.243	S. Korea
78	Nippon Yusen	0.256	0.838	0.305	0.243	Japan
79	Star Bulk Carriers	0.297	0.394	0.752	0.242	Greece
80	COSCO Shipping Holdings	0.247	1.000	0.247	0.241	China
81	Costamare	0.304	0.422	0.721	0.239	Monaco
82	Korea Line	0.307	0.426	0.719	0.238	S. Korea
83	Diana Shipping	0.331	0.343	0.963	0.232	Greece
84	Losinjska Plovidba Holding	0.234	0.307	0.762	0.226	Croatia
85	Regional Container Lines	0.233	0.457	0.509	0.223	Thailand
86	Kawasaki Kisen Kaisha	0.226	0.827	0.274	0.223	Japan
87	Mitrabahtera Segara Sejati	0.218	0.231	0.944	0.217	Indonesia
88	Atlas	0.343	0.516	0.664	0.217	UK
89	COSCO SHIPPING Specialized	0.218	0.295	0.738	0.216	China
90	Ningbo Marine	0.220	0.220	1.000	0.210	China
91	shipping corporation of India	0.215	0.244	0.883	0.196	India
92	Evergreen Marine	0.215	0.594	0.362	0.195	Taiwan
93	Safe Bulkers	0.247	0.250	0.988	0.191	Monaco
94	Inui Global Logistics	0.196	0.198	0.989	0.189	Japan
95	HMM	0.204	0.810	0.252	0.188	S. Korea
96	Maritima de Inversiones	0.336	0.655	0.513	0.180	Chile
97	Genco Shipping & Trading	0.183	0.235	0.779	0.176	USA
98	Golden Ocean Group	0.201	0.261	0.772	0.175	Bermuda

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99	Mitsui O.S.K. Lines	0.178	0.584	0.305	0.172	Japan
100	Transport and Chartering	0.010	1.000	0.010	0.171	Vietnam
101	Soechi Lines	0.179	0.180	0.994	0.160	Indonesia
102	Grupo TMM SAB	0.165	0.172	0.960	0.159	Mexico
103	Yang Ming Marine Transport	0.164	0.436	0.375	0.158	Taiwan
104	Eidesvik Offshore	0.174	0.178	0.976	0.157	Norway
105	First Ship Lease Trust	0.155	0.228	0.679	0.154	Singapore
106	Qatar Navigation	0.192	0.465	0.414	0.153	Qatar
107	Franbo Lines	0.174	0.176	0.991	0.146	Taiwan
108	Precious Shipping	0.156	0.157	0.994	0.139	Thailand
109	Taiwan Navigation	0.163	0.163	0.998	0.137	Taiwan
110	Wisdom Marine Lines	0.159	0.185	0.859	0.136	Taiwan
111	U-Ming Marine Transport	0.162	0.179	0.904	0.132	Taiwan
112	Wan Hai Lines	0.136	0.241	0.565	0.129	Taiwan
113	Seanergy Maritime Holdings	0.131	0.133	0.984	0.127	Greece
114	Wilh Wilhelmsen Holding	0.121	0.206	0.586	0.113	Norway
115	Jadroplov	0.118	0.131	0.900	0.110	Croatia
116	Jordan National Shipping Lines	0.115	0.164	0.699	0.107	Jordan
117	Sincere Navigation	0.099	0.102	0.972	0.099	Taiwan
118	Shreyas Shipping and Logistics	0.102	0.112	0.911	0.097	India
119	Viking Supply Ships	0.099	0.104	0.952	0.094	Sweden
120	Andino Investment Holding	0.096	0.099	0.972	0.094	Peru
121	Cosco Shipping International	0.094	0.096	0.982	0.091	Singapore
122	Quemchi	0.113	0.131	0.859	0.090	Chile
123	MHC	0.086	0.241	0.356	0.085	Vietnam
124	Chinese Maritime Transport	0.086	0.087	0.986	0.082	Taiwan
125	Kyoei Tanker	0.087	0.090	0.968	0.082	Japan
126	Atlantska Plovidba	0.088	0.092	0.955	0.080	Croatia
127	Jinhui Shipping and Transportation	0.077	0.080	0.967	0.076	Hong Kong
128	Shih Wei Navigation	0.073	0.075	0.976	0.068	Taiwan
129	Globus Maritime	0.065	0.082	0.792	0.063	Greece
130	Great Harvest Maeta	0.073	0.103	0.708	0.061	Hong Kong

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131	Gsd Denizcilik Gayrimenkul	0.051	0.107	0.480	0.049	Turkey
132	Gulf Navigation Holding	0.047	0.053	0.895	0.045	UAE
133	MIG Holdings	0.016	0.023	0.709	0.016	Greece
134	Compania Sud Americana	0.000	0.008	0.032	0.000	Chile
	Average	**0.505**	**0.646**	**0.802**	**0.510**	

3.2. Malmquist Productivity Index

In addition to adopting three alternative DEA models described in prior subsections, we employed the Malmquist Productivity Index (MPI) to evaluate the change in performance levels (DEA efficiency scores) over time. This section expounds on its conceptual foundation and summarizes the results obtained from the longitudinal analysis of the multi-year (2014–2023) financial data. The MPI is designed to measure a DMU's efficiency changes over time [41]. MPI can be calculated using the following equation [33].

Malmquist productivity index (MPI) or Total Factor Productivity Index (TFPI)
= (Catching-up) × (Frontier-shift)
= [TECI (Technical Efficiency Change Index)] × [TCI (Technical Change Index)]

MPI is an index representing the Total Factor Productivity of the DMU, in that it reflects progress or regress in the efficiency of the DMU along with progress or regress of frontier technology. In an input-oriented evaluation, TFPI > 1 indicates progress in relative efficiency or a positive growth from period t to period t+1, while TFPI = 1 and TFPI < 1 indicate the status quo and the regressed efficiency, respectively. TFPI can be decomposed into two mutually exclusive components: one measures a change in technical efficiency (catching-up effect), and another measures a technology change (frontier shift). The catching-up effect is simply a ratio between two successive output distance functions and is related to the degree of effort the DMU attains to improve its efficiency. Put simply, it measures the carrier's ability to move closer to or further away from the frontier technology from t to t+1. The frontier effect reflects a change in the efficient frontiers surrounding the DMUs between the two consecutive periods and measures the shift in the output set or the movement of the production frontier between the periods. As such, TECI is defined as an index measuring the degree of catching up to the best-practice frontier for each observation between period t and t+1. That is to say, TECI is designed to examine whether or not the unit is getting closer to its efficiency frontier over time. On the other hand, TCI is defined as a frontier shift that measures the shift in the frontier of technology or innovation between two adjacent periods [41]. TCI aims to examine whether or not the frontier is shifting out over time. However, it does not tell us which unit caused the frontier to shift [34]. Values of either TECI or TCI of greater than unity suggest an improvement, while values of less than one suggest the opposite. Put simply, TCI reflecting the technical change is closely related to external factors such as shifts in government policies, rapid advances in technology, and changes in the economic environment such as the COVID-induced economic downturn.

3.3. Specification of Inputs and Outputs

The evaluation of comparative efficiency using DEA begins with the selection of appropriate input and output measures that can be aggregated into a composite index of overall performance standards. Although any resources used by DMU should be included as input, we selected two categories of inputs: equity and liability, as shown in Figure 1. These inputs were chosen since the DEA inputs should capture all indicators affecting carrier performance (or financial health). As specified in Figure 1, the equity category is divided into physical assets (e.g., vessels, containers, equipment, facility), liquid assets (e.g., cash reserves or equivalents), and human capital (e.g., crews). The liability category is classified into cost of carrier services, cost of financing, interest payment and fees on loans, and other accrued expenses, including fees and commission expenses. On the other hand, since the DEA outputs should reflect the performance outcomes (i.e., financial health), we

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selected the extent of the carrier's overall sales revenue and profitability (operating income) as outputs [43,44].

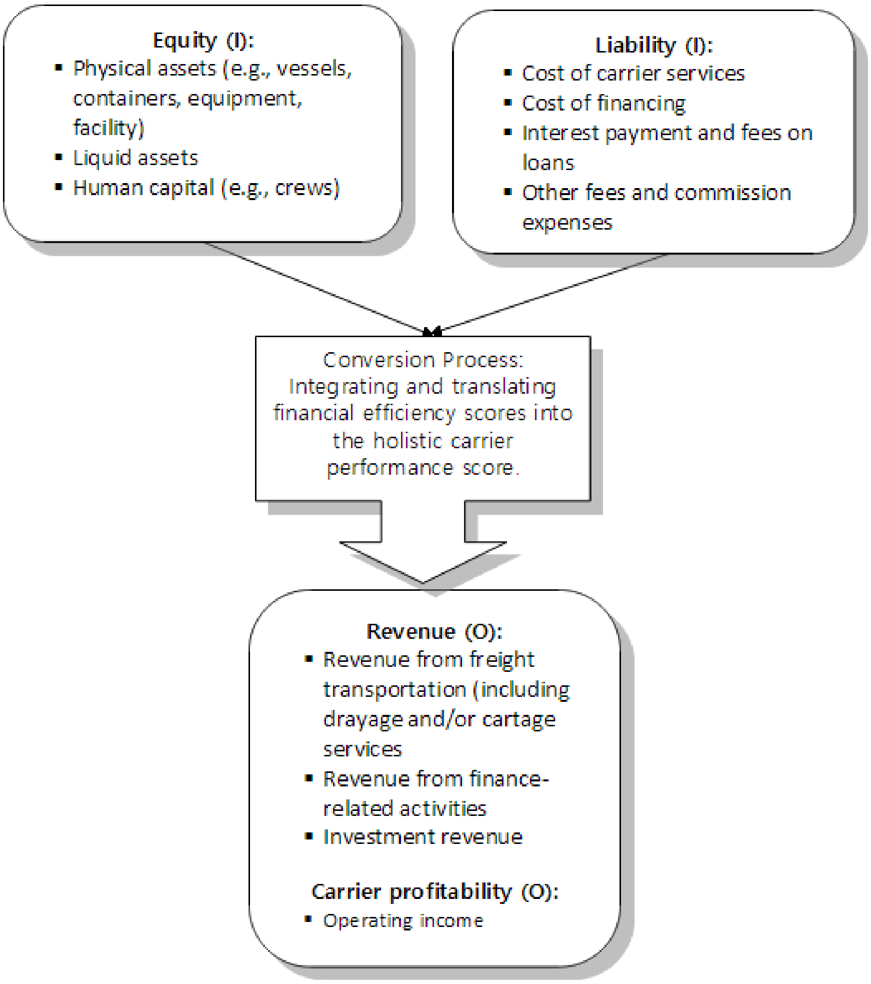

Figure 1. The Input and Output Variables for the DEA Model.

4. Analysis Results and Key Findings

4.1. Comparing Efficiency Socres

The DEA experiment begins with selecting appropriate input and output measures that can be aggregated into a composite index of overall performance standards. To discern the differences in the carrier's financial status, we developed and tested different forms of DEA models described earlier using the Frontier Analyst Software [45]. Table 1 shows the DEA efficiency scores (representing the degree of financial health) of the 134 global ocean carriers in 2023, given the inputs and outputs specified in Figure 1. As a surrogate measure of carrier performance, we considered CCR (or CRS) and BCC (or VRS) efficiency scores along with scale and super efficiency scores. Among 134 carriers, six stand out in terms of financial efficiencies (i.e., at least CCR and BBC scores of 1 and super efficiency score exceeding 1), as summarized in Table 1

4.2. Cluster Analysis

To identify the best-performing ocean carriers (benchmarks) and their common traits that may have contributed to their financial stability and success, we conducted a cluster analysis using *k*-means clustering on two key performance metrics: BCC and scale efficiencies. Herein, *k*-mean clustering is an unsupervised machine learning algorithm that groups the unlabeled dataset into clusters with similar features [46]. This analysis identified four distinct clusters, each with unique geographical compositions and operational profiles. The scatter plot shown in Figure 2 displays the common patterns of ocean carriers according to their pure technical efficiency (PTE), represented by BCC, and their scale efficiency (S.E.). Each dot on the graph represents an ocean carrier, with the x-axis representing BCC (PTE) and the y-axis representing Scale (S.E.).

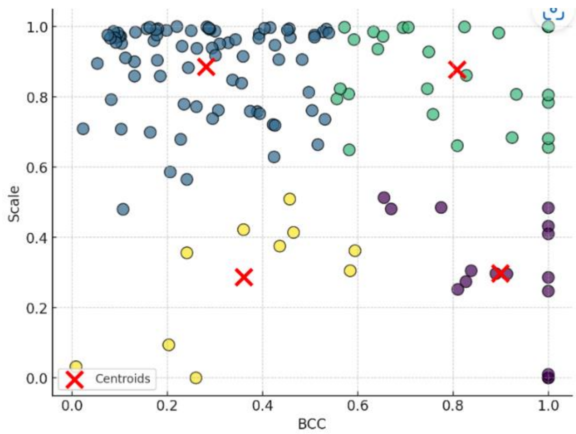

Figure 2. Cluster patterns of the ocean carrier's efficiencies.

To develop these carriers' common profiles, we first analyzed their common traits in the clusters to which they belonged. Table 2 recapitulates the common features of each cluster in terms of geographical coverage and financial PTE and S.E.

Table 2. A summary of cluster analysis.

Cluster 1	**Cluster 2**
Average pure technical efficiency (PTE): 0.932 Average scale efficiency (S.E.): 0.270 Regional Composition: 14 carriers East Asia: 6 carriers Europe: 4 carriers North America: 1 carrier Other countries: 3 carriers	Average pure Technical Efficiency (PTE): 0.280 Average scale Efficiency (S.E.): 0.907 Regional Composition: 73 carriers East Asia: 28 carriers Europe: 17 carriers North America: 8 carriers Other countries: 20 carriers
Cluster 3	**Cluster 4**
Average pure Technical Efficiency (PTE): 0.816 Average scale Efficiency (S.E.): 0.886 Regional Composition: 29 carriers East Asia: 6 carriers Europe: 12 carriers North America: 4 carriers Other countries: 7 carriers	Average pure Technical Efficiency (PTE): 0.389 Average scale Efficiency (S.E.): 0.413 Regional Composition: 18 carriers East Asia: 6 carriers Europe: 4 carriers North America: 0 carriers Other countries: 8 carriers

4.2.1. Common Features of Cluster 1

Carriers in this cluster exhibit high PTE but low scale efficiency. This suggests that these carriers utilized their resources well, given their scales, but might not operate optimally. The imbalance between PTE and S.E. implies that these carriers are likely smaller or specialized firms, potentially limited by their size (or a lack of economies of scale) in achieving their overall efficiencies. Cluster 1 is characterized by a balanced representation of carriers from East Asia and Europe, with a limited presence from North America.

4.2.2. Common Features of Cluster 2

This cluster is characterized by low PTE but high S.E. The disparity between PTE and S.E. suggests that carriers in this cluster possess economies of scale but failed to utilize their resources optimally with ample room for improvement. Cluster 2 emerges as the most geographically diverse cluster, with the largest number of carriers from multiple continents.

4.2.3. Common Features of Cluster 3

Carriers in this cluster demonstrate both high PTE efficiency and high S.E. This indicates that these carriers are effectively managing their resources and operating at a scale that is close to optimal. The balance between PTE and S.E. suggests that these carriers are considered best-performing carriers, benefiting from both effective resource utilization and economies of scale. Cluster 3 is predominantly European-centric. This cluster includes leading carriers identified by Table 1, such as Clasquin, AIT, Pakistan National Shipping, Naigai Trans Lines, EA Technique, and Pelayaran Nelly Dwi Putri. These leading carriers share several common traits that set them apart in their industry as the benchmarks who performed best-in-class practices. Some of these practices are as follows.

(1) Strong financial health: As evidenced by high super-efficiency scores, these leading ocean carriers are financially stable, which allows them to invest in new technologies, expand their fleets, and weather economic downturns. This stability provides shippers with confidence in the carrier's ability to deliver various services on their commitments. They can also offer tailor-made services to meet the specific needs of their shippers, including special handling services for fragile goods and expedited shipping.

(2) Extensive global network with wide geographical coverage: These carriers typically have a robust global network, offering services across multiple regions and countries. For example, Clasquin boasts an integrated network of more than 85 offices across 25 countries with a strong presence in the Asia-Pacific region (Clasquin company website, 2024). This allows them to provide comprehensive end-to-end solutions, including door-to-door delivery, cross-border shipping, and access to major shipping lanes such as Europe-Asia routes through established strategic alliances with other local freight forwarders and local shipping agents to diversify their service offerings (e.g., one-stop services including custom brokerage, warehousing, and trade consulting).

(3) Advanced multi-modal fleet management: Leading carriers maintain a modern and diverse fleet of vessels and leverage cutting-edge technology for real-time shipping tracking, automation of processes, and optimization of routes, ensuring that they can handle various types of cargo, including containerized bulk and specialized shipments. For instance, Clasquin, AIT, and Nagai Trans Line offer ocean and air freight services simultaneously, making intermodal cargo transfer easier.

4.2.4. Common Features of Cluster 4

This cluster has relatively low scores in both PTE and S.E. Carriers in this cluster are laggards that have struggled financially and are vulnerable to financial insolvency (or bankruptcy). This cluster rarely includes North American carriers, while it shows a higher representation of carriers operating in challenging business environments or less developed economic regions.

4.3. Longitudinal Analysis

As discussed earlier, we need to evaluate the change in carrier performances (in terms of DEA efficiency scores) over time. Thus, MPI (or TFPI) was calculated to measure a DMU's efficiency changes based on the longitudinal analysis of multi-year (2014–2023) financial data. As displayed in Table 3 and Figure 3, both the TCI and Total Factor Productivity Index (TFPI) exhibited somewhat similar patterns for the ten years, whereas the TECI exhibited a pattern quite different from TFPI with its stiff rise during 2018-2019 and then continuous declines during the three consecutive periods (e.g., opposite patterns during 2018-2021 and 2022-203). However, notice that all of TFPI, TECI, and TCI fell between 2021-2022, reflecting the lingering COVID-19 crisis impact. Although TECI showed a slight rebound during 2022-2023, its latest increase was not high enough to support the optimism emanating from thoughts of a COVID recovery. This observation indicates that all external and internal factors adversely influenced carrier performance during the height of the COVID crisis (2021-2022). In other words, the ocean carrier's survival or competitiveness depended on its ability to acclimate to changing government interventions and its effort to utilize financial resources. The overall ocean carrier performance across the industry has not reached its full potential since the latest TFPI and TCI were still below average.

Table 3. A summary of TECI, TCI, and TFPI changing patterns (2014-2023).

	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	2021-2022	2022-2023	Ave.
TECH	2.059	1.267	1.488	1.079	2.743	2.297	2.131	1.893	2.015	1.886
TCI	0.997	0.818	1.015	1.567	0.524	1.352	1.469	1.156	0.724	1.069
TFPI	1.845	1.036	1.501	1.542	1.163	2.416	2.826	2.171	1.678	1.798

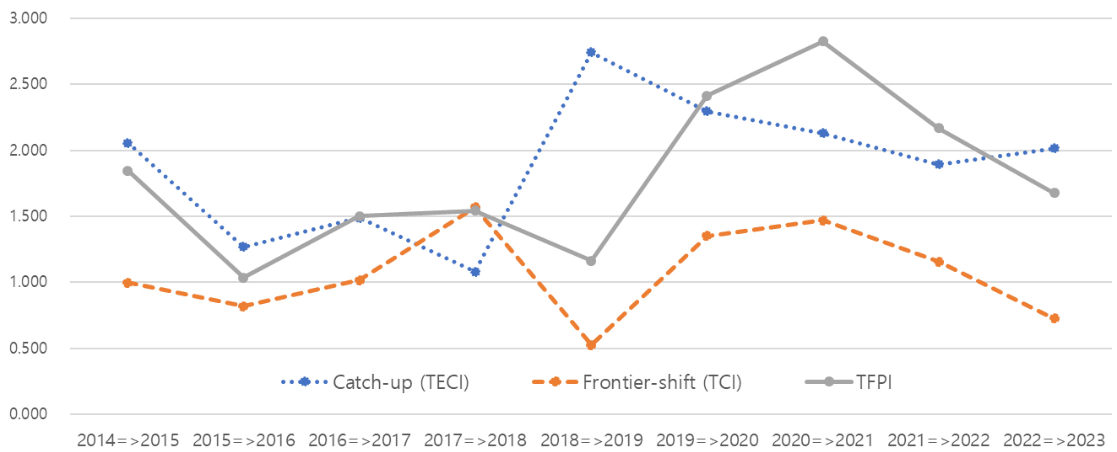

Figure 3. Carrier Productivity Trends.

5. Concluding Remarks and Future Strategic Directions

The maritime logistics industry still has not fully recovered from the financial instability caused by the COVID crisis and geopolitical tensions in East Europe and Middle-Eastern regions. In this challenging time, global ocean carriers' future lies in their ability to improve operating, financial, and sustainable efficiencies. With that in mind, this paper evaluated the comparative financial health, sustainability, and subsequent potential competitiveness of 134 ocean carriers worldwide for the first time. This paper is also one of the first studies that captured multiple years of industry trends over a ten-year span and identified common best-in-class practices performed by leading ocean carriers in the market. Those best-in-class practices include the formation of a vast global network with multicontinental geographical coverage, one-stop service offerings, and cutting-edge technology adoption for creating customer-centric (customer-tailored) logistics solutions.

To stay competitive in the fast-evolving maritime market, we suggest that global ocean carriers take a proactive stance beyond the conventional maritime logistics strategy, financial management practices, and incorporate sustainable practices. Such strategies and practices may include more energy-efficient smart vessels equipped with battery-powered or wind-assisted engines and AI-assisted shipping route scheduling to enhance sustainability. In addition, following recent trends toward mergers and acquisitions (M&As) and strategic alliances, ocean carriers should continue to seek economies of scale and share resources with their trading partners. These suggestions allow ocean carriers to save operating costs, improve their financial health, and enhance their sustainability during this transformative period for the ocean carrier industry.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the designof the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, orin the decision to publish the results

References

1. International Transport Forum. Global shocks reshape trade routes and supply chains. Available online: https://www.itf-oecd.org/global-shocks-reshape-trade-routes-and-supply-chains (accessed on 31 July 2024).
2. U.N. Trade and Development. Navigating troubled water: Impact to global trade of disruption of shipping routes in the Red Sea, Black Sea and Panama Canal. Available online: https://unctad.org/publication/navigating-troubled-waters-impact-global-trade-disruption-shipping-routes-red-sea-black#anchor_download (accessed on 1 August 2024).
3. Carranza, A. What's behind the unsettling rise in ocean rates?. *Supply Chain Dive*, July 2, 2024. Available online: https://www.supplychaindive.com/news/ocean-freight-market-rates-increase-us-east-west-coast-asia-europe/717698/ (accessed on 1 August 2024).
4. Maritime Executive. Seafarer labor shortage reaches 17-year high reports. 1 August 2024. Available online: https://maritime-executive.com/article/seafarer-labor-shortage-reaches-17-year-high-reports-drewry (accessed on 1 August 2024).
5. Winck, B. McKinsey economists lay out 9 potential coronavirus recession scenarios-ranging from a summer recovery to a 'black swan of black swans'. *Business Insider*, 1 May 2020. Available online: https://www.businessinsider.com/economic-outlook-9-scenarios-coronavirus-recovery-recession-mckinsey-experts-2020-4 (accessed on 1 May 2020).
6. Min, H.; Ahn, Y.H.; Ma, J.H. Measuring dynamic supply chain risks for the offshoring decision in the post-COVID-19 era: A longitudinal study. *Transp. J*. **2024**. *63* 188-206/ https://doi.org/10.1002/tjo3.12026
7. Statistica. Operating profit of the global container shipping industry 2010–2023. 23 May 2024. Available online: https://www.statista.com/statistics/1299477/operating-profit-container-carriers/#:~:text=The%20global%20container%20shipping%20industry%20generated%20a%20record%20loss%20in,U.S.%20dollars%20recorded%20in%202022 (accessed on 5 August 2024).
8. Van Marie, G. ONE reports 2023 profit collapse due to rates decline, but volumes were up. *Loadstar*, 4 March 2024. Available online: https://theloadstar.com/one-reports-2023-profit-collapse-due-to-rates-decline-but-volumes-were-up/ (accessed on 5 August 2024).
9. Container News. Ocean carrier financial figures drop to pre-Covid levels, Sea-Intelligence reports. 28 November 2023. Available online: https://container-news.com/ocean-carrier-financial-figures-drop-to-pre-covid-levels-sea-intelligence-reports/ (accessed on 5 August 2024).
10. DHL. Ocean Freight Market Update: August 2024; Unpublished Report; DHL: Bonn, Germany, 2024.
11. Lin, W.C.; Liu, C.F.; Chu, C.W. Performance efficiency evaluation of the Taiwan's shipping industry: An application of data envelopment analysis. *Proc. East. Asia Soc. Transp. Stud*. **2005**, *5*, 467–476.
12. Saldanha, J.P.; Russell, D.M.; Tyworth, J.E. A disaggregate analysis of ocean carriers' transit time performance. *Transp. J*. **2006**, *45*, 39–60.
13. Kannan, V. Benchmarking the service quality of ocean container carriers using AHP. *Benchmarking* 2010, *17*, 637–656. https://doi.org/10.1108/14635771011076417
14. Konsta, K.; Plomaritou, E. Key performance indicators (KPIs) and shipping companies performance evaluation: The case of Greek tanker shipping companies. *Int. J. Bus. Manag*. **2012**, *7*, 142–155. https://doi.org/10.5539/ijbm.v7n10p142

15. Wang, Y.J. The evaluation of financial performance for Taiwan container shipping companies by fuzzy TOPSIS. *Appl. Soft Comput*. **2014**, *22*, 28–35. https://doi.org/10.1016/j.asoc.2014.04.008
16. Yoon, D.G.; Ngo, P.T.; Keum, J.S. Fuzzy AHP evaluation for performance of container shipping companies in Vietnam. *J. Navig. Port Res*. **2018**, *42*, 365–370. https://doi.org/10.5394/KINPR.2018.42.5.365
17. Chao, S.L.; Yu, M.M.; Hsieh, W.F. Evaluating the efficiency of major container shipping companies: A framework of dynamic network DEA with shared inputs. *Transp. Res. Part A Policy Pract*. **2018**, *117*, 44–57. https://doi.org/10.1016/j.tra.2018.08.007
18. Kuroda, M.; Sugimoto, Y. Evaluation of ship performance in terms of shipping route and weather condition. *Ocean Eng*. **2022**, *254*, 111335. https://doi.org/10.1016/j.oceaneng.2022.111335
19. Wang, C.N.; Dang, T.T.; Nguyen, N.A.T.; Chou, C.C.; Hsu, H.P.; Dang, L.T.H. Evaluating global container shipping companies: A novel approach to investigating both qualitative and quantitative criteria for sustainable development. *Axioms* **2022**, *11*, 610. https://doi.org/10.3390/axioms11110610
20. Ergin, A.; Alkan, G. The selection of ocean container carrier: An analytic network process (ANP) approach. *J. ETA Marit. Sci*. **2023**, *11*, 159–167. https://doi.org/10.4274/jems.2023.159
21. Min, H.; Min, H.; Joo, S.-J.; Kim, J. A data envelopment analysis for establishing the financial benchmark of Korean hotels. *Int. J. Serv. Oper. Manag*. **2008**, *4*, 201–217. https://doi.org/10.1504/IJSOM.2008.018618
22. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision-making units. *Eur. J. Oper. Res*. **1978**, *2*, 429–444. https://doi.org/10.1016/0377-2217(78)90138-8
23. Saaty, T.L. *The Analytic Hierarchy Process*; McGraw-Hill: New York, NY, USA, 1980.
24. Ali, A.I.; Lerme, C.S. Comparative advantage and disadvantage in DEA. Ann. *Oper. Res*. **1997**, *73*, 215–232. https://doi.org/10.1023/A:1018940912365
25. Rostamzadeh, R.; Akbarian, O.; Banaitis, A.; Soltani, Z. Application of DEA in benchmarking: a systematic literature review from 2003–2020. *Technol. Econ. Dev. Econ*. **2021**, *27*, 175–222. https://doi.org/10.3846/tede.2020.14144
26. Panwar, A.; Olfati, M.; Pant, M.; Snasel, V. A review on the 40 years of existence of data envelopment analysis models: Historic development and current trends. *Arch. Comput. Methods Eng*. **2022**, *29*, 5397–5426. https://doi.org/10.1007/s11831-022-09756-w
27. Zhu, J. Robustness of the efficient DMUs in data envelopment analysis. *Eur. J. Oper. Res*. **1996**, *90*, 451–460. https://doi.org/10.1016/0377-2217(94)00357-5
28. Zhu, J. Quantitative Models for Performance Evaluation and Benchmarking: Data Envelopment Analysis with Spreadsheets and DEA Excel Solver; Kluwer Academic Publishers: Norwell, MA, USA, 2003. https://doi.org/10.1007/978-1-4615-0405-6
29. Nasrabadi, N.; Dehnokhalaji, A.; Korhonen, P.; Lokman, B.; Wallenius, J. Robustness of efficiency scores in data envelopment analysis with interval scale data. *Eur. J. Oper. Res*. **2022**, *297*, 1151–1161. https://doi.org/10.1016/j.ejor.2021.05.003
30. Ahn, T.; Charnes, A.; Cooper, W.W. Efficiency characterizations in different DEA models. *Socio-Econ. Plan. Sci*. **1988**, *22*, 253–257. https://doi.org/10.1016/0038-0121(88)90012-5
31. Adler, N.; Friedman, L.; Sinuany-Stern, Z. Review of ranking methods in the data envelopment analysis context. *Eur. J. Oper. Res*. **2002**, *140*, 249–265. https://doi.org/10.1016/S0377-2217(02)00068-1
32. Banker, R.D.; Charnes, A.; Cooper, W.W. Models for the estimation of technical and scale efficiencies in data envelopment analysis. *Manag. Sci*. **1984**, *30*, 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078
33. Banker, R.D.; Cooper, W.W.; Seiford, L.M.; Thrall, R.M.; Zhu, J. Returns to scale in different DEA models. *Eur. J. Oper. Res*. **2004**, *154*, 345–362. https://doi.org/10.1016/S0377-2217(03)00174-7
34. Fare, R.; Grosskopf, S.; Knox Lovell, C.A. *Production Frontiers*; Cambridge University Press: Boston, MA, USA, 1994. https://doi.org/10.1017/CBO9780511666841
35. Nolan, J.F.; Ritchie, P.C.; Rowcroft, J.R. Measuring efficiency in the public sector using nonparametric frontier estimators: A study of transit agencies in the USA. *Appl. Econ*. **2001**, *33*, 913–922. https://doi.org/10.1080/00036840121906
36. Garcia-Sanchez, I.M. The efficiency measurement in Spanish local government: The case of municipal water services. *Rev. Policy Res*. **2006**, *23*, 355–371. https://doi.org/10.1111/j.1541-1338.2006.00208.x
37. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res*. **2001**, *130*, 498–509. https://doi.org/10.1016/S0377-2217(99)00407-5
38. Tone, K. A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res*. **2002**, *143*, 32–41. https://doi.org/10.1016/S0377-2217(01)00324-1
39. Li, S.; Jahanshahloo, G.R.; Khodabakhshi, M. A super-efficiency model for ranking efficient units in data envelopment analysis. *Appl. Math. Comput*. **2007**, *184*, 638–648. https://doi.org/10.1016/j.amc.2006.06.077
40. Andersen, P.; Petersen, N.C. A procedure for ranking efficient units in data envelopment analysis. *Manag. Sci*. **1993**, *39*, 1261–1264. https://doi.org/10.1287/mnsc.39.10.1261

41. Nishimizu, M.; Page, J.M. Productivity change and dynamic comparative advantage. *Rev. Econ. Stat*. **1986**, *68*, 241–257. https://doi.org/10.2307/1925518
42. Candemir, M.; Deliktas, E. Production efficiency and total factor productivity growth in Turkish state agricultural enterprises. *Agric. Econ. Rev*. **2007**, *8*, 27–41.
43. Dyson, R.G.; Allen, R.; Camanho, A.S.; Podinovski, V.V.; Sarrico, C.S.; Shale, E.A. Pitfalls and protocols in DEA. *Eur. J. Oper. Res*. **2001**, *132*, 245–259. https://doi.org/10.1016/S0377-2217(00)00149-1
44. Min, H.; Park, H.; Ahn, S.B. Measuring the supply chain risk in offshoring countries using data envelopment analysis and the analytic hierarchy process. *Benchmarking* **2017**, *24*, 1977–1994. https://doi.org/10.1108/BIJ-08-2015-0084
45. Frontier Analyst Software. Decision Support and Analysis Tools from Banxia; Banxia Software Ltd.: Cumbria, United Kingdom, 2024.
46. Sinaga, K.P.; Yang, M.S. Unsupervised K-means clustering algorithm. *IEEE Access* **2020**, *8*, 80716–80727. https://doi.org/10.1109/ACCESS.2020.2990712