https://doi.org/10.22306/al.v12i1.602 *Received: 05 Aug. 2024; Revised: 04 Oct. 2024; Accepted: 25 Nov. 2024*

Green performance in the Vietnamese water transport industry: a directional distance function with undesirable outputs approach

Thanh Khac Mai
Vietnam Maritime University, Faculty of Management and Finance, 484 Lach Tray Street, Haiphong City, Vietnam, mkthanh@vimaru.edu.vn
Ha Thi Quach
Vietnam Maritime University, Faculty of Political Theory, 484 Lach Tray Street, Haiphong City, Vietnam, vanhahanghai.llct@vimaru.edu.vn
Van Nguyen
Vietnam Maritime University, Faculty of Fundamental Science, 484 Lach Tray Street, Haiphong City, Vietnam, vanxpo@vimaru.edu.vn (corresponding author)
Trang Huyen Thi Vu
Thuongmai University, Faculty of Mathematical Economics, 79 Ho Tung Mau Street, Hanoi City, Vietnam, trang.vth@tmu.edu.vn

Keywords: undesirable outputs, directional distance function, environmental efficiency, total factor productivity, Malmquist-Luenberger productivity index.
Abstract: This study investigates the environmental efficiency and green total factor productivity (GTFP) of the Vietnamese water transport industry. By applying the directional distance function model with undesirable outputs to the annual enterprise census data sample collected by the General Statistics Office of Vietnam, the study estimated the environmental efficiency score and the Malmquist-Luenberger productivity index of the industry for the period from 2015 to 2020. The estimated results from the models show that the average efficiency score of the industry is 37.4%, indicating a low level of environmental efficiency. This implies that the Vietnamese water transport industry has not effectively used resources and technology to minimize negative impacts on the environment. The average GTFP growth reached 2.0% and was mainly contributed by improvements in technical efficiency (2.2%). Meanwhile, the decline in technological change (-0.2%) is the reason for the slowdown in GTFP growth of the industry. The research results also show the difference in efficiency and productivity of the industry when estimated by two approaches of traditional data envelopment analysis and the directional distance function with undesirable outputs.

1 Introduction

Efficiency and productivity analysis aims to evaluate the performance of firms in converting inputs into outputs. Traditional analyses often assume that inputs should be reduced and outputs should be expanded. However, in reality, the production process not only produces desired products or services but it can also create negative impacts such as environmental pollution, waste, or other factors that adversely affect the community and the environment. Ignoring these outputs can lead to an erroneous assessment of the true efficiency and productivity of the production process (Fare et al., 1989; Yang and Pollitt, 2009; Lozano and Gutierrez, 2011) [1-3]. In the case of undesirable outputs, they should be reduced to improve efficiency (Wang et al., 2022) [4]. Economists have recognized the importance of considering unintended outcomes in performance evaluation to promote sustainability and social responsibility of organizations, contributing to building a healthier and more sustainable business environment (Chung et al., 1997; Mahlberg and Sahoo, 2011) [5,6].

The water transport industry plays an important role in economic and trade development of Vietnam. It is not only an efficient mode of transporting goods but also an indispensable part of the global supply chain. As a coastal country with the advantage of a long coastline, close to international shipping routes, there are 3 ports in the list of 50 container ports with the largest throughput in the world (Ho Chi Minh City Port, Hai Phong Port and Cai Mep-Thi Vai Port). The seaport system of Vietnam has received the largest tonnage ships in the world, attracting 40 major international shipping lines to operate. In addition, Vietnam also has a dense river system with 2,360 rivers and canals with a total length of nearly 41,900 km. Along with that are 202 cargo ports, 11 passenger ports, 97 specialized ports and 4,791 inland water wharves. These are advantages for the Vietnamese water transport industry to develop and achieve good operational efficiency (Mai et al., 2023) [7]. However, along with the rapid development of the industry, environmental issues have been becoming increasingly urgent. The use of fossil energy sources and greenhouse gas emissions from water transport activities have contributed to increased environmental pollution and climate change. This poses major challenges for managers and policy makers. The current development trends of the water transport industry are digital technology, green ports, energy conversion, emission reduction and the use of large tonnage ships. These are challenges that require firms to have development plans to adapt promptly.

The issue of environmental efficiency and green total factor productivity (GTFP) growth has garnered the attention of many researchers worldwide. Pioneering studies such as Fare et al. (1989) and Chung et al. (1997) [1,5] proposed the Data Envelopment Analysis (DEA) model with undesirable outputs as an effective method for measuring these concepts. These studies paved the way for analyses of environmental efficiency and GTFP growth in developed economies (Zhang and Choi, 2014) [8], as well as in various industries ranging from energy to manufacturing (Yang and Pollitt, 2009; Li and Lin, 2016) [2,9]. However, this research topic remains relatively new in the fields of maritime transport and coastal ports, with only a handful of studies addressing it. Parris et al. (2023) [10] evaluated and measured the ecological efficiency of 93 largest shipping firms in the world from 2018 to 2022 using the dynamic slack-based non-oriented DEA methodology. Their findings indicate that nations with smaller fleets, such as Canada and Taiwan, achieved higher ecological efficiency due to government sustainability policies. In contrast, tax haven countries like the Marshall Islands, Panama, and Singapore exhibited lower efficiency, as shipping firms in these regions showed less concern for mitigating environmental impacts due to a lack of strict environmental policies. On the other hand, major shipping nations like China have made significant investments in emission reduction through decarbonization strategies and the use of alternative energy sources. The growing emphasis on environmental, social, and governance (ESG) principles among Chinese firms has contributed to improved ecological efficiency. Liu et al. (2023) [11] examined the dynamic development of green growth quality at Chinese coastal ports through the lens of GTFP growth. Using the directional distance function (DDF), the authors estimated the Global Malmquist-Luenberger index following the methodology of Oh (2010) [12] to measure GTFP growth at the ports. Furthermore, the dynamic development of GTFP growth at these ports was explored through kernel density estimation. The results of the study indicated continuous improvement in GTFP growth at coastal ports during the research period. Nevertheless, an issue arises where the inputs for port construction fail to yield efficient outputs, leading to a divergence that shows signs of stabilizing in coastal ports. In the context of Vietnam, a literature review reveals that studies in the water transport industry primarily rely on traditional performance assessment models, without integrating undesirable outputs into productivity growth analyses. This leads to outcomes that do not accurately reflect the actual performance of firms. This represents a significant research gap in terms of environmental efficiency and GTFP growth in the industry, especially as sustainable development has become a critical strategic goal for the country. Thus, this study aims to fill that gap by applying the DEA model with undesirable outputs to measure environmental efficiency and GTFP growth in Vietnamese water transport industry. This approach not only provides a more comprehensive view of the performance of firms but also offers crucial data to help policymakers make informed decisions related to sustainable development, while raising awareness of the role environmental factors play in production activities.

2 Methodology

In the DEA literature, approaches to managing desirable and undesirable outputs are typically classified into three primary methodological frameworks. The first framework involves transforming conventional DEA models such as employing the hyperbolic efficiency measure (Fare et al., 1989) [1], using separate measures for desirable and undesirable outputs (Scheel, 2001) [13], applying a linear monotone decreasing transformation to undesirable outputs (Seiford and Zhu, 2002) [14], and treating undesirable outputs as inputs (Yang and Pollitt, 2009) [2]. The second framework consists of modifications to the slacks-based measure (SBM), as discussed by Tone (2004) and Lozano and Gutierrez (2011) [3,15]. The third framework includes modifications to the DDF, originally proposed by Chung et al. (1997) [5]. Among these, the DDF is particularly prevalent in applications dealing with both desirable and undesirable outputs (Lozano and Gutierrez, 2011; Podinovski and Kuosmanen, 2011) [3,16].

Consider a firm that converts a vector of nonnegative inputs into a vector of nonnegative desirable outputs and a vector of undesirable outputs such as pollution, under the constraints of a fixed technology. Within this production framework, both inputs and desirable outputs are assumed to be strongly disposable, meaning they can increase without affecting the feasibility of the production process. However, undesirable outputs are considered to be weakly disposable, indicating that reducing these outputs is not without cost and will result in a reduction of desirable outputs. Denote the inputs as x, the desirable outputs as y, and the undesirable outputs as u. The production technology described can then be characterized by the technology set P (1), which encompasses all feasible combinations of inputs, desirable outputs, and undesirable outputs.

$$\mathrm{P} = \{(x, y, u) : x \text{ can produce } (y, u)\} \quad (1)$$

The radial DDF is defined by Chung et al. (1997) [5] as follows (2):

$$D_r(x, y, u; g) = sup[\beta : \{(x, y, u) + \beta g\} \in P] \quad (2)$$

where $g = (g_x, g_y, g_u)$ is a preassigned nonzero vector that specifies the direction in which the distance between the data point (x, y, u) and the production frontier is measured.

The equation (2) presents the most general form of the radial DDF. The distance between the firm and the production frontier can be defined in a specific direction by setting different vectors g. For illustration, we consider three commonly used cases in the literature: $g_1 = (0, y, 0)$, $g_2 = (0,0,-u)$ và $g_3 = (0, y, -u)$.

To estimate technical efficiency using the DDF measure in DEA, one needs to construct a production technology set from observed data. For cross-sectional data consisting of I individuals, the production technology set assuming constant returns to scale (CRS) is constructed as follows (3):

$$P = \{(x, y, u): \sum_{i=1}^{I} \alpha_i x_i \leq x, \sum_{i=1}^{I} \alpha_i y_i \geq y, \sum_{i=1}^{I} \alpha_i u_i = u, \alpha_i \geq 0\} \quad (3)$$

For the case of variable returns to scale (VRS) assumption, condition $\sum_{i=1}^{I} \alpha_i = 1$ is added to the equation (3). Then the equation (3) becomes (4)

$$P = \{(x, y, u): \sum_{i=1}^{I} \alpha_i x_i \leq x, \sum_{i=1}^{I} \alpha_i y_i \geq y, \sum_{i=1}^{I} \alpha_i u_i = u, \sum_{i=1}^{I} \alpha_i = 1, \alpha_i \geq 0\} \quad (4)$$

In the context of panel data, the time-series dimension offers additional insights into the production technology. Economists have proposed various types of production technology sets, including global, window, sequential, biennial, and contemporaneous production technologies. The production technology set at time t is defined as follows (5):

$$P(t) = \left\{(x, y, u): \sum_{\tau \in \Gamma_t} \sum_{i=1}^{I} \alpha_{i\tau} x_{i\tau} \leq x, \sum_{\tau \in \Gamma_t} \sum_{i=1}^{I} \alpha_{i\tau} y_{i\tau} \geq y, \sum_{\tau \in \Gamma_t} \sum_{i=1}^{I} \alpha_{i\tau} u_{i\tau} = u, \alpha_i \geq 0\right\} \quad (5)$$

The radial DDF measure for technical inefficiency under the CRS assumption can then be estimated by solving the following linear programming problem (6):

$$D_r(x, y, u; g) = \max_{\beta, \alpha} \beta \quad (6)$$
$$s.t. \sum_{i=1}^{I} \alpha_i x_i \leq x + \beta g_x$$
$$\sum_{i=1}^{I} \alpha_i y_i \geq y + \beta g_y$$
$$\sum_{i=1}^{I} \alpha_i u_i = u + \beta g_u$$
$$\alpha_i \geq 0, i = 1, \ldots, I$$

As for the VRS assumption, condition $\sum_{i=1}^{I} \alpha_i = 1$ is added to the above constraints.

In the equation (6), the constraints on the left-hand side establish the production frontier using the convex hull of the observed data. The right-hand side enables the evaluated firm to modify the inputs (x), desirable outputs (y), and undesirable outputs (u) in the direction of (g_x, g_y, g_u). The DDF aims to maximize the reduction of inputs and undesirable outputs while increasing the desirable outputs, within the parameters defined by the production technology $(x + \beta g_x, y + \beta g_y, u + \beta g_u)$.

The conventional method of assessing productivity change has centered on evaluating the desirable outputs of firms relative to the paid inputs they utilize. This methodology often neglects the production of by-products such as pollution, resulting in potentially biased measures of productivity growth (Chung et al., 1997) [5]. For instance, firms in sectors subject to environmental regulations may find their productivity negatively impacted, as the costs of pollution abatement are included as inputs without accounting for the reduction of pollutants as outputs. To address this, Chung et al. (1997) [5] introduced a productivity index based on the radial DDF measure, known as the Malmquist-Luenberger Productivity Index (MLPI). This index acknowledges both the reduction of undesirable outputs and the increase of desirable outputs. Considering two adjacent periods, labeled *s* and *t*, and choosing the direction as $g = (0, y, -u)$, the output-oriented MLPI with undesirable outputs is defined as follows (7):

$$MLPI = \left\{\frac{1+D_r^t(x^s,y^s,u^s;g)}{1+D_r^t(x^t,y^t,u^t;g)} \times \frac{1+D_r^s(x^s,y^s,u^s;g)}{1+D_r^s(x^t,y^t,u^t;g)}\right\}^{1/2} \quad (7)$$

To eliminate the arbitrary selection of base years, a geometric mean of a fraction-based MLPI is calculated using both the base year t and year s. The MLPI indicates productivity improvement when the value exceeds 1, and a decline in productivity when the value is less than 1. According to Chung et al. (1997) [5], the MLPI can be decomposed into two components: one that accounts for technical efficiency change (MLTECH) and another that measures technological change (MLTECCH) (8), (9).

$$MLTECH = \frac{1+D_r^s(x^s,y^s,u^s;g)}{1+D_r^t(x^t,y^t,u^t;g)} \quad (8)$$

$$MLTECCH = \left\{\frac{1+D_r^t(x^s,y^s,u^s;g)}{1+D_r^s(x^t,y^t,u^t;g)} \times \frac{1+D_r^t(x^s,y^s,u^s;g)}{1+D_r^s(x^t,y^t,u^t;g)}\right\}^{1/2} \quad (9)$$

3 Data and variables

The dataset for this study was sourced from the annual enterprise survey data of the General Statistics Office of Vietnam (GSO) covering the period from 2015 to 2020. We exclusively selected data pertaining to water transport firms, specifically those classified under industry code 50 in the Vietnam Standard Industrial Classification (VSIC) system as per Decision 27/2018/QD-TTg by the Prime Minister (VSIC 2018). Firms were excluded if they did not report energy consumption, reported negative numbers of workers, assets, or revenue, or provided incomplete responses. The necessary variables were processed and calculated for each year, after which the data were merged across years using firms' tax codes. This process resulted in a balanced panel dataset of 166 water transport firms over six years (996 observations), including 115 sea and coastal water transport firms (690 observations) and 51 inland water transport firms (306 observations).

In this study, three input variables were used for each firm: capital (K), labor (L), and energy consumption (E). Capital (K), measured in million VND and adjusted to constant prices based on the World Bank's 2010 data, is determined by the average value of total assets at the beginning and end of the year. Labor (L) is calculated as the average number of employees at the beginning and end of the year. Energy consumption (E) involves various energy sources such as electricity, coal, oil, gasoline, and natural gas, each with different technical parameters, complicating the assessment of total energy consumption. To address this, energy consumption is standardized to "Tons of Oil Equivalent - TOE," as specified in Document No. 3505/BCT-KHCN, April 19, 2011, by the Ministry of Industry and Trade. Consequently, E is calculated as the total energy consumption of the firm for the year in "tons of standard TOE".

Regarding output variables, the primary desired output is the value added (VA) of the firm, measured in million VND and adjusted to the World Bank's 2010 constant prices. VA is calculated by summing labor income, fixed asset depreciation, profit before tax, and indirect taxes. CO_2 emissions are considered an undesirable output. Given the lack of detailed CO_2 emission data for each firm in Vietnam, CO_2 emissions from energy consumption were estimated based on the Intergovernmental Panel on Climate Change (IPCC, 2006) [17] guidelines and studies by Chen et al. (2010) and Lan and Minh (2023) [18,19]. Accordingly, the CO_2 emissions are calculated as follows: coal at 2.259 tons CO2 per ton, oil at 3.153 tons CO_2 per ton, natural gas at 2.983 tons CO_2 per 1000 cubic meters, and gasoline at 3.069 tons CO_2 per 1000 liters.

Table 1 Descriptive statistics of input and output variables of the Vietnamese water transport industry in the period 2015-2020

Variables	Inputs			Outputs	
	L (persons)	**K** (million VND)	**E** (tons)	**VA** (million VND)	**CO_2** (tons)
Mean	74.5507	139539.3	125870.5	21990.78	393539
Std. dev.	142.9181	378527.6	3590005	53526.36	1.12e+07
Min	3	1057	1.408	82.7	3.497938
Max	1246	4823784	1.13e+08	566931	3.53e+08
Skewness	5.091395	7.327462	31.18578	5.343329	31.17702
Kurtosis	34.03907	71.17768	979.5736	39.63687	979.1753

Table 1 presents descriptive statistics of inputs and outputs in the research sample of the Vietnamese water transport industry in the period from 2015 to 2020. During this period, data on input variables show that the average number of employees per firm tends to decrease (-4.82%). The average capital per firm increases by 1.42% per year, but the standard deviation decreases, indicating that the dispersion of investment capital also decreases. The average total energy consumption increases by 7.99% per year and has large fluctuations (average standard deviation of 9.37%). Regarding output variables, the average value added (VA) tends to decrease slightly (-0.17%). The average CO_2 emissions increase by 9.04% with an average standard deviation of 3.38%. We find that there are large fluctuations in energy consumption and CO_2 emissions of firms during the research period. This shows a significant change in production factors and environmental performance of the Vietnamese water transport firms in the period 2015-2020.

4 Results and discussion

By using the equation (6), we calculated the efficiency scores of 166 Vietnamese water transport firms over the period 2015-2020. The estimation procedure in Stata software, created by Wang et al. (2022) [4], was utilized for solving the equation (6). Here, the optimal value β_0 in the equation (6) signifies the inefficiency score. Therefore, a higher β_0 indicates that a particular water transport firm is inefficient or achieves a lower efficiency level. A $\beta_0$value of zezo means that it is impossible to simultaneously expand and contract the desirable and undesirable outputs. Conversely, it suggests that the desirable outputs can be expanded and the undesirable outputs can be contracted whenβ_0 is multiplied by the original values. We also calculate the efficiency scores of the firms using the classical DEA model of Charnes et al. (1978) [20] (CCR), which does not consider the undesirable output, specifically CO_2 emissions. To compare the DDF scores with the CCR scores, the value $(1-\beta_0)/(1+\beta_0)$is used to represent the environmental efficiency of the observed water transport firms. This adjustment reflects the scenario where the desirable output increases by $(1+\beta_0)$times and the undesirable output decreases by$(1-\beta_0)$times the original value. It is important to note that the equation (6), when excluding CO_2 emissions, results in an efficiency score of $1/(1+\beta_0)$, which matches the efficiency score derived from the input-oriented CCR model.

Table 2 Technical efficiency score of the Vietnamese water transport industry in the period 2015-2020

Technical efficiency	**CCR**	**DDF**
Mean	0.687	0.374
Std. dev.	0.131	0.262
Min	0.506	0.011
Max	1.000	1.000

We find that there is a large difference in technical efficiency scores when estimating using both CCR and DDF methods. The estimated results are depicted in Table 2, showing that the technical efficiency scores range from 0.506 to 1.000 on the CCR measure. The average technical efficiency score is 0.687, which means that the overall technical inefficiency under CCR is 31.3%. Our analysis follows input-oriented efficiency measures, so this result implies that inefficient water transport firms can improve their efficiency by reducing their inputs to 31.3% while keeping their outputs unchanged. In contrast, the average technical efficiency score under the DDF measure is only 0.374. We examined the null hypothesis which states that there is no significant difference between the average technical efficiency scores obtained using the CCR method and those derived from the DDF method. The t-test results support the rejection of the null hypothesis at the 1% significance level. This indicates that, on average, the efficiency of the Vietnamese water transport firms varies when considering undesirable outputs, specifically CO_2 emissions.

Table 3 Distribution of environmental efficiency of the Vietnamese water transport industry in the period 2015-2020

Year	**Variable**	**Mean**	**Std. dev.**	**Min**	**Max**
2015	TE_DDF	0.349	0.250	0.049	1.000
2016	TE_DDF	0.399	0.233	0.047	1.000
2017	TE_DDF	0.318	0.270	0.031	1.000
2018	TE_DDF	0.383	0.279	0.011	1.000
2019	TE_DDF	0.331	0.256	0.011	1.000
2020	TE_DDF	0.466	0.257	0.027	1.000

The results of estimating the environmental efficiency score for the Vietnamese water transport industry during the 2015-2020 period, as shown through the TE_DDF variable in Table 3, indicate significant fluctuations and instability, with an average efficiency of only 37.4%. The TE_DDF value reflects technical efficiency while accounting for undesirable outputs, such as CO_2 emissions. The lowest efficiency level was recorded in 2017 at 31.8%, while a marked improvement was observed in 2020, reaching 46.6%, highlighting the industry's ongoing challenges in optimizing technical efficiency and controlling emissions. The expansion of the water fleet to meet growing trade and logistics demand has contributed to increased CO_2 emissions, as most vessels still rely on fossil fuels, particularly diesel. Alternative solutions, such as clean fuels or renewable energy, have not been widely adopted, and the low fuel efficiency of older vessels results in greater emissions and waste compared to modern ships. Additionally, limitations in the Vietnamese seaport system and supporting services for water transport, including a lack of infrastructure for clean fuels and green docking facilities, as well as insufficient policies supporting environmentally friendly transport, continue to undermine the environmental efficiency of the industry and hinder long-term improvements in technical efficiency.

We continue to analyze the environmental efficiency of the Vietnamese water transport sector by three-digit VSIC (sea and coastal transport and inland water transport); by firm size (small-sized, medium-sized and large-sized); and by firm ownership (state and non-state). The estimated results of efficiency scores using the DDF model are shown in Figure 1.

We find that the environmental efficiency scores by sea and coastal transport and inland water transport sectors have significant differences. Specifically, the density of environmental efficiency scores of the sea and coastal transport sector is highest at around 0.2, then gradually decreases and has a second small peak near 1. This shows that there are a large number of firms in this sector achieving low environmental efficiency, but there are also a few firms achieving high environmental efficiency. In contrast, for the inland water transport sector, the density of environmental efficiency scores peaks at around 0.3 and then gradually declines. This density does not have a second small peak near 1 like the sea and coastal transport sector, indicating that fewer firms in this sector achieve higher environmental efficiency. This difference can be explained by the operational characteristics and scale of the two sectors groups. The sea and coastal transport sector is usually larger in scale and has more complex technical requirements, leading to a clear differentiation in environmental efficiency. Meanwhile, the inland water transport sector is usually smaller in scale and has less technical requirements, leading to a higher density concentration at the average efficiency score.

When analyzed by firm size, the results indicate distinct patterns in environmental efficiency among water transport firms. Small-sized firms exhibit the highest density of environmental efficiency scores around 0.2, which gradually decreases, with a secondary peak near 1. This distribution suggests that most small-sized firms have low environmental efficiency, while a few achieve very high efficiency. Medium-sized firms show the highest density of efficiency scores around 0.3, which then gradually declines without a secondary peak, indicating a focus on average efficiency. In contrast, large-sized firms display a more widely distributed density of efficiency scores, primarily between 0.2 and 0.4, with a secondary peak near 1. This indicates significant variation in the environmental efficiency of large-sized firms, with some achieving high efficiency and others only average. These differences can be attributed to operational and managerial capacities linked to firm size. Small-sized water transport firms often struggle with optimizing processes and resources, leading to lower environmental efficiency. Conversely, large-scale firms can leverage technology and effective management, though disparities in efficiency remain.

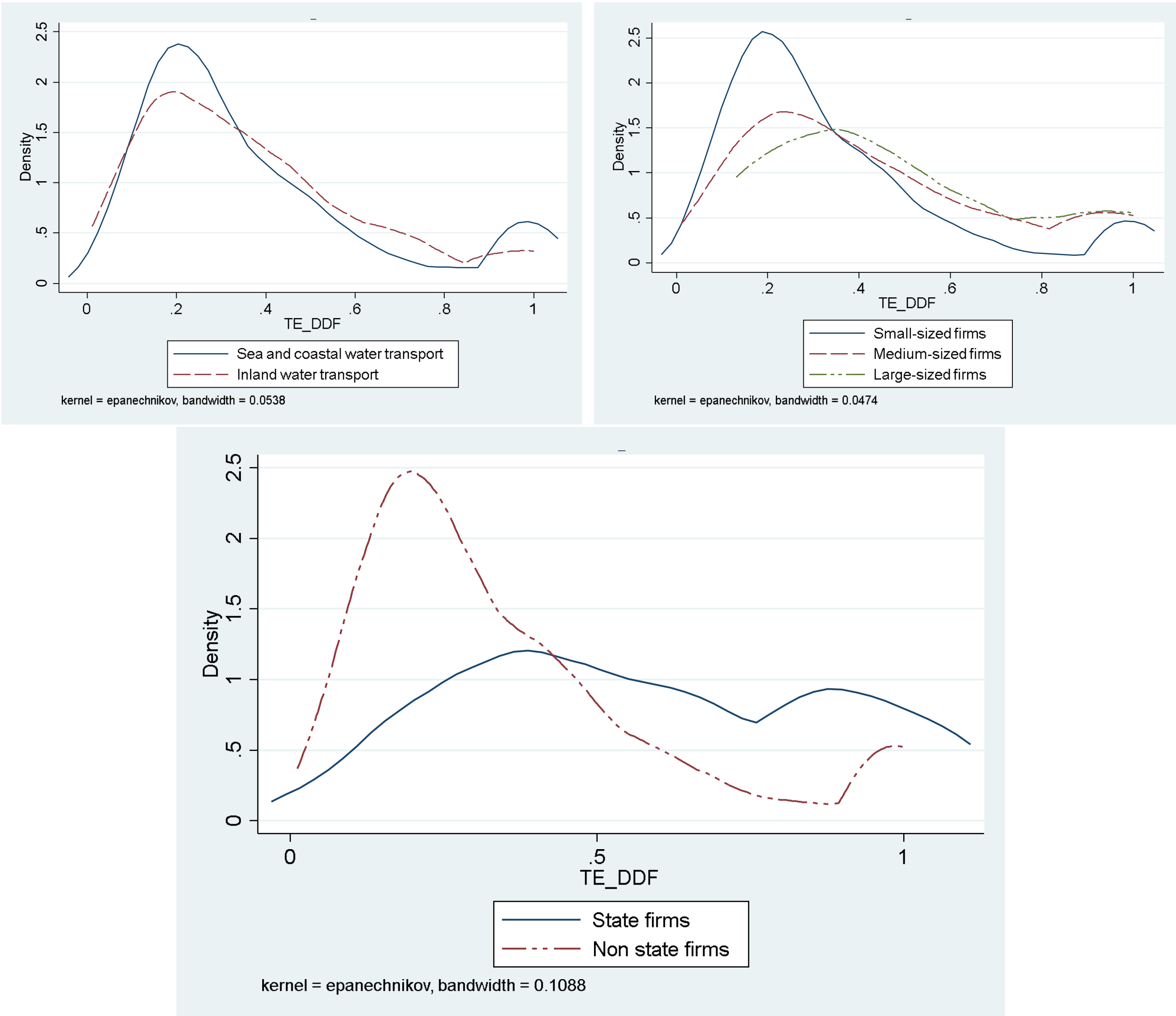

Figure 1 Environmental efficiency of the Vietnamese water transport industry by three-digit VSIC, by firm size and by firm ownership

The analysis of environmental efficiency by firm ownership reveals further differentiation. State firms have a widely distributed density of efficiency scores, concentrated between 0.1 and 0.4, with a secondary peak near 1. This suggests that while many state firms achieve average efficiency, a few attain high efficiency. Non-state firms, however, show the highest concentration of efficiency scores around 0.2, which rapidly decreases without a secondary peak, indicating that most achieve low to average efficiency with few high performers. This divergence can be explained by differences in management, scale, and operational structure. State firms, typically larger and supported by the government, face unique challenges in management and operational efficiency. Non-state firms, despite their flexibility and dynamism, often encounter financial and technological constraints, resulting in lower environmental efficiency.

In summary, the analysis reveals clear disparities in environmental efficiency among water transport firms in Vietnam, based on three-digit VSIC, firm size, and firm ownership. These findings highlight the need for targeted measures to improve environmental efficiency within specific groups of firms.

In the following, based on the DDF specified in the equation (6), we compute the MLPI of the Vietnamese water transport industry by the equation (7) and its components (MLTECH, MLTECCH) by the equations (8) and (9). For comparison, we also calculate the traditional Malmquist productivity index (MPI) by the model of Fare et al. (1994) [21], ignoring the undesirable outputs and decomposing its results by the components of technical efficiency change (MTECH) and technological change (MTECCH). The estimated results are presented in Table 4.

Table 4 Malmquist–Luenberger productivity index of the Vietnamese water transport industry in the period 2015-2020

Year	Malmquist-Luenberger productivity index			Malmquist productivity index		
	MLPI	MLTECH	MLTECCH	MPI	MTECH	MTECCH
2015-2016	1.001	0.969	1.033	1.002	1.017	0.986
2016-2017	0.987	1.014	0.973	0.933	1.013	0.922
2017-2018	1.031	1.037	0.994	1.011	0.993	1.019
2018-2019	1.027	1.054	0.974	1.038	1.014	1.025
2019-2020	1.051	1.036	1.014	1.026	1.025	1.001
Mean	**1.020**	**1.022**	**0.998**	**1.002**	**1.012**	**0.990**

The traditional Malmquist productivity index estimates show that the Vietnamese water transport industry has seen an average annual productivity growth of 0.2%. Decomposing this index shows that although average efficiency (MTECH) increased by 1.2% during 2015-2020, the decline in technological change (MTECCH) of -1.0% was the source of the total factor productivity drag. Technological progress exhibited negative growth during 2015-2017, and the highest increase in 2018-2019 was 2.5%. Meanwhile, the average annual growth of the MLPI was 2.0%. This average GTFP measure is a combination of the improvement in technical efficiency (MLTECH) of 2.2% and the decline in technological change (MLTECCH) of -0.2%. Overall, we find that the MLPI captures GTFP change, technical efficiency change, and technological change better than the traditional Malmquist productivity index. We also ran a paired two-sample t-test to examine whether the MLPI and the MPI, along with their components, were statistically different. The test results support the rejection of the null hypothesis that the MLPI and the MPI, and their components, are similar at the 5.0% significance level. This suggests that applying the MLPI to the Vietnamese water transport industry provides a different and possibly more accurate view of productivity when considering the undesirable output of CO_2 emissions.

Table 5 Malmquist–Luenberger productivity index of the Vietnamese water transport industry by three-digit VSIC, by firm size and by firm ownership

Malmquist-Luenberger productivity index and its components		MLPI	MLTECH	MLTECCH
By three-digit VSIC	Sea and coastal water transport	1.021	1.031	0.991
	Inland water transport	1.014	1.000	1.014
By firm size	Small-sized firms	1.017	1.019	0.998
	Medium-sized firms	1.021	1.026	0.995
	Large-sized firms	1.048	1.034	1.013
By firm ownership	State firms	1.012	1.012	1.000
	Non state firms	1.020	1.023	0.997

The results of estimating and decomposing the Malmquist-Luenberger total factor productivity index of the Vietnamese water transport industry in the period of 2015-2020 show important trends and characteristics when divided by three-digit VSIC, by firm size, and by firm ownership (Table 5). By three-digit VSIC, the sea and coastal transport sector had a GTFP increase of 2.1%, with the contribution from technical efficiency change (MLTECH) being 3.1%, while technological change (MLTECH) decreased by -0.9%. In contrast, the inland water transport sector had a GTFP increase of 1.4%, in which technical efficiency remained stable and technological change increased by 1.4%. By firm size, small-sized firms had a GTFP increase of 1.7%, in which technical efficiency increased by 1.9% but technological progress decreased slightly by -0.2%. Medium-sized firms saw a 2.1% increase in GTFP, with technical efficiency increasing by 2.6% and technological change decreasing by 0.5%. Large-sized firms had an impressive increase in GTFP (4.8%) as both technical efficiency and technological progress increased by 3.4% and 1.3%, respectively. When divided by firm ownership, state firms saw a 1.2% increase in GTFP, with both technology and technical efficiency remaining stable. Non-state firms saw a 2.0% increase in GTFP, with technical efficiency increasing by 2.3% but technological change decreasing slightly by -0.3%. In summary, the Vietnamese water transport industry has seen positive growth in GTFP during 2015-2020, mainly due to improvements in technical efficiency. However, technological progress remains limited, especially among small and medium-sized firms and non-state firms. Large-sized firms and the inland water transport sector were the groups with the most significant technological improvements during this period.

The above results reflect the fact that the real total factor productivity growth of the industry is overestimated when undesirable outputs are taken into account. This finding is consistent with the results of Chung et al. (1997), Oh (2010), and Li and Lin (2016) [5,9,12]. In these studies, the evaluated firms show more pronounced productivity improvements when using the MLPI, rather than the traditional Malmquist productivity index, in which undesirable outputs are ignored. This suggests that when traditional productivity measures ignore undesirable output changes, they underestimate real productivity growth. The main reason for the underestimation of real productivity growth is that environmental regulations affect the production activities of firms. With environmental regulations, resources must be diverted from producing good outputs to activities that reduce pollution. The traditional Malmquist productivity index does not recognize the positive effects of shifting resources to reduce pollution and assumes that these inputs are inefficient in producing the desirable outputs. However, in practice, the result of these inputs is a reduction in emissions or an improvement in the environment because environmental regulations encourage the adoption of modern pollution-reducing technologies, the transition to less wasteful production processes, and the use of cleaner energy. The traditional Malmquist productivity index does not recognize firms that reduce emissions and therefore underestimates true productivity growth. The findings on GTFP growth of the Vietnamese water transport industry support Porter's hypothesis, which posits that environmental regulations not only do not reduce competitiveness but can also promote competition by encouraging innovation (Porter and van der Linde, 1995) [22].

5 Conclusions and recommendations

The study uses the DDF with undesirable outputs and the MLPI to investigate the environmental efficiency and GTFP growth of the Vietnamese water transport industry from 2015 to 2020. The findings indicate that the environmental efficiency score of the industry remains low during this period, averaging 37.4%, with noticeable fluctuations and variations across different three-digit VSIC codes, firm sizes, and ownership types. Specifically, sea and coastal transport firms, large enterprises, and state-owned firms typically achieve higher environmental efficiency due to economies of scale and government support, although significant disparities exist within each category. Additionally, the research reveals a notable increase in the industry's GTFP growth, averaging 2.0%, with larger firms exhibiting greater overall increases compared to small and medium firms. This suggests that larger firms are more adept at enhancing technical efficiency and adopting technological advancements than small and medium-sized firms. Despite uniform improvements in technical efficiency across the industry, technological progress remains limited, particularly among small and medium-sized firms and non-state firms. This trend highlights that, under stringent environmental regulations, larger firms are more capable of investing in advanced technology and managing resources efficiently, whereas SMEs face greater challenges in achieving technological improvements.

Therefore, to enhance environmental efficiency, increase GTFP, and promote sustainable development in the Vietnamese water transport industry, we propose the following recommendations: Firstly, management agencies should implement policies to support the adoption of technology and emission reduction initiatives by firms. Encouraging firms to adopt green technology will improve environmental performance. Technological advancement should be prioritized in technical and financial support programs, particularly for sea and coastal transport firms, small-sized and medium-sized firms, and non-state firms. Secondly, it is essential to focus on training and skill development programs for workers to optimize production processes within firms. Concurrently, improving management practices is crucial for achieving higher efficiency in the industry. Thirdly, reforming management and enhancing transparency in the operations of state firms is necessary. Promoting cooperation between state and non-state firms to share experiences and technologies can further improve overall efficiency and productivity of the industry. Finally, it is vital to continue advancing environmental regulations that encourage technological innovation and improved production processes, thereby incentivizing the entire industry to enhance environmental efficiency and GTFP. These policies not only help firms meet environmental standards but also enhance the industry's competitiveness in the international market. Furthermore, creating a favorable business environment, combined with appropriate support policies, will enable the Vietnamese water transport industry to develop more sustainably and effectively in the future.

References

[1] FARE, R., GROSSKOPF, S., LOVELL, C.K., PASURKA, C.: Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach, *The review of economics and statistics*, Vol. 71, No. 1, pp. 90-98, 1989. https://doi.org/10.2307/1928055
[2] YANG, H., POLLITT, M.: Incorporating both undesirable outputs and uncontrollable variables into DEA: The performance of Chinese coal-fired power

plants, *European journal of operational research*, Vol. 197, No. 3, pp. 1095-1105, 2009. https://doi.org/10.1016/j.ejor.2007.12.052

[3] LOZANO, S., GUTIERREZ, E.: Slacks-based measure of efficiency of airports with airplanes delays as undesirable outputs, *Computers & Operations Research*, Vol. 38, No. 1, pp. 131-139, 2011. https://doi.org/10.1016/j.cor.2010.04.007

[4] WANG, D., DU, K., ZHANG, N.: Measuring technical efficiency and total factor productivity change with undesirable outputs in Stata, *The Stata Journal*, Vol. 22, No. 1, pp. 103-124, 2022. https://doi.org/10.1177/1536867X221083886

[5] CHUNG, Y.H., FARE, R., GROSSKOPF, S.: Productivity and undesirable outputs: a directional distance function approach, *Journal of Environmental Management*, Vol. 51, No. 3, pp. 229-240, 1997. https://doi.org/10.1006/jema.1997.0146

[6] MAHLBERG, B., SAHOO, B.K.: Radial and non-radial decompositions of Luenberger productivity indicator with an illustrative application, *International Journal of Production Economics*, Vol. 131, No. 2, pp. 721-726, 2011. https://doi.org/10.1016/j.ijpe.2011.02.021

[7] MAI, T.K., DINH, Q.T., QUACH, H.T., NGUYEN, V.: Performance of Vietnamese shipping firms: a four random components stochastic frontier approach, *Acta logistica*, Vol. 10, No. 2, pp. 319-329, 2023. https://doi.org/10.22306/al.v10i2.397

[8] ZHANG, N., CHOI, Y.: A note on the evolution of directional distance function and its development in energy and environmental studies 1997-2013, *Renewable and Sustainable Energy Reviews*, Vol. 33, pp. 50-59, 2014. https://doi.org/10.1016/j.rser.2014.01.064

[9] LI, K., LIN, B.: Impact of energy conservation policies on the green productivity in China's manufacturing sector: Evidence from a three-stage DEA model, *Applied energy*, Vol. 168, pp. 351-363, 2016. https://doi.org/10.1016/j.apenergy.2016.01.104

[10] PARRIS, D., SPINTHIROPOULOS, K., RAGAZOU, K., KANAVAS, V., TSANAKTSIDIS, C.: Measuring Eco-Efficiency of the Global Shipping Sector Based on an Energy and Environmental Approach: A Dynamic Slack-Based Measure Non-Oriented Model, *Energies*, Vol. 16, No. 19, 6997, pp. 1-19, 2023. https://doi.org/10.3390/en16196997

[11] LIU, P., PAN, Q., ZHU, B.: Dynamic evolution of green total factor productivity growth of China's coastal ports, *Maritime Policy & Management*, Vol, 51, No. 7, pp. 1535-1557, 2023. https://doi.org/10.1080/03088839.2023.2205845

[12] OH, D.H.: A global Malmquist-Luenberger productivity index, *Journal of productivity analysis*, Vol. 34, No. 3, pp. 183-197. https://doi.org/10.1007/s11123-010-0178-y

[13] SCHEEL, H.: Undesirable outputs in efficiency valuations, *European journal of operational research*, Vol. 132, No. 2, pp. 400-410, 2001. https://doi.org/10.1016/S0377-2217(00)00160-0

[14] SEIFORD, L.M., ZHU, J.: Modeling undesirable factors in efficiency evaluation, *European Journal of Operational Research*, Vol. 142, No. 1, pp. 16-20, 2002. https://doi.org/10.1016/S0377-2217(01)00293-4

[15] TONE, K.: *Dealing with undesirable outputs in DEA: a slacks-based measure (SBM) approach*, North American Productivity Workshop 2004, Toronto, 23-25 June 2004, pp. 44-45, 2024.

[16] PODINOVSKI, V.V., KUOSMANEN, T.: Modelling weak disposability in data envelopment analysis under relaxed convexity assumptions, *European Journal of Operational Research*, Vol. 211, No. 3, pp. 577-585, 2011. https://doi.org/10.1016/j.ejor.2010.12.003

[17] IPCC, IPCC Guidelines for National Greenhouse Gas Inventories, [Online], Available: https://www.ipcc-nggip.iges.or.jp/public/2006gl/ [08 Jul 2024], 2006.

[18] CHEN, J., SONG, M., XU, L.: Evaluation of environmental efficiency in China using data envelopment analysis, *Ecological indicators*, Vol. 52, pp. 577-583, 2015. https://doi.org/10.1016/j.ecolind.2014.05.008

[19] LAN, P.M., MINH, N.K.: Environmental efficiency evaluation in vietnam textile and garment industry: super-SBM model with undesirable output approach, *Nature Environment and Pollution Technology*, Vol. 22, No. 2, pp. 731-740, 2023. https://doi.org/10.46488/NEPT.2023.v22i02.016

[20] CHARNES, A., COOPER, W.W., RHODES, E.: Measuring the efficiency of decision making units, *European Journal of Operational Research*, Vol. 2, No. 6, pp. 429-444, 1978. https://doi.org/10.1016/0377-2217(78)90138-8

[21] FARE, R., GROSSKOPF, S., NORRIS, M., ZHANG, Z.: Productivity growth, technical progress, and efficiency change in industrialized countries, *The American economic review*, Vol. 84, No. 1, pp. 66-83, 1994.

[22] PORTER, M.E., LINDE, C.V.D.: Toward a new conception of the environment-competitiveness relationship, *Journal of Economic Perspectives*, Vol. 9, No. 4, pp. 97-118, 1995. https://doi.org/10.1257/jep.9.4.97

Review process

Single-blind peer review process.