The Economics of Shipping Decarbonisation: Carbon, Production, Cost, and Allocative Efficiencies

Highlights

- Applied an economic measure of shipping efficiency using stochastic frontier analysis.
- Carbon and production efficiencies have increased, but cost efficiency has decreased.
- Vessels that spend more time at sea and are newer exhibit higher production efficiency.
- Comparing productivity with price, fuel is underused, and capital is overused.
- Allocative inefficiency has a higher impact on total cost than technical inefficiency.

Abstract

We investigate the trade-off between environmental and economic performance in the case of the shipping industry. Existing environmental regulations largely omit the economic efficiency dimension which, in turn, delays the industry's clean energy transition. We apply a stochastic frontier analysis to assess the relationship between carbon emissions and economic factors as capital, labour, earnings, and transport work, both across all major shipping segments and at an individual-vessel level. The empirical results suggest that, during the post-pandemic period, vessels have become more carbon and production efficient but less cost efficient. Technical and operational inefficiencies raise the total cost of owning and operating a vessel by 6%, with market price dynamics and inefficient allocation of economic resources increasing it by 17%. There is scope for the average vessel to reduce its carbon emissions by 31% although carbon efficiency varies significantly depending on the vessel type and period. As such, policy interventions need to be carefully designed in order not to cause an undersupply of specific vessel types which can negatively impact the trade of various commodities globally.

Keywords

Decarbonisation regulation; carbon efficiency; allocative efficiency; greenhouse gas pricing; net zero shipping; stochastic frontier analysis.

1. Introduction

Various policies have been adopted across industries to facilitate the net-zero energy transition in line with the Paris Agreement. To minimise the risk of market distortion, greenhouse gas (GHG) reduction measures shall be designed comprehensively to combine socioeconomic elements with technical feasibility (Fisch-Romito et al. 2025). This study focuses on the shipping industry to highlight the importance of explicitly incorporating the economic dimension when designing environmental regulations.

The maritime industry facilitates more than 85% of international trade in goods (Clarksons' SIN 2024) but, at the same time, is responsible for nearly 3% of GHG emissions (UNCTAD 2023). In response, the International Maritime Organization (IMO) – the United Nations' specialised body responsible for preventing the marine and atmospheric pollution caused by ships – has set a target of achieving net-zero shipping by or around 2050 (IMO 2023).

Efficiency maximisation is at the forefront of the net-zero transition with various strategies and measures implemented to achieve that. In the short run, vessels can improve energy efficiency through naval engineering improvements (e.g., energy-saving devices), by using renewable energy sources (e.g., wind propulsion) to cover part of their energy needs, by burning fuels with lower carbon intensity than oil (e.g. liquefied natural gas [LNG]), and by optimising their operations (mainly through speed reduction). However, alignment with the IMO's mid- and long-term targets will require most vessels to burn net-zero fuels such as green methanol, ammonia, hydrogen, and biofuels instead of fossil fuels.

To encourage the adoption of such practices and improve the technical and operational efficiency of vessels, the IMO has introduced a series of measures in recent years, including the Energy Efficiency Design Index (EEDI), the Energy Efficiency Existing Ship Index (EEXI), and the Carbon Intensity Indicator (CII). These can have significant economic implications.

Nevertheless, those measures do not account for the economic-environmental trade-off faced by market participants and, thus, fail to mobilise green investment. Such intervention is crucial as the income generated by greener vessels does not seem to justify the required capital expenditure (Petropoulos 2022). Therefore, for shipowners to undertake the riskier and more expensive greener investment, there need to be strong economic (dis)incentives which are not provided by the existing measures.

In response to that, regulators are proposing economic, market-based, measures that integrate financial (dis)incentives into energy efficiency requirements or carbon intensity restrictions. At an international level, there have been ongoing discussions regarding the introduction of a maritime GHG emissions pricing mechanism (IMO 2024). At regional level, the most prominent economic measure is the European Union’s Emissions Trading System (EU ETS), implemented in 2024.

Such measures, however, seem to overlook the interrelation between carbon dioxide emissions (CO_2) and economic variables as the income generated by a vessel, the capital costs required for its acquisition or retrofitting, and the labour, maintenance, and fuel costs associated with operating it.

To this end, this paper relates those key economic indicators with technological and environmental measures and assesses the carbon, technical, and allocative efficiencies of the shipping fleet. Furthermore, it introduces a measure that directly relates the economic and carbon performances of a vessel. Based on that, it analyses the performance of each major shipping segment over the period 2021-2024. Such economic assessments are important for the well-functioning of the industry. Informed by those, policymakers can evaluate the economic implications that environmental measures have on investors and establish a fair system that incentivises them towards net-zero shipping. The shipping industry, in turn, can identify ways to improve its economic efficiency while complying with the decarbonisation regulations.

There are several research gaps this paper aims to fill. First, it proposes an economic measurement of shipping carbon efficiency. Second, it develops carbon, technical, and allocative efficiency measures and assesses the performance of the shipping fleet in recent years. Third, it distinguishes the impacts of economic resource allocation from the effects of technical improvements on the energy demand and total cost of a vessel. Fourth, it compares the price and productivity of energy with other economic inputs at both sector and vessel levels. Finally, it estimates how the above measures vary according to changes in economic inputs and discusses their potential market implications. To the best of our knowledge, this is the first research that thoroughly discusses the economic-environmental trade-off in relation to international trade and transportation.

The remainder of this paper is organised as follows. Section 2 reviews the existing literature on energy efficiency and identifies the gaps that our research aims to address. Sections 3 and 4 describe the incorporated methodology and data, respectively. Section 5 presents and discusses the results. Finally, Section 6 concludes and provides policy and industry recommendations.

2. Literature review

There exist two areas of research in shipping energy efficiencies: one identifies the determinants of energy efficiency; the other investigates the barriers to the adoption of energy efficiency practices (Anderson et al., 2015; Barreiro, Zaragoza and Diaz-Casas, 2022; Jimenez, Kim and Munim, 2022).

The former typically assesses the impact of technical and operational factors on energy efficiency. Sou et al. (2022) decompose the carbon intensity of vessel types into modal shift, capacity utilisation, energy intensity and carbon intensity. Their findings suggest that energy intensity reduction is the main contributor to the improvement of the Energy Efficiency Operational Indicator (EEOI) and Annual Efficiency Ratio (AER) from 2012 to 2018 while modal shift and capacity utilisation play a minimal role. Rehmatulla and Smith (2015b) survey 170 companies on their implementation measures to improve EEDI, including fuel consumption monitoring, weather routing, and speed reduction. They find that company size and sector influence the implementation of decisions, probably due to different hidden costs, access to capital, and risk perception. Johnson and Styhre (2015) study a bulk shipping company through quantitative and qualitative data and find that enhanced port operation can increase energy efficiency by at least 2-8%. There are further publications that focus on the operational and technical aspects of energy efficiency (e.g., Lassesson and Andersson (2009), Lu et al. (2015), Nuchturee, Li and Xia (2020), and Duan et al. (2023).

The other group of research typically uses surveys or interviews to identify the barriers to adopting energy efficiency measures. Jafarzadeh and Utne (2014) interview 12 participants from five shipowners in Norway and construct a framework of barriers to adopting energy efficiency practices, which include information uncertainty and risk in economics, technology, policy, and organisational structures. Johnson and Andersson (2016) interview 19 people in shipping companies and find that information asymmetry and organisational structures are the main barriers to energy efficiency adoption. Other researchers have similar findings (Rehmatulla and Smith, 2015a, 2015b; Dewan, Yaakob and Suzana, 2018; Hansen, Rasmussen and Lützen, 2020).

Few researchers have considered maritime economics and maritime financial markets when analysing either shipping energy or carbon efficiency. There are two main strands of related literature. One focuses on the cost to comply with energy efficiency regulations. Namely, Ammar (2018) investigates the cost of speed reduction to comply with EEDI for a Roll on-Roll off (Ro-Ro) cargo vessel and finds that, for the first and second phases, reducing ship speed by 40% will reduce CO_2 by 78.39% with a cost-effectiveness of \$287.6/ton CO_2. Ammar and Seddiek (2020) compare the cost effectiveness of dual-fuel engines, treatment equipment and speed reduction for EEDI compliance for containerships; they find that, for an A19 container ship, it is better to install dual-fuel engine infrastructure onboard which will generate annual fuel savings of \$23.73 million. Rojon et al. (2021) review the literature on carbon pricing and suggest that, in general, carbon pricing increases transport costs by 0.4-16% and the prices of imported goods by 0-0.7%. Elkafas and Shouman (2022) compare the energy efficiency and annual cost of a diesel-electric system with a conventional one in a case study of a passenger ship; they find that the former has 10% less CO_2 and 22% less cost than the latter. There are other studies examining the cost effectiveness of energy efficiency measures (Mermiris et al., 2011; Yuan et al., 2019; Cullinane and Yang, 2022; Czermański et al., 2022) but none have gone beyond basic arithmetic calculations with monetary values.

The other literature strand applies econometric modelling to study the determinants or barriers to energy efficiency. Agnolucci, Smith and Rehmatulla (2014) study the relationship between time-charter (TC) rates and EEDI in the dry bulk Panamax sector and find that only 40% of financial savings accrue to shipowners. Acciaro and McKinnon (2015) run an econometric model analysing the energy efficiency of 2,300 containership voyages in 2012. They find that energy efficiency, as measured by fuel consumption per transport work, is influenced by sailing speed, vessel age, vessel size, whether the vessel is owned or chartered, the operator and the route. Longarela-Ares, Calvo-Silvosa and Pérez-López (2020) study the determinants of energy efficiency investment for 6,750 vessels. They find that the vessel's age and the existence of a TC contract (as opposed to a voyage contract) are negatively related to energy efficiency improvement, while the vessel's size and EEDI are positively related to it.

Nevertheless, none of the above studies consider the energy efficiency or carbon efficiency measurement itself. Focusing only on a physical-thermal measurement neglects key information on the economic trade-offs associated with shipping decarbonisation, thereby presuming that decarbonisation will be either a self-driven process or an obligation to comply with policy. It is essential to investigate the economic interactions to quantify the losses and gains, the drivers of carbon efficiencies, and the degree of distortion in resource allocation.

Data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are two widely incorporated economic methods to measure energy efficiency and carbon efficiency (Filippini and Hunt, 2015) as they have the advantage of simultaneously considering the output and multiple inputs. For instance, a vessel may be more carbon efficient because it has installed energy saving technologies and, at the same time, uses low-carbon fuels. Traditional economic methods would either measure the carbon reduction per capital investment, or carbon reduction per fuel cost, but fail to consider the carbon reduction due to both capital and fuel inputs.

Recent papers have documented the applications of DEA and SFA in energy efficiency and carbon efficiency in various fields, such as building (Önüt and Soner, 2006), carbon regulation (Tan et al. 2020), and global comparison (Cui and Li, 2015; Jin and Kim, 2019). DEA and SFA have also been used in transportation (Cui and Li, 2015; Cullinane and Yang, 2022; Zhang, Luo and Yang, 2025). For instance, Cullinane et al. (2006) applied DEA and SFA to examine the technical efficiency of container ports. However, few, if any research has applied either method in evaluating decarbonisation regulation. This paper applies SFA in shipping, which is responsible for close to 3% of global GHG emissions (UNCTAD 2023). Compared to DEA, SFA has the advantage of distinguishing stochastic noise from efficiency. Since the shipping industry is well known for its high volatility (Greenwood and Hanson, 2015; Moutzouris and Nomikos, 2019), the SFA method is preferred in this paper.

We consider SFA the best approach for estimating cost, production, carbon, and allocative efficiencies in shipping. Similar to the appropriate technology model for measuring relative efficiency (Caselli and Coleman, 2006; Rossi, 2022), using SFA to estimate allocative efficiency also involves comparing input prices with marginal productivity. However, our method does not assume that vessels choose technologies, as most vessels in the current fleet still use fossil fuel. In contrast, we assume that vessels choose input levels based on the prevalent technologies. Furthermore, we do not decompose total factor productivity into allocative efficiency and other factors as in many publications (e.g., Casey (2024), Hornbeck and Rotemberg (2024)), because output in shipping is largely driven by global demand. For instance, during market downturns, newer and efficient vessels are used first while, during market booms, older and inefficient vessels are also heavily utilised (Moutzouris et al. 2024).

Finally, relevant research emphasises the usefulness of simulation and sensitivity analysis in estimating the effects of carbon taxes and fuel prices on the energy transition, identifying the optimal choices to balance climate change mitigation and economic turbulence (Aghion et al., 2016; Barrage, 2020; Coulomb, Henriet and Reitzmann, 2021). We also perform sensitivity analysis to examine the potential effects of regulation interventions and market dynamics on the carbon and economic efficiency of shipping which, in turn, strengthens the paper's recommendations.

3. Methodology

In general terms, efficiency is the ratio of the useful outputs from a system to the inputs to it. These inputs and outputs can be defined and measured in both physical-thermodynamic and economic-thermodynamic terms (Patterson, 1996; Allan et al., 2009). This paper focuses on economic inputs and outputs using a stochastic frontier analysis. This measures efficiency relative to the frontier, i.e., it provides a relative measurement compared to the best practice on the frontier (Kumbhakar and Lovell, 2003).

As CO2 is closely related to energy use, it can be considered as an input in production. *Technical carbon efficiency* refers to a firm's objective to minimise CO2 subject to output and other inputs, Optimisation (1). *Production efficiency*, Optimisation (2), corresponds to maximising output given energy and other inputs. *Cost efficiency*, Optimisation (3), is related to minimising the total cost given a fixed level of output and inputs.

Carbon efficiency: $min\ (CO2|given\ output\ and\ other\ inputs)$ (1)

Production efficiency: $max\ (output|given\ energy\ and\ other\ inputs)$ (2)

Cost efficiency: $min\ (total\ cost|given\ output\ and\ inputs)$ (3)

To illustrate technical carbon efficiency, consider a simple model with only two inputs, CO2 and another input, such as capital. In Figure 1, Vessel E is not on the frontier, indicating inefficiency. Vessel A and Vessel B are on the frontier with 100% efficiency. The technical carbon efficiency of Vessel E is OC/OE. The isoquant line defines relative prices. The allocative carbon efficiency of Vessel E is OA/OC. The overall cost efficiency of Vessel E is expressed as OA/OE.

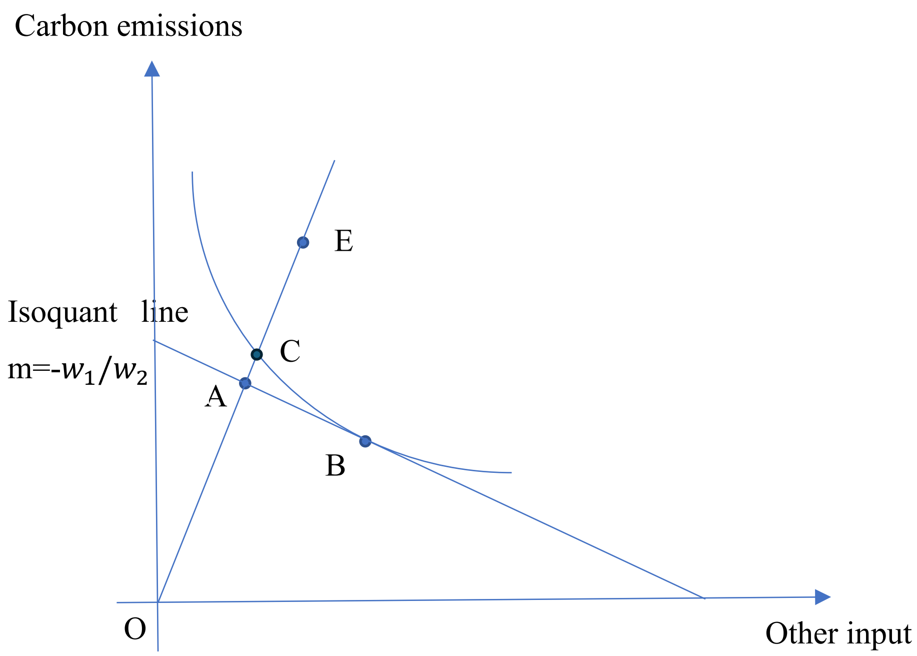


Figure 1 Technical carbon efficiency and allocative carbon efficiency

In general, technical carbon efficiency is the carbon emission difference between Vessel i ($CO2_i$) and the minimum level ($CO2^*$) at the frontier, given the vessel's economic outputs and other inputs.

CO2 is used as an input to measure carbon efficiency (Dong et al., 2013; Sun and Huang, 2020; Tan et al., 2020); especially in the transport sector (Cui and Li, 2015; Wanke et al., 2020). As various studies suggest (Gandhi, 1996; Lin and Ahmad, 2016; Kosmas and Acciaro, 2017), capital, operation and energy can be considered as inputs in the transport production function. In line with recent literature (Garcia-Marin and Voigtländer, 2019; Orr, 2022), output can be measured by either production quantity, such as the vessel's transport work (expressed in ton-miles), or the economic income generated (e.g., vessel earnings).

Capital in shipping is measured as the newbuilding or resale price minus depreciation. Operation comprises the crew onboard the vessel, and staff and materials required for repair, maintenance, and technological upgrades. As energy consumption is associated with CO2, the latter can be used as a proxy for the former. Therefore, we specify the inputs as operation, capital, and energy in the production function. Then, carbon efficiency is measured as the relative CO2 given the vessel's outputs, operation, and capital inputs.

If we specify a functional form for $CO2^{*}$ and assume that the output corresponds to TC earnings, the technical carbon efficiency of Vessel *i* can be expressed as:

$$D(TC, K, OP) = \frac{CO2^{*}}{CO2_i} = \frac{f(TC, K, OP)}{CO2_i} \tag{4}$$

where *OP* is operation, *K* is capital, *E* is energy, and *TC* is time charter earnings.

Then, taking the natural logarithm on both sides of Equation (4) and re-arranging yields:

$$lnCO2_i = \ln[f(TC, K, OP)] - \ln\,[D(TC, K, OP)] \tag{5}$$

Incorporating a Cobb-Douglas production function, we obtain Equation (6):[1]

$$lnCO2_{it} = \alpha_0 + \alpha_1 lnTC_{it} + \alpha_2 lnK_{it} + \alpha_3 lnL_{it} - \ln[D(TC, K, OP)] \tag{6}$$

where $\ln[D(TC, K, OP)]$ is the inefficiency term which is also denoted by u_i as it is part of an error term. The technical carbon efficiency of firm *i* is $D(TC, K, OP) = e^{u_i}$, ranging from 0 to 1.

In a stochastic frontier analysis, the error term also includes a stochastic noise, v_i:

$$lnCO2_{it} = \alpha_0 + \alpha_1 lnTC_{it} + \alpha_2 lnK_{it} + \alpha_3 lnOP_{it} - u_{it} + v_{it} \tag{7}$$

Following Battese and Coelli (1992), for the panel data analysis part of the empirical estimation, we use an Error Components Model as it allows for time-varying efficiencies. For the cross-sectional data analysis part, in line with Aigner, Lovell and Schmidt (1977), Meeusen and van Den Broeck (1977) and Stevenson (1980), we assume half normal, exponential and truncated normal distributions of the inefficiency term and compare their goodness of fit.

Vessels achieve production efficiency when maximising output subject to a given set of inputs (Equation (2)). The production function in shipping may be expressed as:

$$D * V = f(OP, K, E) \tag{8}$$

where total world seaborne trade $(D * V)$ is aggregated by cargo type and measured in ton-miles. To disaggregate cargo types into the associated vessel types, we use the deadweight

[1] For robustness, we have also examined translog models.

tonnage (DWT) of each type as weights. To illustrate the procedure, Equation (9) shows the estimation of the transport work of one Suezmax oil tanker:

$$\begin{aligned} &Transport\ work\ of\ one\ Suezmax\ oil\ tanker \\ &\qquad \approx World\ seaborne\ oil\ transported \\ &\qquad \times \frac{DWT\ of\ all\ Suezmax\ oil\ tankers}{DWT\ of\ all\ oil\ tankers \times number\ of\ Suezmax\ Oil\ tankers} \end{aligned} \tag{9}$$

Production efficiency can be written as:

$$ln(D * V)_{it} = \beta_0 + \beta_1 lnOP_{it} + \beta_2 lnE_{it} + \beta_3 lnK_{it} + \delta_{it} + v_{it} \tag{10}$$

where δ_{it} is the technical production inefficiency. In contrast to u_{it} in Equation (7), the sign of δ_{it} is positive; since the objective is to *maximise* production, inefficiency reduces the optimal production level.

Cost efficiency aims to minimise total cost subject to given output and prices of inputs. Equation (11) shows cost efficiency with transport work as an output:

$$lnC_{it} = \gamma_0 + \gamma_1 ln(D * V)_{it} + \gamma_2 lnLp_{it} + \gamma_3 lnFp_{it} + \gamma_2 lnKp_{it} - \theta_{it} + v_{it} \tag{11}$$

where C is total cost, Lp is cost of operation (approximated by wage), Kp is cost of capital (loan rate), Fp is the unit cost of energy (fuel price), and θ_{it} is the cost inefficiency.

Economists decompose cost efficiency into technical and allocative components (Farrell 1957).

Allocative efficiency compares the marginal rate of technical substitution (MRTS) of a pair of inputs with their relative prices (Kumbhakar, Wang and Horncastle, 2015). For example, if the MRTS of energy input over capital input is larger than their relative prices, then energy input is underused and capital input is overused. This study uses the output-oriented method of measuring allocative efficiency, following Schmidt and Lovell (1979), Kopp and Diewert (1982) and Kumbhakar, Wang and Horncastle (2015).

Consider minimising the total cost subject to the production function:

$$\begin{aligned} &min\ \ C = (Lp * OP + Fp * E + Kp * K) \\ &\text{subject to} \\ &ln(D * V)_{it} = \beta_0 + \beta_1 lnOP_i + \beta_2 lnE_i + \beta_3 lnK_i - u_i + v_i \end{aligned} \tag{12}$$

The returns to scale, *r*, correspond to:

$$r = \beta_1 + \beta_2 + \beta_3 \quad (13)$$

The constraint minimisation yields:

$$f_E/f_L = Lp/Fp * exp\ (\varepsilon_1) \quad (14)$$

$$f_K/f_L = Lp/Kp * exp\ (\varepsilon_2) \quad (15)$$

$$f_K/f_E = Fp/Kp * exp\ (\varepsilon_3) \quad (16)$$

where f_K, f_E and f_L are the first-order partial derivatives with respect to capital, energy and operation respectively; ε_1, ε_2 and ε_3 are the allocative inefficiencies for the input pairs (operation, energy), (operation, capital) and (energy, capital) respectively. Subscripts i are omitted for simplicity and all variables are in vector form.

Since allocative efficiency measures the relative usage of a pair of inputs, e.g., energy input compared to operation input, switching the input pair can derive a different allocative efficiency ratio for capital input versus operation input. For instance, ε_1' measures the input pair (energy, operation) in Equation (17) while ε_2' measures the input pair (capital, operation) in Equation (18):

$$f_L/f_E = Fp/Lp * exp\ (\varepsilon_1') \quad (17)$$

$$f_L/f_K = Kp/Lp * exp\ (\varepsilon_2') \quad (18)$$

Taking the natural logarithm of Equations (14), (15), (16), (17) ,and (18), and replacing the first-order conditions, these equations can be further transformed into Equations (19), (20), (21), (22) and (23):

$$\varepsilon_1 = ln(\beta_2/\beta_1) - ln(Fp/Lp) - lnE + lnOP \quad (19)$$

$$\varepsilon_2 = ln(\beta_3/\beta_1) - ln(Kp/Lp) - lnK + lnOP \quad (20)$$

$$\varepsilon_3 = ln(\beta_3/\beta_2) - ln(Kp/Fp) - lnK + lnE \quad (21)$$

$$\varepsilon_1' = ln(\beta_1/\beta_2) - ln(Lp/Fp) - lnOP + lnE \quad (22)$$

$$\varepsilon_2' = ln(\beta_1/\beta_3) - ln(Lp/Kp) - lnOP + lnK \quad (23)$$

Following Kumbhakar, Wang and Horncastle (2015), the effects of technical and allocative efficiencies on input demand can be estimated by solving the simultaneous equations obtained from Equation (12), which yields Equations (24), (25) and (26):

$$lnOP = \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D * V) + \frac{1}{r}(\beta_2 \varepsilon_1' + \beta_3 \varepsilon_2') - \frac{1}{r}(v - u) \quad (24)$$

$$lnE = \beta_2 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnEp + \frac{1}{r}\ln(D * V) + \frac{1}{r}(\beta_2 \varepsilon_1' + \beta_3 \varepsilon_2') - \varepsilon_1' - \frac{1}{r}(v - u) \quad (25)$$

$$lnK = \beta_3 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnKp + \frac{1}{r}\ln(D * V) + \frac{1}{r}(\beta_2 \varepsilon_1 + \beta_3 \varepsilon_2) - \varepsilon_2' - \frac{1}{r}(v - u) \quad (26)$$

In Equations (24), (25) and (26), there are four parts: Part 1 is dependent on allocative efficiency ε; Part 2 is dependent on technical efficiency u; Part 3 is dependent on stochastic noise v; and Part 4 is independent of ε, u or v. We can estimate input demand without any efficiency ($none$), with technical efficiency (te), with allocative efficiency (a), and with both technical and allocative efficiencies ($both$).

For instance, for operation input:

Assuming $\varepsilon = 0$, $u = 0$ and $v = 0$, operation input demand without efficiencies, L^{none}, is:

$$lnOP^{none} = \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D * V) \quad (27)$$

Assuming $\varepsilon = 0$, $u = \widehat{u}$ and $v = 0$, operation input demand with technical inefficiency, L^{te}, is:

$$lnOP^{te} = \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D * V) - \frac{1}{r}(-u) \quad (28)$$

Assuming $\varepsilon = \widehat{\varepsilon}$, $u = 0$ and $v = 0$, operation input demand with allocative inefficiency, L^{a}, is: (29)

$$lnOP^{a} = \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D * V) + \frac{1}{r}(\beta_2 \varepsilon_1' + \beta_3 \varepsilon_2')$$

Assuming $\varepsilon = \widehat{\varepsilon}, u = \widehat{u}$ and $v = 0$, operation input demand with both inefficiencies, L^{both}, is:

$$lnOP^{both} = \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D * V) + \frac{1}{r}(\beta_2 \varepsilon_1' + \beta_3 \varepsilon_2') - \frac{1}{r}(-u) \quad (30)$$

The input demand functions for the energy and capital inputs can be derived in a similar manner. Accordingly, by adding up all the effects from each individual input, the overall effect on costs can be estimated:

$$c^{none} = Lp * OP^{none} + Fp * E^{none} + Kp * K^{none} \quad (31)$$

$$c^{te} = Lp * OP^{te} + Fp * E^{te} + Kp * K^{te} \quad (32)$$

$$c^{a} = Lp * OP^{a} + Fp * E^{a} + Kp * K^{a} \quad (33)$$

$$c^{both} = Lp * OP^{both} + Fp * E^{both} + Kp * K^{both} \quad (34)$$

Finally, we can estimate the effects of technical and allocative efficiencies on the total cost by comparing the values of the latter with efficiency and without efficiency:

Effects of technical efficiency on total cost: $\Delta c^{te} = c^{te} - c^{none}$ (35)

Effects of allocative efficiency on total cost: $\Delta c^{a} = c^{a} - c^{none}$ (36)

Effects of both technical and allocative efficiencies on total cost: $\Delta c^{both} = c^{both} - c^{none}$ (37)

4. Data

Data are obtained from Clarksons' Shipping Intelligence Network (SIN) and World Fleet Register (WFR). These are at vessel type level and individual vessel level for two separate analyses. The first analysis employs panel data for 15 vessel types from 2021 to 2024 at an annual frequency. Table A1 in Appendix A summarises key characteristics of each vessel type. The second analysis utilises cross-sectional data from 664 individual vessels in 2023, which is the most recent full calendar year for which actual data were available when performing the analysis. Cross-sectional data is used for individual vessels due to data availability and to avoid the effects of price volatility and global shipping demand on efficiency estimates. The individual vessels correspond to either Capesize bulk carriers or very large crude carriers (VLCCs) as they constitute the largest vessel types in the two most important shipping sectors in terms of volume transported.[2]

Table 1 shows summary statistics of the panel data where all monetary values are adjusted for inflation by the US Consumer Price Index. Capital is approximated by the average newbuilding price, which includes the cost of any technology installed at the time of purchase. Operating expenses (OPEX) serve as a proxy for the total labour costs plus any maintenance costs and technological upgrades of the vessel after purchase. Carbon emissions are the average CO2 when the vessel is being operated for a day. The revenue is approximated by the time charter earnings which is the income that the shipowner receives by leasing it out to a charterer. Transport work is the weight of the cargo carried times the distance travelled, measured in billion ton-miles. Operation is proxied by the average number of crew working on a vessel. The cost of capital is approximated by the rates for shipping loans, provided by Marine Money. Due to data availability and the fact that most vessels are around 10 years old, we use loan rates from 10 years ago (2011-2014). Fuel price is approximated by the average price of Very Low

Table 1: Summary statistics for panel data for 15 vessel types from 2021 to 2024 (annual frequency)

	Min	Median	Mean	Max	s.d.
Newbuilding price (*$m*)	17.1	42.2	47.6	103.8	23.7
Operating expenses (*$/day*)	4,524	6,447	6,669	9,430	1,464
Carbon emissions (*tons/day*)	52.3	99.1	112.4	230.7	55.0
Time charter earnings (*$/day*)	10,708	24,203	31,106	105,452	17,912
Transport work (*billion ton-miles*)	0.9	2.5	3.2	7.3	2.1
Number of crew	17.0	23.6	23.0	27.0	2.4
Loan rate (*%*)	2.7	2.9	2.9	3.1	0.15
Fuel price (*$/ton*)	526	535	588	756	113

Notes: The total number of observations is 60. The data for 2024 are adjusted for the full calendar year. The 15 vessel types include Aframax, Panamax, MR, and Handy product tankers; VLCC, Suezmax, and Aframax crude oil tankers; Post-Panamax, Neo-Panamax, Intermediate, and Feeder containerships; Capesize, Panamax, Handymax, and Handysize bulk carriers.

[2] In 2024, the dry bulk and tanker sectors accounted for 52.7% and 24.4% of the total seaborne trade (Clarksons' SIN 2024).

Sulphur Fuel Oil (VLSFO) from 13 major ports worldwide (Clarksons' SIN 2024).[3] For robustness, we carry out a sensitivity analysis with respect to the loan rate and fuel price in Appendix B.

Table 2 summarises the cross-sectional data. Age is based on the year that the vessel was built. Distance refers to the total nautical miles (NM) a vessel travelled in 2023. Deadweight tonnage measures the cargo-carrying capacity of the vessel. Design speed corresponds to the optimal speed of the vessel according to its design. Time at sea is calculated by dividing the distance by the design speed of the vessel. Fuel efficiency is the fuel consumption per NM at the vessel's design speed. The operating expenses are calculated as the daily average of the annual total labour cost plus maintenance and upgrade costs. Reduced usage of a vessel will result in lower OPEX.

Table 2: Summary statistics for cross-sectional data of individual vessels in 2023

	Min	Mean	Median	Max	s.d.
Age (*years*)	1	13	13	27	5
Distance (*NM*)	307	62,014	66,704	92,847	19,299
Deadweight tonnage	178,438	250,941	209,191	442,470	71,568
Design speed (*knots*)	8.0	14.8	14.8	21.5	1.3
Time at sea (*day*)	0.8	220	238	325	71
Fuel consumption at design speed (*tons per day*)	28	72	67	145	22
Capital *($ m)*	10	70	57	2350	108
Operating expenses (*$/day*)	28	3,953	3,731	9,413	1,597
Transport work (*million tons cargo * NM*)	93	15,437	13,437	36,529	7,288
Total fuel consumption (*thousand tons/year*)	1.9	371	337	857	165
Loan rate (*%*)	1.5	4.5	3.9	8.0	1.6
Wage (*$/year*)	24,120	39,824	34,198	82,637	12,239
Fuel price (*$/ton*)	494	552	494	620	63

Notes: The total number of observations is 664. The individual vessels include Capesize bulk carriers and VLCCs.

[3] In 2024, circa 95% of vessels in the world fleet are not fitted with scrubbers and therefore require burning VLSFO to comply with the IMO's sulphur emission limit, implemented in 2020 (IMO 2020). The 13 ports are Fujairah, Genoa, Gibraltar, Hong Kong, Houston, Japan, Korea, Los Angeles, Panama, Philadelphia, Rotterdam, Shanghai, and Singapore.

In Table 2, the total fuel consumption for 2023 is calculated by multiplying the fuel efficiency by the distance travelled. Similar to Table 1, the loan rate is from 10 years ago (2011-2014) but adjusted according to the country the vessel owning company is based in. The wage is estimated by calibrating the minimum and maximum wage at 24,000 USD/year and 83,000 USD/year, respectively ((Maritime Zone 2025; Crewell 2025) and then adjusting by the labour cost by country and year, as provided by the International Labour Organization (ILO 2024). The fuel price is the average price of either High Sulphur Fuel Oil (HSFO) or Very Low Sulphur Fuel Oil (VLSFO) from 13 major ports worldwide in 2023, depending on whether the vessel is equipped with a scrubber. For robustness, Appendix B presents the results from a sensitivity analysis, varying the loan rate, the wage, the fuel price, and the speed.

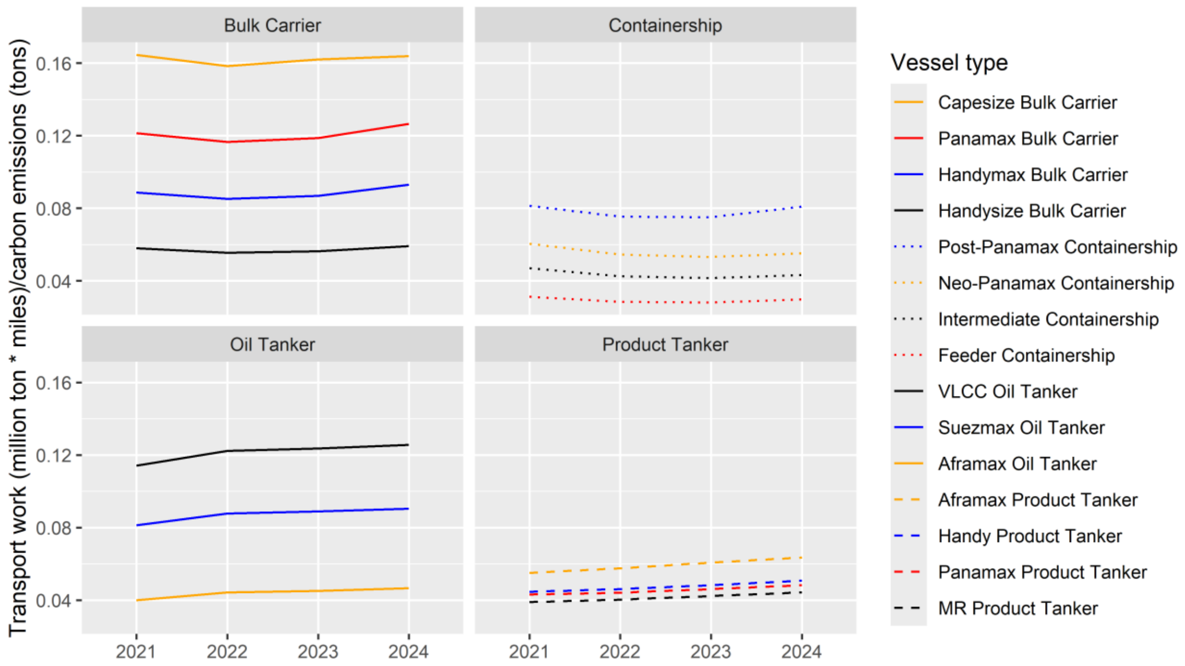
5. Results

The empirical analysis consists of three parts. Section 5.1 provides a preliminary analysis of carbon efficiency based on 15 main vessel types, while Section 5.2 uses SFA to assess the carbon, production, and cost efficiencies of those. This allows us to examine how the results vary across the main shipping segments. On the one hand, these findings can offer insights to shipping investors when deciding in which sector to allocate their resources when optimising their economic-sustainability trade-off. On the other hand, they can indicate to policymakers which sectors may require more attention henceforth in terms of sustainability efforts. However, these two sections do not account for within segment variation. Thus, to obtain a more complete view of the trade-off under consideration, Section 5.3 performs the SFA analysis based on individual vessels in the two biggest segments, i.e. Capesize bulk carriers and VLCCs.

5.1 Preliminary analysis by vessel type

A prevalent measure of carbon efficiency is the transport work per ton of CO2 – this refers to the ratio of a vessel's nominal cargo-carrying capacity (i.e. the DWT) times the distance the vessel sailed over the carbon emissions incurred during that period. Our findings suggest that, from 2021 to 2024, the average vessel transported 0.072 million ton-miles of cargo per ton of CO2 emitted.

Figure 2: Transport work per ton of carbon emissions by vessel type (D*V/CO2)



Note: D is distance, V is deadweight.

According to Figure 2, while transport work per ton of CO2 for a given vessel type is relatively stable over time, it varies largely across sectors and segments. Overall, bulk carriers and oil tankers perform better than containerships. This finding is in line with UNCTAD (2023) and can be explained by the fact that containerships sail at much higher average speeds (i.e. by roughly 3 knots according to Clarksons SIN (Clarksons' SIN 2024)) and, thus, emit disproportionately more CO2 than the other vessels. Furthermore, they typically spend more time at ports loading/unloading cargo where, while they emit CO2, they do not produce any transport work. Bulk carriers, which seem to be the best performing ones, have higher productivity than the others as they sail for more distance – and at relatively lower speed – for each ton of cargo transported.

Product tankers have a lower volume of transport work per ton of CO2, which may be due to their lower cargo capacity, the shorter routes they serve, and their longer port stays compared to the crude oil ones. Finally, bulk carriers and oil tankers have higher variation in transport work per ton of CO2 because of the large differences in the sizes across the vessel types.

An alternative measure of carbon efficiency is the vessel earnings per ton of CO2. This quantifies the trade-off that the vessel owner faces between the economic benefit and the environmental cost from running a vessel. We find that, from 2021 to 2024, the average vessel earned (in TC terms) roughly 295 US dollars per ton of CO2 emitted.

Figure 3: Time charter earnings per ton of carbon emissions of tankers

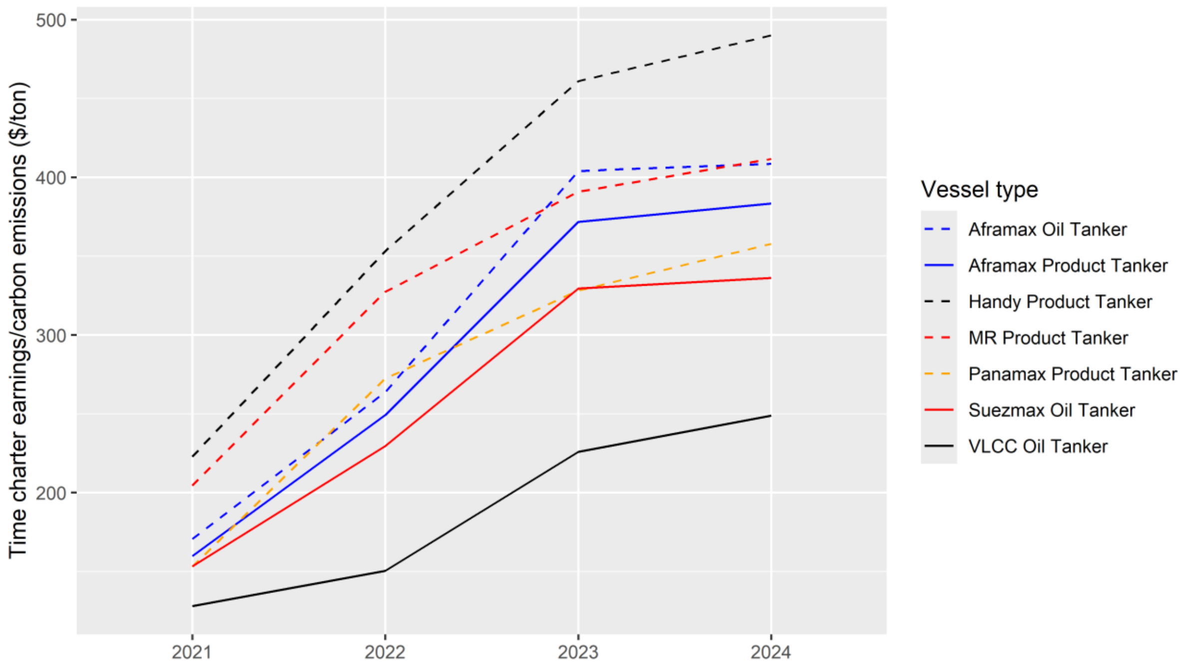


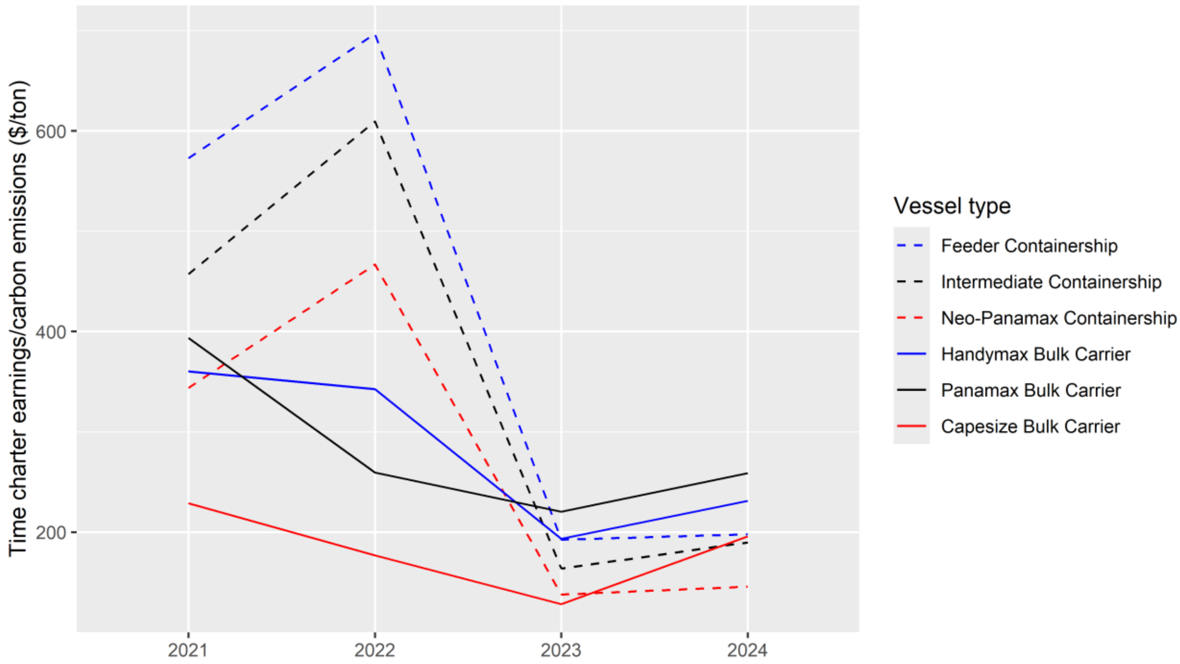
Figure 3 suggests that the TC earnings per ton of CO2, that is carbon efficiency, for oil and product tankers experienced a significant rise from 2021 to 2023. This can be attributed to higher TC rates during those years caused by the increased global oil demand, mainly due to the end of the COVID-19 lockdowns and the war in Ukraine. As the growth of oil demand slowed down after 2023 though (IEA 2024), carbon efficiency did not increase at the same rate in the next year.

For containerships (Figure 4), TC earnings per ton of CO2 increased significantly from 2021 to 2022 because of the prosperous shipping freight market conditions during COVID-19. When the market reverted to its normal levels in the next year, carbon efficiency rapidly decreased. From 2023 to 2024, there were two opposing effects due to the Red Sea Crisis. On the one hand, the additional distance that containerships had to sail – by not being able to transit through the Suez Canal but navigating around the Cape of Good Hope instead – reduced the effective supply of the fleet, thus, driving TC earnings up. On the other hand, the increased sailing time resulted in more shipping emissions for a given trip, e.g. from China to the Mediterranean Sea. As a result, carbon efficiency only mildly increased in 2023-2024.

In the case of dry bulk vessels, TC earnings movements are the main factor for the fluctuations in carbon efficiency and its overall mild decrease from 2021 to 2024 (Figure 4). Note that the

Red Sea Crisis did not affect the tanker and dry bulk sectors as much as the container one as the latter is much more reliant on trading routes involving the Suez Canal.

Figure 4: Time charter earnings per ton of carbon emissions of bulk carriers and containerships



A further important finding is that the smaller the vessel within a sector, the higher TC earnings per ton of CO2 it generally has; e.g. Aframax tankers are more carbon efficient than Suezmax and VLCC ones. This is because, while larger vessels typically enjoy higher TC earnings, they also have much more significant energy needs and, thus, fuel consumption and emissions than smaller ones. Therefore, for a ship operator that wants to maximise their revenue subject to CO2, it is optimal to focus on smaller vessel segments.

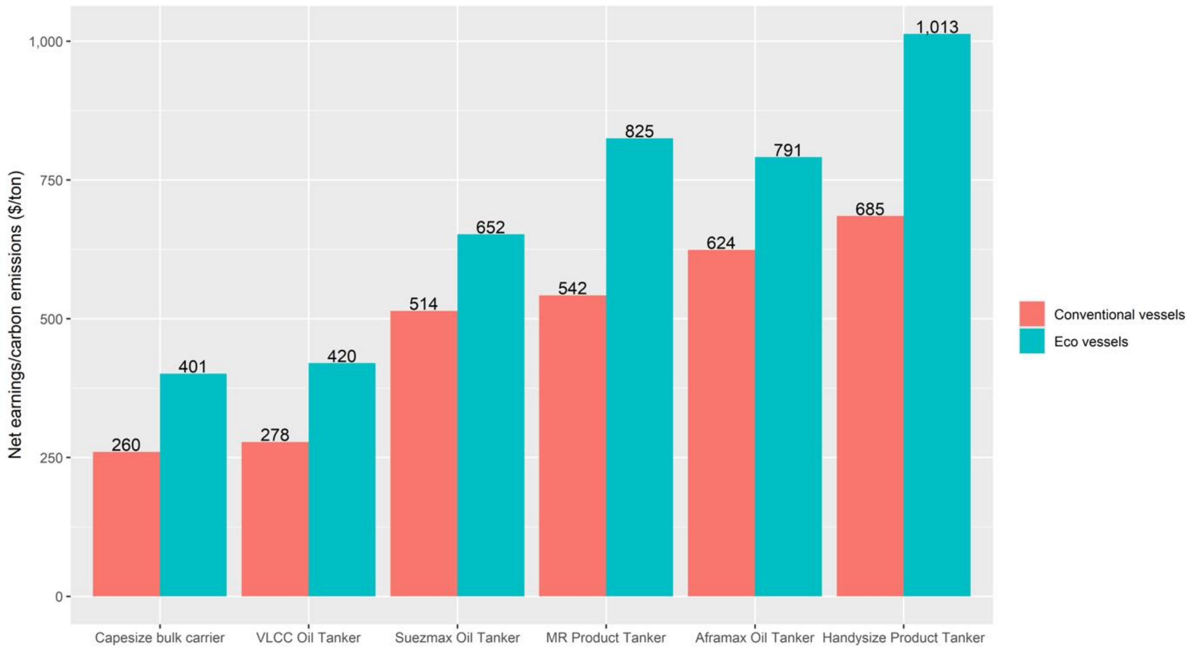
Our findings indicate that vessel size has a positive effect on transport work per ton of CO2 but a negative one on earnings per ton of CO2. From an economic perspective, this suggests that larger vessels are more carbon efficient in transporting goods while smaller ones in generating revenue.

Figure 5 compares the net earnings per ton of CO2 between eco-engine vessels and conventional-engine ones for various vessel types.[4] In contrast to the previous analysis for which the relevant data are not available, we now use net earnings instead of TC earnings as

[4] Figure A1 in Appendix A also compares net earnings per ton of CO2 between various vessels but further classifies by scrubber-fitting status.

they capture more accurately theshipowner’s/operator’s inflows. Namely, those correspond to the respective TC earnings minus the fuel, port, canal, and EU ETS (if any) costs.

Figure 5: Net earnings per ton of carbon emissions by built year



Note: The carbon emissions values are obtained by taking the average of the carbon intensity from LPG, LNG, LSFO, and HSFO. “eco vessel” refers to all ships with a 2-stroke engine which have an electronically controlled fuel injection system. Those are typically built in 2015 while the ones with a conventional engine in 2010. Clarksons’ SIN do not provide any data on the net earnings of containerships.

Eco vessels have 27-54% more net earnings per ton of CO2 than conventional ones. In line with recent papers (Jia, Jiang and Azevedo, 2024; Moutzouris et al., 2024), this is not only due to their reduced CO2 but also because they receive larger TC rates. The documented, significantly higher carbon efficiency of eco vessels can also improve the environmental, social and governance (ESG) profiles of shipping companies, which might be particularly important to publicly listed ones.

Furthermore, potential implementation of a GHG emissions pricing mechanism will have a significantly less adverse impact on eco vessels compared to conventional ones. A point for consideration by policymakers is that such a mechanism may have heterogeneous effects on the various shipping sectors. Namely, larger vessel sizes might be impacted significantly more as they have much lower earnings per ton of CO2 than smaller ones.

However, neither earnings per ton of CO2 nor transport work per ton of CO2 is an ideal measure of carbon efficiency as they fail to consider other input factors, such as operation and capital, and are highly dependent on the numerator of the respective ratio. As a result, TC earnings per ton of CO2 may overestimate carbon efficiency for small vessels while transport work per ton of CO2 may underestimate it – and vice versa for large vessels. To that end, the next subsection presents a more holistic measurement of carbon efficiency, incorporating the SFA framework.

5.2 Stochastic frontier analysis by vessel type

This subsection applies SFA to analyse the carbon, production and cost efficiencies of the same vessel types and for the same period as above.

We begin by estimating the carbon efficiency using Equation (7). This input-oriented measure estimates how much CO2 (dependent variable) can be reduced subject to given values of capital, operation, and TC earnings (independent variables). Hence, by also considering capital and operation inputs, it is a more advanced economic measurement than those employed in Section 5.1. Namely, it mitigates potential significant fluctuations of TC earnings and avoids estimation bias resulting from the absence of cost estimation.

Table 3 displays the results from three representative models which vary depending on the assumptions about the efficiency effect, the time trend and the distribution of the error term. Sigma squared tests if the model captures the total variance of inefficiency and noise. Gamma examines whether the inefficiency component is a main factor of the total variance. Log likelihood examines if the model is better with an inefficiency term than without one. Based on those statistics, Model (3) clearly has the highest goodness of fit and, thus, we focus on the associated estimation results.

Table 3: Carbon efficiency of vessel types

	(1)	(2)	(3)
		Dependent variable: ln(CO2)	
Efficiency trend[1]	Increase	Increase	Increase
Time effect	Yes	No	Yes
Distribution	Half normal	Truncated normal	Truncated normal
(Intercept)	4.61***	4.61***	0.98***
ln(K)	0.79	0.73	0.09***
ln(OP)	-0.46**	-0.38	0.12***
ln(TC)	0.06	0.01	0.04
Mu		0.32	0.07***
Time			0.05***
Sigma Squared	0.07	0.06	0.005***
Gamma	0.78	0.82	0.08***
log likelihood	19.84***	22.96***	42.27***
Mean efficiency	0.83	0.75	0.69

*Note: significance levels: 0.01 '***' 0.05 '**' 0.1 '*'. The total number of observations is 52.*

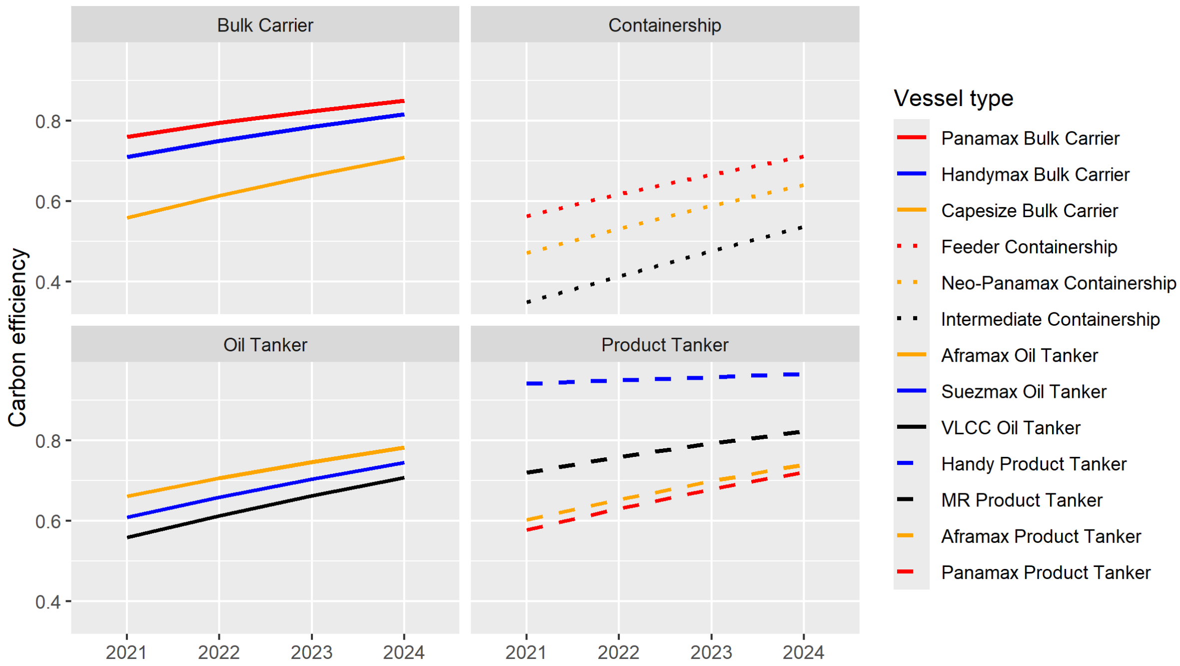
According to Table 3, the mean efficiency across all vessel types is 69%, suggesting that there is potential to reduce CO2 by 31% on average subject to the given levels of capital (newbuilding price), operation (crew plus maintenance and upgrades), and TC earnings.

The significantly positive time trend indicates that carbon efficiency has increased over the years or, equivalently, for a given level of TC earnings subject to the same operation and capital input, less CO2 is emitted. This may be due to increased operational efficiency of vessels over time, possibly accelerated by the implementation of CII since January 2023. Other recently imposed measures, such as EEXI and EU ETS, might have played a role in that too.

Capital and operation are significantly positively associated with CO2. However, the magnitude of the impact is low as a 1% increase in capital (operation) is associated with a 0.09% (0.12%) increase in carbon emissions. This is because higher newbuilding price and OPEX typically relate to larger vessels which, in turn, are more energy and, thus, CO2 intensive. On the other hand, TC earnings are not significantly related to CO2. This is in line with shipping economic theory where TC earnings are determined in equilibrium by the demand for time-chartered vessels and the available fleet for long-term contracts. In prosperous markets, vessels in the spot market sail at higher speeds (to serve as many voyages as possible and maximise the shipowner's revenue) and, thus, increase their CO2. In contrast, this is not the case in the TC market where the vessel is fixed for a standard period. Furthermore, the implementation of CII might have further disentangled speed from market conditions.

Figure 6 disaggregates the carbon efficiency results by vessel type and year. As discussed in Section 3, the minimum carbon efficiency score is 0 and the highest is 1.

Figure 6: Carbon efficiency by vessel type and year



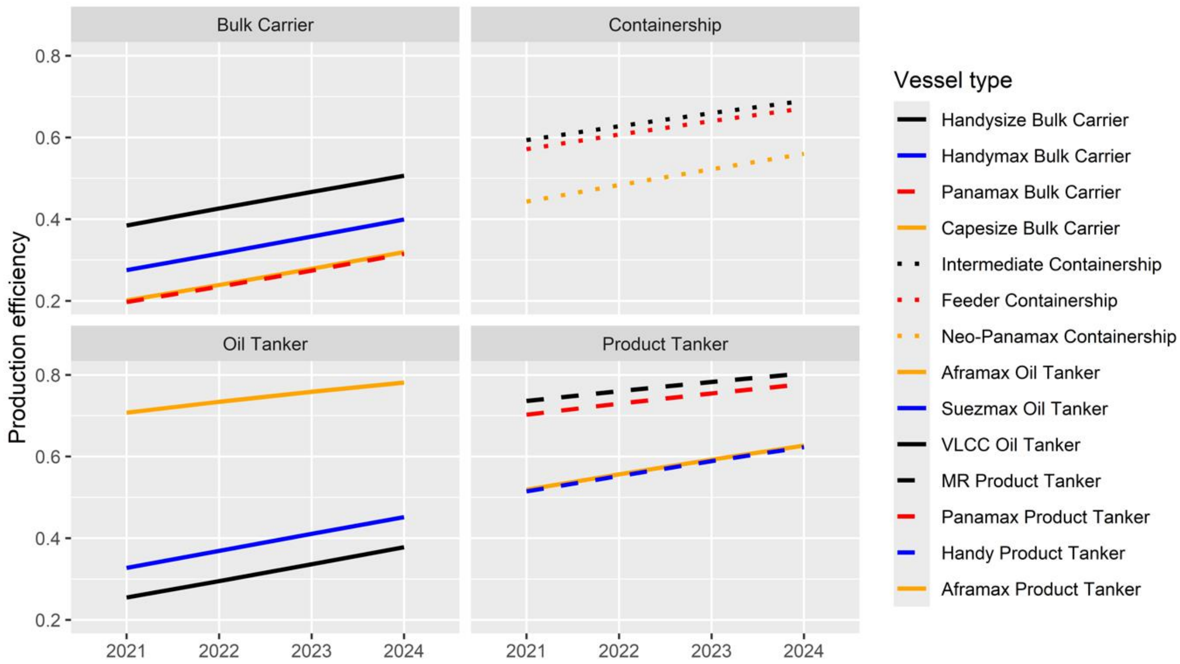
Evidently, carbon efficiency strictly increases in all cases. As discussed above, this suggests improved operational efficiency of vessels, possibly due to recent regulatory measures. In contrast, Figures 2 and 3 – that were based on a more simplified measure of carbon efficiency – provided a cloudy picture across time and sectors.

The rest of the results are overall in line with the findings and economic justifications presented in Subsection 5.1. First, containerships are less carbon efficient than bulk carriers and tankers. Therefore, there is more scope for improvement and policy intervention in that sector. Second, the larger the vessel within a sector, the lower the carbon efficiency it generally has. In other words, larger vessels produce more CO2 for a given level of TC earnings. Future environmental regulations should consider the differences in carbon efficiency across vessel types. A simplified linear model of carbon pricing may cause an undersupply of specific vessel types, negatively impacting the trade of certain commodities.

Production efficiency is estimated based on Equation (10) for three model specifications (Table A2 in Appendix A). The mean production efficiency of 60% implies that the average vessel can improve its transport work by 67% (i.e. increasing from 60% to 100% efficiency) for a given level of emissions, operation, and capital. From a policy perspective, this finding suggests that vessels should be producing more transport work for their current emissions or, in the language of IMO, they should have much better carbon intensity performance. From the ship operator's point of view, it suggests that vessels are sub-optimally utilised.

On the bright side, Figure 7 demonstrates that production efficiency has been strictly increasing in the period 2021-2024 across all vessel types. This trend is in line with the increasing trend of carbon efficiency (Figure 6) and reinforces the argument that progress is being made in the operational efficiency of vessels; although, stricter regulatory measures might be needed in the coming years.

Figure 7: Production efficiency by vessel type and year



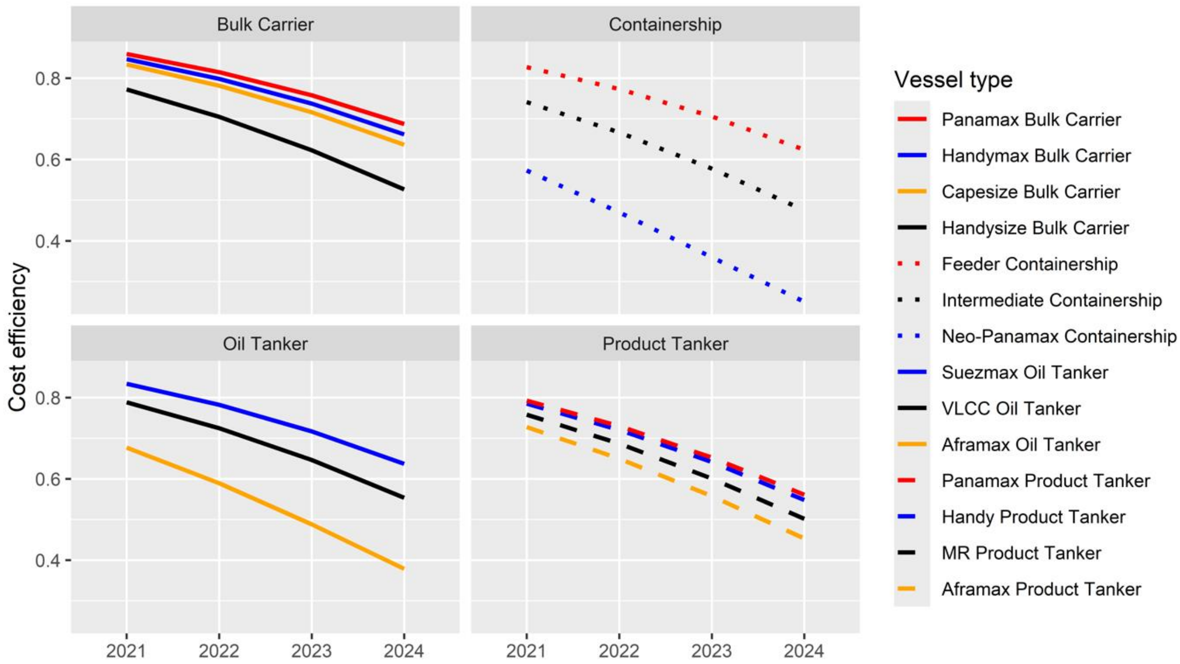
Specifically, bulk carriers and oil tankers generally have lower production efficiency than containerships. This is because, in contrast to the former, containerships typically operate as liner services, i.e. fixed itineraries over fixed schedules, which increases the utilisation of the vessel. The relatively good performance of product tankers can be explained by the highly competitive nature of that sector where, to realise profits, very efficient vessel utilisation is required. Furthermore, production efficiency in general decreases with the size of the vessel.

As discussed in Subsection 5.1, this may be due to the fact that smaller vessels are more efficiently utilised than larger ones.

Cost efficiency is estimated based on Equation (11) for three model specifications (Table A3 in Appendix A). The mean cost efficiency across all vessel types is 66%, suggesting that there is potential for the average vessel to reduce its total cost by 52%[5] while producing the same level of transport work.

The significantly negative time trend indicates that cost efficiency has decreased over the years or, equivalently, that it has become more expensive to produce the same level of transport work. This is the case across all vessel types as demonstrated in Figure 8.

Figure 8: Cost efficiency by vessel type and year



The declining cost efficiency may be explained by the rising costs in shipping due to stricter environmental regulations. Indicatively, eco vessels cost roughly 25% more than their conventional counterparts (Moutzouris et al. 2024). In line with this argument, Table A3 shows that the cost of capital has the highest influence on the vessel's total cost. Of particular interest is the fact that cost efficiency has deteriorated more rapidly from 2023 to 2024. One reason for this is the inclusion of shipping in the EU ETS since 2023 which has increased the voyage costs of a vessel. The most important factor though is the Red Sea Crisis and the fact that, as analysed

[5] Calculated as (100%-66%)/66% ≈ 52%

above, vessels need to sail a significantly larger distance and, thus, burn more fuel when diverting around the Cape of Good Hope instead of transiting through the Suez Canal. Table A3 demonstrates the significance of increased sailing distance (through the transport work variable) on the total cost.

5.3 Stochastic frontier analysis by individual vessel

This subsection incorporates SFA to estimate the production and allocative efficiencies of individual vessels based on cross-sectional data of 664 Capesize bulk carriers and VLCCs in 2023.

Similar to Subsection 5.2, production efficiency is estimated based on Equation (10). However, incorporating individual-vessel data in this subsection allows us to control for additional variables such as vessel age and time travelled at sea, as well as a dummy variable to distinguish between the Capesize and VLCC sectors. This enables more thorough investigation and interpretation of the findings.

Table 4: Production efficiency of individual vessels

	(1)	(2)	(3)	(4)
	Dependent variable: ln(D*V)			
ln(OP)	0.07***	0.03	0.07***	0.07***
ln(E)	0.80***	0.72***	0.80***	0.80***
ln(K)	0.12***	0.17***	0.12***	0.12***
Constant	10.89***	11.14***	10.91***	10.93***
Age	0.32***		0.32***	0.34***
Time		-0.001***	-0.00002	
Capesize (dummy)				0.22
U sigma	0.11***	0.07***	0.11***	0.11***
V sigma	0.16***	0.17***	0.16***	0.16***
Log likelihood	181***	163***	181***	181***
Returns to scale	0.99	0.92	0.99	0.99
Mean efficiency	0.89	0.87	0.79	0.89

*Note: significance levels: 0.01 '***' 0.05 '**' 0.1 '*'. The total number of observations is 664. All models assume exponential distribution for the inefficiency term. We present the standard deviations of the inefficiency effect (U sigma) and that of the stochastic noise (V sigma). The returns to scale are estimated through Equation (13).*

Accordingly, four representative models that differ in terms of the incorporated control variables have been estimated (Table 4).[6] All models have significant log likelihood values and U and V sigmas, implying that both inefficiency effect and stochastic noise are present, and the inclusion of an inefficiency term improves their performance.

Energy (fuel) is highly significant in all models and has the largest magnitude by far. This is due to its direct positive relationship with transport work; the more cargo is transported and for longer distances, the higher the vessel's energy needs. Capital is also strongly positively related to transport work in all cases, although, with a much smaller coefficient. More expensive vessels usually have larger capacity and improved technical specifications which, in turn, can improve the transport work. Operation is significantly positively associated with transport work in all but one case. Similar to capital, higher OPEX is typically for larger vessels which, in turn, have more transport capacity.

The above implies that higher fuel consumption, capital expenditure and OPEX are associated with higher annual transport work of each vessel. In particular, the constant returns to scale (the respective coefficients are close to one) indicate that doubling the inputs may result in approximately double the output.

The signs of the control variables are in line with economic theory (n.b. a positive sign means a negative effect on production efficiency, and vice versa). Namely, higher production efficiency is achieved by younger vessels, and vessels sailing for more time. Furthermore, production efficiency does not significantly differ between the two vessel types, which is in line with Figure 7 and the associated analysis.

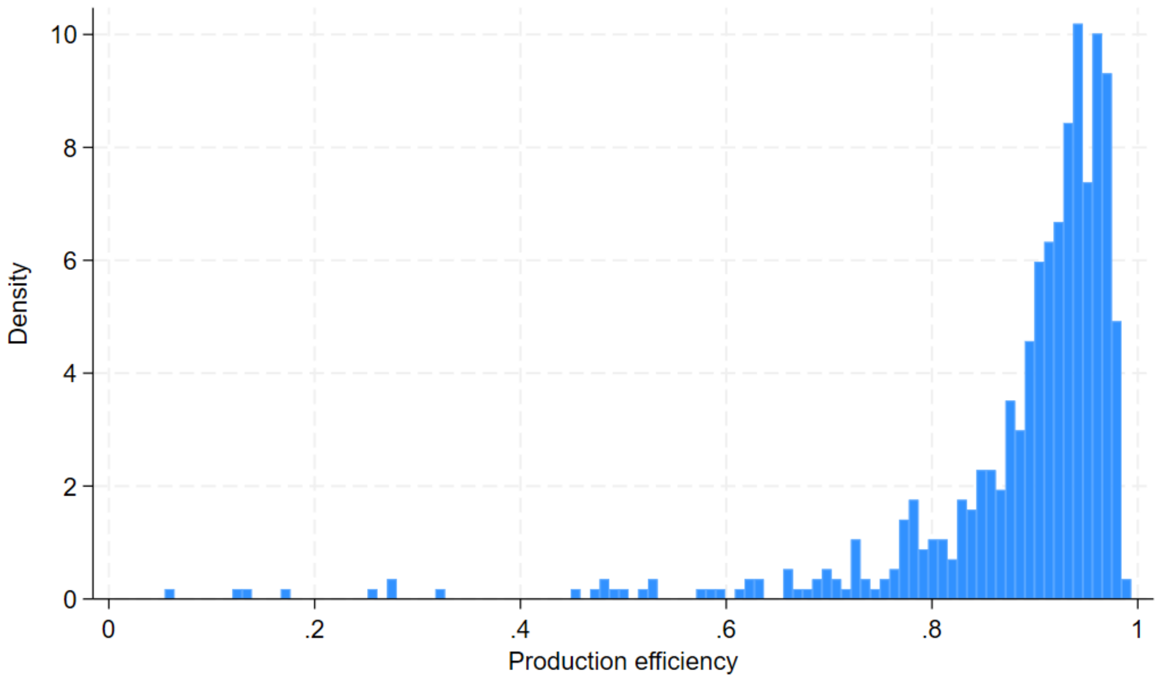
Figure 9 shows the distribution of the production efficiency of the individual vessels, which can range from 0 (lowest feasible) to 1 (highest feasible). This is a measurement of a vessel's technical and operational capacity to transport goods subject to given levels of capital, operation and energy inputs, and relative to their peers among those vessel types.

Evidently, most vessels have rather similar production efficiency, i.e. between 90% and 98%. Subsection 5.2 identified that Capesize and VLCC vessels have relatively low production

[6] All models assume that the inefficiency term follows an exponential distribution. Table A4 (Appendix A) presents additional models with different assumptions for the distributions of the inefficiency term. Furthermore, various translog models have been estimated with principal component analysis and the estimation results for the control variables and overall efficiencies are similar.

efficiency compared to the other vessel types and that additional policy measures might be required to improve their performance subject to their emissions.

Figure 9: Histogram of production efficiency of individual vessels



To further investigate the performance of vessels, Equations (35)-(37) estimate the average effects of technical, allocative, and both inefficiencies combined on the demand for operation, energy, and capital.

The technical efficiency focuses on the production and operational capacity of the vessel, i.e. how to maximise transport work with respect to the units of input but without considering their prices. In the "Technical inefficiency" column in Table 5, a positive value indicates that the average vessel requires a higher amount of input to reach the same level of output compared to

Table 5: The effects of inefficiencies on input demand of individual vessels

	Technical inefficiency	Allocative inefficiency	Both inefficiencies
Operation	7.1%	255.9%	278.0%
Energy	6.1%	-36.5%	-32.6%
Capital	5.9%	57.7%	70.6%

Note: a positive value indicates that, due to inefficiency, the input demand is higher; a negative value indicates the opposite.

the vessel(s) on the efficient frontier. The respective results suggest that the average vessel overuses operation, energy, and capital by around 6-7%. Such input overuse results in substantial additional costs for the average shipowner/operator.

The allocative efficiency investigates how resources can be allocated more efficiently, i.e. how to minimise the total cost for a given level of transport work based on the prices and productivity of operation, energy, and capital. Combining the two efficiencies accounts for both transport work maximisation and cost minimisation. In the “Allocative inefficiency” column in Table 5, a positive (negative) value indicates that the average vessel has overused (underused) the input, i.e., the average vessel should have used less (more) of this input because its price is relatively high (low) compared to the transport work it produces. In the “Both inefficiencies” column, a positive (negative) value indicates that the average vessel has overused (underused) the input due to the combined effects of technical and allocative inefficiencies.

The effects from allocative inefficiency are much larger in magnitude than those from the technical one, indicating that resource allocation plays a more crucial role in improving the overall vessel efficiency compared to operational or technical adjustments. Specifically, the magnitude of the operation allocative inefficiency suggests that operation is overused by more than 2.5 times. With the development of digitisation and automation, shipping companies may be able to reduce the operation input required to reach the same level of transport work (subject to safety regulations). In the meantime, better maintenance of vessels might assist with bringing down the total operating expenses of the vessel.

The results further suggest that capital is overused by 58%. However, it is rather challenging for shipowners to reduce the capital invested due to regulations that require vessels with higher carbon efficiency. Regulation has been a known contributor to input misallocation in the transportation industry (Kumbhakar 1988; Bitzan and Peoples 2014). If we consider capital as a quasi-fixed input, an overuse of capital may indicate that the excess capital expenditure needed to comply with the increasingly strict environmental regulations does not generate sufficient return to shipowners.

Currently, the prices of vessels with modern electronic eco engines are 25% higher than of conventional ones, but their income premia are only 9-15% (Moutzouris et al. 2024). As discussed in Subsection 5.1, vessels have significantly improved economic performance relative to their CO_2: for Capesizes, the eco figure is \$401/ton CO_2 against \$280/ton CO_2 for the non-eco one; for VLCCs, \$420/ton CO2 and \$278/ton CO2, respectively (Figure 4). However, this does not seem sufficient to justify, in purely financial terms, the significant excess investment required (Petropoulos, 2022; Jia, Jiang and Azevedo, 2024). Looking forward, this is also the case for vessels that are capable of burning alternative fuels as LNG. Indicatively, the prices for an LNG dual-fuel containership are between 12% and 28% higher compared to an oil-fuelled one (Clarksons' SIN 2024).

Therefore, for shipowners to undertake greener investments, there need to be strong economic (dis)incentives which are not provided by the existing measures of carbon and energy efficiencies. In response to that, a major topic of discussion in recent IMO meetings is the introduction of market-based measures to reward and, thus, accelerate the investment in alternative-fuelled vessels and technologies (IMO 2024).

The energy allocative inefficiency of -37% (Table 5) suggests that fuel input is underused, i.e., fuel is relatively cheap for the transport work it produces. If we consider fuel as a quasi-fixed input due to the exogenous global shipping demand, we may conclude that currently fuel is underpriced. The use of alternative fuels or the introduction of decarbonisation regulation would raise the fuel costs. Within a range of 0-37% increase, this would not severely impact vessels' output, other things being equal. In Appendix B, we conduct a sensitivity analysis simulating the impacts of hypothetical changes in fuel price and speed (as speed reduction is a straightforward method to reduce fuel consumption).

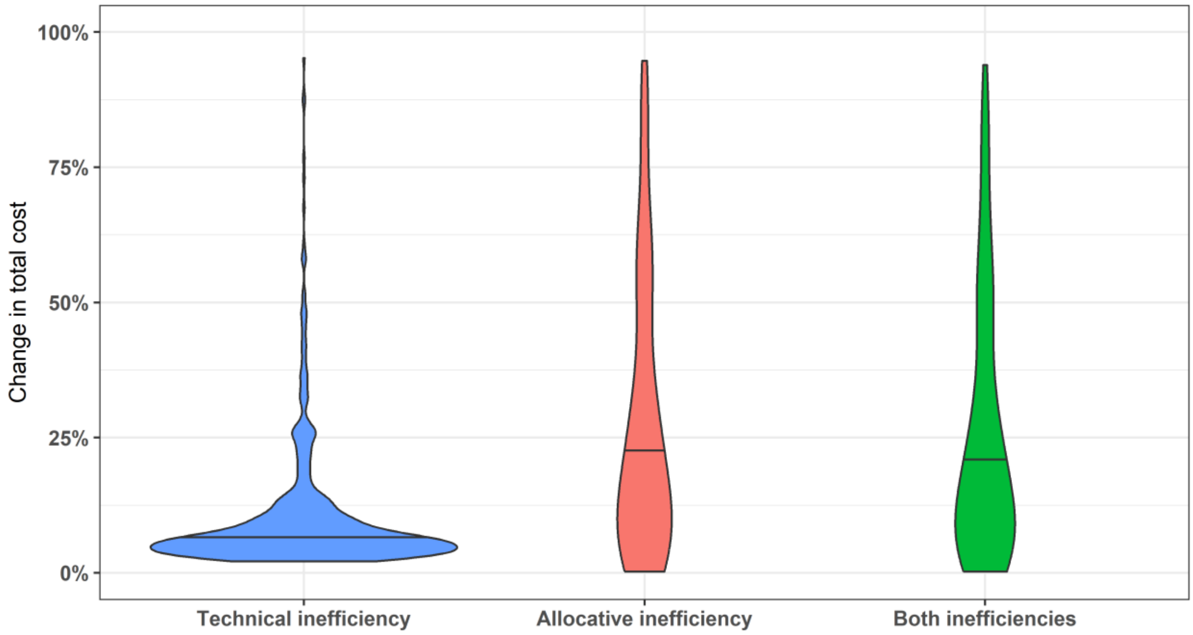
The sensitivity results (Figures B5, B7, and B8) suggest that an increase in fuel price of up to 37% does not severely affect a vessel's overall efficiency and total cost. The increase in fuel price can be even higher if the fuel input needs of vessels decrease with the use of more efficient engines, vessel designs, and energy-saving technologies. Indicatively, the price of LNG – which is a transitional and not net zero fuel – in 2024 has been 17% higher on average compared to the fuel oil equivalent (Clarksons' SIN 2024);[7] thus, within the acceptable range mentioned above. However, currently, most net-zero fuels (e.g., biofuel, green ammonia, green methanol) are priced more than 37% higher than oil (S&P Global 2025; IMO 2025). Long-term strategic planning is required, such as monetary incentives (subsidies), for the use of green fuels. Without supportive measures for the operators of greener-fuelled vessels, enforcing a net-zero

[7] This calculation is based on the LNG bunker price in Northwest Europe (in terms of intermediate fuel oil 380 cSt equivalent) and the average price of HSFO (380 cSt) across bunkering locations in Antwerp, Hamburg, and Rotterdam.

transition could significantly affect the well-functioning of the shipping fleet and the financial health of companies.

To explore how the technical, allocative, and both inefficiencies affect the annualised cost of financing and running a vessel, Figure 10 presents the distributions of the individual vessels through violin plots. For a given effect on the total cost (y value), the wider the plot, the more observations.

Figure 10: Change in total cost of an individual vessel



Notes: the wider the plot for a given y, the more observations correspond to that value. The line in the middle denotes the median value. Outliers, i.e., observations above 100%, have been removed.

The relatively flat plot of technical inefficiency in Figure 10 suggests that its effect on the total cost is similar across vessels. In contrast, the allocative inefficiency plot is more spread out, indicating that its effect varies largely depending on the vessel. For the median vessel, the technical and allocative inefficiencies have increased the total cost by roughly 6% and 22%, respectively. The median in the violin plot of the combined inefficiencies is around 20%, very similar to that of the allocative one, implying that the latter is the dominating factor.

The large difference between the technical and allocative inefficiencies shows that allocating economic resources appropriately is more important from a cost reduction perspective than the benefit that technical and operational improvements can yield with respect to productivity. In turn, environmental regulations could have a relatively high impact on the total cost of individual vessels if resource allocation cannot be optimised. For instance, if vessels are required to equip the more expensive alternative-fuel engines, the impact on their total cost will be substantially higher than the benefit this can bring to their operational performance.

The current decarbonisation pathway requires significant capital investment in low-carbon technologies (Klaaßen and Steffen, 2023; Calcaterra et al., 2024), which also applies to the upgrade to alternative-fuel vessels in the shipping industry. However, the rise in interest rates in recent years poses a concern for easy access to capital for shipping investors. Our sensitivity analysis in Appendix B shows that, if the loan rate (cost of capital), increases from an average of 4.5% to over 6.5%, the typical shipping investor may start to consider switching from investment in newbuilding vessels to more expenditure on energy, vessel maintenance, and vessel upgrades, such as energy saving technology instalment. At the end of 2024, only 7.2% of the existing fleet (in gross tonnage terms) can burn alternative fuels while roughly half of the newbuilding orderbook is still for vessels that will be burning oil (Clarksons' SIN 2024). Our findings in Table 5 and Figure 10 imply that this underinvestment can be more effectively addressed with economic measures that can optimise the resource allocation of shipping companies rather than with purely technical improvements.

The findings and analysis above identify potential effects that environmental regulations can have on productivity, shipping costs, and resource allocation. Appropriate economic measures and resource allocation are crucial in facilitating the transition towards net zero (Coulomb, Henriet and Reitzmann, 2021; Oehmke and Opp, 2024; Mengesha and Roy, 2025). In the shipping context, regulatory interventions can improve the carbon efficiency of vessels, but need to be applied with careful consideration.

6. Conclusion

With the increasing focus on the transition towards net-zero shipping, multiple regulatory measures have been implemented for the industry to comply with. However, those measures do not account for the economic aspect of the transition. Assessing the dynamic relationship between environmental performance, monetary income, and expenditure can be of significant value to shipowners, capital providers, charterers, and regulators alike.

This research aims to address this gap by examining the carbon, production, cost, and allocative efficiencies of the shipping fleet. To that end, it applies a stochastic frontier analysis at an aggregate level across 14 major vessel types from 2021 to 2024, but also for 664 individual Capesize bulk carriers and VLCCs. To estimate carbon efficiency, carbon emissions are regressed on capital expenditure, operating expenditure, and vessel earnings. Allocative efficiency is estimated by comparing the productivity of capital, operation, and energy with their relative prices. An input with low productivity relative to its price is overused, and vice versa.

Our findings suggest that the average vessel transported 0.072 million ton-miles of cargo per ton of CO_2 emitted and earned USD 295.1 per ton of CO_2 emitted over the period 2021-2024. Vessels with electronic eco engines have 27-54% higher earnings per ton of CO_2 than conventional ones. As expected, production efficiency decreases with the age of the vessel and increases with the time it spends at sea. Larger vessels are overall more carbon efficient in transporting goods while smaller ones in generating revenue. Notably, it has become more expensive over the years to produce the same level of transport work.

The empirical estimation indicates that there is scope for the average vessel to reduce its CO_2 by 31% subject to given levels of earnings, capital, and operating expenses. Additionally, the average vessel can improve its transport work by 67% for a given level of CO_2, capital, and operating expenses. Furthermore, there is potential to reduce its total cost by 52% while maintaining the same level of transport work.

The technical and allocative inefficiencies combined increase the owning and operating costs for the median vessel by roughly 20%. Allocating economic resources appropriately can play the most important role in reducing those costs. We find that fuel is relatively cheap for the transport work it produces. Therefore, while the use of alternative fuels or the introduction of greenhouse gas pricing mechanisms would raise the fuel costs, within a range of 0-37% increase, this would not severely impact vessels' output, other things being equal.

These findings have strong implications for the industry as they imply that investing in and operating certain vessel types might optimise the economic-sustainability profile of a company. They also yield significant policy recommendations regarding the introduction of economic measures to accelerate the energy transition of the shipping industry. Overall, this research demonstrates the importance of explicitly accounting for the economic dimension when drafting environmental policies for capital and energy intensive sectors with construction lags and volatile cash flows.

Data availability statement

The data underlying this article were provided by Clarksons under licence. Data will be shared on request to the corresponding author with permission of Clarksons.

References

Acciaro, Michele, and Alan C McKinnon. 2015. “Carbon Emissions from Container Shipping: An Analysis of New Empirical Evidence.” *International Journal of Transport Economics* 42 (2): 211–28.

Adland, Roar, Pierre Cariou, and Francois-Charles Wolff. 2020. “Optimal Ship Speed and the Cubic Law Revisited: Empirical Evidence from an Oil Tanker Fleet.” *Transportation Research Part E: Logistics and Transportation Review* 140:101972.

Aghion, Philippe, Antoine Dechezleprêtre, David Hemous, Ralf Martin, and John Van Reenen. 2016. “Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry.” *Journal of Political Economy* 124 (1): 1–51.

Agnolucci, Paolo, Tristan Smith, and Nishat Rehmatulla. 2014. “Energy Efficiency and Time Charter Rates: Energy Efficiency Savings Recovered by Ship Owners in the Panamax Market.” *Transportation Research Part A: Policy and Practice* 66:173–84.

Aigner, Dennis, C A Knox Lovell, and Peter Schmidt. 1977. “Formulation and Estimation of Stochastic Frontier Production Function Models.” *Journal of Econometrics* 6 (1): 21–37.

Allan, Grant, Michelle Gilmartin, Peter McGregor, Karen Turner, and J Kim Swales. 2009. “Economics of Energy Efficiency.” In *International Handbook on the Economics of Energy*. Edward Elgar Publishing.

Ammar, Nader R. 2018. “Energy-and Cost-Efficiency Analysis of Greenhouse Gas Emission Reduction Using Slow Steaming of Ships: Case Study RO-RO Cargo Vessel.” *Ships and Offshore Structures* 13 (8): 868–76.

Ammar, Nader R, and Ibrahim S Seddiek. 2020. “An Environmental and Economic Analysis of Emission Reduction Strategies for Container Ships with Emphasis on the Improved Energy Efficiency Indexes.” *Environmental Science and Pollution Research* 27:23342–55.

Anderson, Bruce, E Den Boer, S Ng, L Dunlap, G Hon, D Nelissen, A Agrawal, J Faber, and J Ray. 2015. “Study of Emission Control and Energy Efficiency Measures for Ships in the Port Area.” *Retrieved from International Maritime Organization (IMO), London, UK* 24:52.

Barrage, Lint. 2020. “Optimal Dynamic Carbon Taxes in a Climate–Economy Model with Distortionary Fiscal Policy.” *The Review of Economic Studies* 87 (1): 1–39.

Barreiro, Julio, Sonia Zaragoza, and Vicente Diaz-Casas. 2022. “Review of Ship Energy Efficiency.” *Ocean Engineering* 257:111594.

Battese, George E, and Tim J Coelli. 1992. “Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India.” *Journal of Productivity Analysis* 3:153–69.

Bitzan, John, and James Peoples. 2014. “US Air Carriers and Work-Rule Constraints–Do Airlines Employ an Allocatively Efficient Mix of Inputs?” *Research in Transportation Economics* 45:9–17.

Calcaterra, Matteo, Lara Aleluia Reis, Panagiotis Fragkos, Thibault Briera, Harmen Sytze de Boer, Florian Egli, Johannes Emmerling, Gokul Iyer, Shivika Mittal, and F H J Polzin. 2024. “Reducing the Cost of Capital to Finance the Energy Transition in Developing Countries.” *Nature Energy* 9 (10): 1241–51.

Caselli, Francesco, and Wilbur John Coleman. 2006. “The World Technology Frontier.” *American Economic Review* 96 (3): 499–522.

Casey, Gregory. 2024. “Energy Efficiency and Directed Technical Change: Implications for Climate Change Mitigation.” *Review of Economic Studies* 91 (1): 192–228.

Clarksons’ SIN. 2024. “Clarksons’ Shipping Intelligence Network.” https://sin.clarksons.net/.

Coulomb, Renaud, Fanny Henriet, and Léo Reitzmann. 2021. “’Bad’Oil,’Worse’Oil and Carbon Misallocation.”

Crewell. 2025. “Vacancies for Seamen.” 2025. https://crewell.net/en/.

Cui, Qiang, and Ye Li. 2015. “An Empirical Study on the Influencing Factors of Transportation Carbon Efficiency: Evidences from Fifteen Countries.” *Applied Energy* 141:209–17.

Cullinane, Kevin, Teng-Fei Wang, Dong-Wook Song, and Ping Ji. 2006. “The Technical Efficiency of Container Ports: Comparing Data Envelopment Analysis and Stochastic Frontier Analysis.” *Transportation Research Part A: Policy and Practice* 40 (4): 354–74.

Cullinane, Kevin, and Jialin Yang. 2022. “Evaluating the Costs of Decarbonizing the Shipping Industry: A Review of the Literature.” *Journal of Marine Science and Engineering* 10 (7): 946.

Czermański, Ernest, Aneta Oniszczuk-Jastrząbek, Eugen F Spangenberg, Łukasz Kozłowski, Magdalena Adamowicz, Jakub Jankiewicz, and Giuseppe T Cirella. 2022. “Implementation of the Energy Efficiency Existing Ship Index: An Important but Costly Step towards Ocean Protection.” *Marine Policy* 145:105259.

Dewan, Mohammud Hanif, Omar Yaakob, and Aini Suzana. 2018. “Barriers for Adoption of Energy Efficiency Operational Measures in Shipping Industry.” *WMU Journal of Maritime Affairs* 17:169–93.

Dong, Feng, Xiaohui Li, Ruyin Long, and Xiaoyan Liu. 2013. “Regional Carbon Emission Performance in China According to a Stochastic Frontier Model.” *Renewable and Sustainable Energy Reviews* 28:525–30.

Duan, Minghua, Yi Wang, Ailong Fan, Jian Yang, and Xuelong Fan. 2023. “Comprehensive Analysis and Evaluation of Ship Energy Efficiency Practices.” *Ocean & Coastal Management* 231:106397.

Elkafas, Ahmed G, and Mohamed R Shouman. 2022. “A Study of the Performance of Ship Diesel-Electric Propulsion Systems from an Environmental, Energy Efficiency, and Economic Perspective.” *Marine Technology Society Journal* 56 (1): 52–58.

Farrell, Michael James. 1957. “The Measurement of Productive Efficiency.” *Journal of the Royal Statistical Society: Series A (General)* 120 (3): 253–81.

Filippini, Massimo, and Lester C Hunt. 2015. “Measurement of Energy Efficiency Based on Economic Foundations.” *Energy Economics* 52:S5–16.

Fisch-Romito, Vivien, Marc Jaxa-Rozen, Xin Wen, and Evelina Trutnevyte. 2025. “Multi-Country Evidence on Societal Factors to Include in Energy Transition Modelling.” *Nature Energy*, 1–10.

Gandhi, P Jegadish. 1996. “Production Function and Transport Operations-A Case Study.” *The Indian Economic Journal* 44 (2): 130–42.

Garcia-Marin, Alvaro, and Nico Voigtländer. 2019. "Exporting and Plant-Level Efficiency Gains: It's in the Measure." *Journal of Political Economy* 127 (4): 1777–1825.

Greenwood, Robin, and Samuel G Hanson. 2015. "Waves in Ship Prices and Investment." *The Quarterly Journal of Economics* 130 (1): 55–109.

Hansen, Elin Kragesand, Hanna Barbara Rasmussen, and Marie Lützen. 2020. "Making Shipping More Carbon-Friendly? Exploring Ship Energy Efficiency Management Plans in Legislation and Practice." *Energy Research & Social Science* 65:101459.

Hornbeck, Richard, and Martin Rotemberg. 2024. "Growth off the Rails: Aggregate Productivity Growth in Distorted Economies." *Journal of Political Economy* 132 (11): 3547–3602.

IEA, International Energy Agency. 2024. "Oil Demand Growing at a Slower Pace as Post-Covid Rebound Runs Its Course." 2024. https://www.iea.org/commentaries/oil-demand-growing-at-a-slower-pace-as-post-covid-rebound-runs-its-course.

ILO. 2024. "Statistics on Labour Costs." 2024. https://ilostat.ilo.org/topics/labour-costs/.

IMO, International Maritime Organization. 2020. "IMO 2020 – Cutting Sulphur Oxide Emissions." 2020. https://www.imo.org/en/MediaCentre/HotTopics/Pages/Sulphur-2020.aspx.

IMO, International Maritime Organization. 2023. "2023 IMO Strategy on Reduction of GHG Emissions from Ships." https://www.imo.org/en/OurWork/Environment/Pages/2023-IMO-Strategy-on-Reduction-of-GHG-Emissions-from-Ships.aspx.

IMO, International Maritime Organization. 2024. "Marine Environment Protection Committee (MEPC 82)." In . https://www.imo.org/en/MediaCentre/MeetingSummaries/Pages/MEPC-82nd-session.aspx.

IMO, International Maritime Organization. 2025. "Alternative Marine Fuel Prices." Argus Media. 2025. https://futurefuels.imo.org/home/latest-information/fuel-prices/#.

Jafarzadeh, Sepideh, and Ingrid Bouwer Utne. 2014. "A Framework to Bridge the Energy Efficiency Gap in Shipping." *Energy* 69:603–12.

Jia, Haiying, Liping Jiang, and Paulo Azevedo. 2024. "Green Premium and the Role of Financial Investors in Sustainable Investment in Container Shipping." *Transportation Research Part E: Logistics and Transportation Review* 189:103658.

Jimenez, Veronica Jaramillo, Hyungju Kim, and Ziaul Haque Munim. 2022. “A Review of Ship Energy Efficiency Research and Directions towards Emission Reduction in the Maritime Industry.” *Journal of Cleaner Production* 366:132888.

Jin, Taeyoung, and Jinsoo Kim. 2019. “A Comparative Study of Energy and Carbon Efficiency for Emerging Countries Using Panel Stochastic Frontier Analysis.” *Scientific Reports* 9 (1): 6647.

Johnson, Hannes, and Karin Andersson. 2016. “Barriers to Energy Efficiency in Shipping.” *WMU Journal of Maritime Affairs* 15:79–96.

Johnson, Hannes, and Linda Styhre. 2015. “Increased Energy Efficiency in Short Sea Shipping through Decreased Time in Port.” *Transportation Research Part A: Policy and Practice* 71:167–78.

Klaaßen, Lena, and Bjarne Steffen. 2023. “Meta-Analysis on Necessary Investment Shifts to Reach Net Zero Pathways in Europe.” *Nature Climate Change* 13 (1): 58–66.

Kopp, Raymond J, and W Erwin Diewert. 1982. “The Decomposition of Frontier Cost Function Deviations into Measures of Technical and Allocative Efficiency.” *Journal of Econometrics* 19 (2–3): 319–31.

Kosmas, Vasileios, and Michele Acciaro. 2017. “Bunker Levy Schemes for Greenhouse Gas (GHG) Emission Reduction in International Shipping.” *Transportation Research Part D: Transport and Environment* 57:195–206.

Kumbhakar, Subal C. 1988. “On the Estimation of Technical and Allocative Inefficiency Using Stochastic Frontier Functions: The Case of US Class 1 Railroads.” *International Economic Review*, 727–43.

Kumbhakar, Subal C, and C A Knox Lovell. 2003. *Stochastic Frontier Analysis*. Cambridge university press.

Kumbhakar, Subal C, Hung-Jen Wang, and Alan P Horncastle. 2015. *A Practitioner’s Guide to Stochastic Frontier Analysis Using Stata*. Cambridge University Press.

Lassesson, HENRIC, and KARIN Andersson. 2009. “Energy Efficiency in Shipping.” *Department of Shipping and Marine Technology, Division of Sustainable Ship Propulsion, Charmers University of Technology: Göteborg, Sweden* 6:12–17.

Lin, Boqiang, and Izhar Ahmad. 2016. “Energy Substitution Effect on Transport Sector of Pakistan Based on Trans-Log Production Function.” *Renewable and Sustainable Energy Reviews* 56:1182–93.

Longarela-Ares, Ángeles, Anxo Calvo-Silvosa, and José-Benito Pérez-López. 2020. “The Influence of Economic Barriers and Drivers on Energy Efficiency Investments in Maritime Shipping, from the Perspective of the Principal-Agent Problem.” *Sustainability* 12 (19): 7943.

Lu, Ruihua, Osman Turan, Evangelos Boulougouris, Charlotte Banks, and Atilla Incecik. 2015. “A Semi-Empirical Ship Operational Performance Prediction Model for Voyage Optimization towards Energy Efficient Shipping.” *Ocean Engineering* 110:18–28.

Maritime Zone. 2025. “Salary Statistics for Seafarers on Merchant and Offshore Vessels.” 2025. https://maritime-zone.com/en/analytics.

Meeusen, Wim, and Julien van Den Broeck. 1977. “Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error.” *International Economic Review*, 435–44.

Mengesha, Isaak, and Debraj Roy. 2025. “Carbon Pricing Drives Critical Transition to Green Growth.” *Nature Communications* 16 (1): 1321.

Mermiris, Dimitrios, Dracos Vassalos, K Dodworth, Dimitrios Sfakianakis, and Georgios Mermiris. 2011. “Dynamic Energy Modeling–a New Approach to Energy Efficiency and Cost Effectiveness in Shipping Operations.” In *Proceedings of International Conference on Technologies, Operations, Logistics and Modelling for Low Carbon Shipping, Glasgow*, 13–22.

Moutzouris, Ioannis C, and Nikos K Nomikos. 2019. “Earnings Yield and Predictability in the Dry Bulk Shipping Industry.” *Transportation Research Part E: Logistics and Transportation Review* 125:140–59.

Moutzouris, Ioannis C, Nikos C Papapostolou, Malvina Marchese, Michael N Tamvakis, and Yao Shi. 2024. “Determinants of the Price Premium for Eco Vessels.” *Transportation Research Part D: Transport and Environment* 136:104414.

Nuchturee, Chalermkiat, Tie Li, and Hongpu Xia. 2020. “Energy Efficiency of Integrated Electric Propulsion for Ships–A Review.” *Renewable and Sustainable Energy Reviews* 134:110145.

Oehmke, Martin, and Marcus M Opp. 2024. "A Theory of Socially Responsible Investment." *Review of Economic Studies*, rdae048.

Önüt, Semih, and Selin Soner. 2006. "Energy Efficiency Assessment for the Antalya Region Hotels in Turkey." *Energy and Buildings* 38 (8): 964–71.

Orr, Scott. 2022. "Within-Firm Productivity Dispersion: Estimates and Implications." *Journal of Political Economy* 130 (11): 2771–2828.

Patterson, Murray G. 1996. "What Is Energy Efficiency?: Concepts, Indicators and Methodological Issues." *Energy Policy* 24 (5): 377–90.

Petropoulos, Ted. 2022. "Key Developments and Growth in Global Ship Finance." *Petrofin Bank Research*, 1–15.

Rehmatulla, Nishatabbas, and Tristan Smith. 2015a. "Barriers to Energy Efficiency in Shipping: A Triangulated Approach to Investigate the Principal Agent Problem." *Energy Policy* 84:44–57.

———. 2015b. "Barriers to Energy Efficient and Low Carbon Shipping." *Ocean Engineering* 110:102–12.

Rojon, Isabelle, Nicholas-Joseph Lazarou, Nishatabbas Rehmatulla, and Tristan Smith. 2021. "The Impacts of Carbon Pricing on Maritime Transport Costs and Their Implications for Developing Economies." *Marine Policy* 132:104653.

Rossi, Federico. 2022. "The Relative Efficiency of Skilled Labor across Countries: Measurement and Interpretation." *American Economic Review* 112 (1): 235–66.

Schmidt, Peter, and C A Knox Lovell. 1979. "Estimating Technical and Allocative Inefficiency Relative to Stochastic Production and Cost Frontiers." *Journal of Econometrics* 9 (3): 343–66.

Sou, Weng Sut, Tian Goh, Xin Ni Lee, Szu Hui Ng, and Kah-Hin Chai. 2022. "Reducing the Carbon Intensity of International Shipping–The Impact of Energy Efficiency Measures." *Energy Policy* 170:113239.

S&P Global. 2025. "Platts Ammonia Price Chart." S&P Global Commodity Insights. 2025. https://www.spglobal.com/commodity-insights/en/news-research/latest-news/energy-transition/051023-interactive-ammonia-price-chart-natural-gas-feedstock-europe-usgc-black-sea.

Stevenson, Rodney E. 1980. “Likelihood Functions for Generalized Stochastic Frontier Estimation.” *Journal of Econometrics* 13 (1): 57–66.

Stopford, Martin. 2008. *Maritime Economics 3e*. Routledge.

Sun, Wei, and Chenchen Huang. 2020. “How Does Urbanization Affect Carbon Emission Efficiency? Evidence from China.” *Journal of Cleaner Production* 272:122828.

Tan, Xiujie, Yongrok Choi, Banban Wang, and Xiaoqi Huang. 2020. “Does China’s Carbon Regulatory Policy Improve Total Factor Carbon Efficiency? A Fixed-Effect Panel Stochastic Frontier Analysis.” *Technological Forecasting and Social Change* 160:120222.

UNCTAD. 2023. “Review of Maritime Transport.” In *Towards a Green and Just Green and Just Transition*. Geneva: United Nations publication. https://unctad.org/publication/review-maritime-transport-2023.

Wanke, Peter, Zhongfei Chen, Xi Zheng, and Jorge Antunes. 2020. “Sustainability Efficiency and Carbon Inequality of the Chinese Transportation System: A Robust Bayesian Stochastic Frontier Analysis.” *Journal of Environmental Management* 260:110163.

Wu, Wei-Ming. 2020. “The Optimal Speed in Container Shipping: Theory and Empirical Evidence.” *Transportation Research Part E: Logistics and Transportation Review* 136:101903.

Yuan, Jun, Victor Nian, Junliang He, and Wei Yan. 2019. “Cost-Effectiveness Analysis of Energy Efficiency Measures for Maritime Shipping Using a Metamodel Based Approach with Different Data Sources.” *Energy* 189:116205.

Zhang, Jing, Meifeng Luo, and Dong Yang. 2025. “Are Efficient Ports for Port Operators Also Those for Shipping Companies? A Meta-Frontier Analysis of Global Top 80 Container Ports.” *Ocean & Coastal Management* 263:107616.

Appendix A: Additional figures and tables

Appendix A provides additional figures and tables for the empirical estimation in Section 5 of the main paper, which includes additional information on vessel types (Section A.1), production efficiency and cost efficiency of vessel types (Section A.2), and additional models of production efficiency (Section A.3).

A.1 Additional information on vessel types

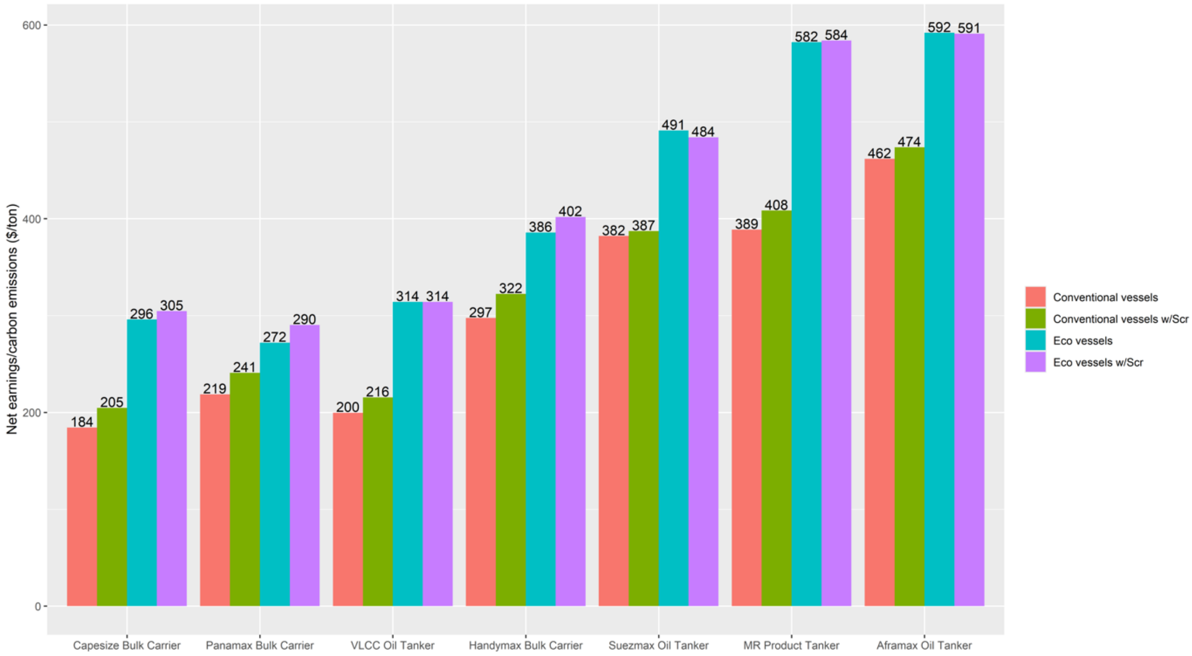
Table A1 shows the typical sizes of the 15 vessel types analysed in this paper. Vessel size is usually measured by deadweight tonnage except for containerships, the size of which is usually measured by Twenty-foot Equivalent Unit (TEU) which is a standard container. The 15 vessel types are classified into four categories by the type of goods carried, i.e., product tanker, crude oil tanker, containership, and bulk carrier.

Table A1 Typical size of each vessel type

Vessel category	**Vessel type**	**Typical deadweight tonnage**	**Typical TEU**
Product tanker	Aframax	115,000	
	Panamax	74,000	
	MR	50,000	
	Handy	37,000	
Crude oil tanker	VLCC	310,000	
	Suezmax	150,000	
	Aframax	115,000	
Containership	Post-Panamax		17,000+
	Neo-Panamax		8,000-16,999
	Intermediate		3,000-7,999
	Feeder		100-2,999
Bulk carrier	Capesize	180,000	
	Panamax	76,000	
	Handymax	60,000	
	Handysize	35,000	

Figure A1 compares the net earnings per ton of CO2 of vessels fitted with a scrubber device (formally known as an exhaust gas cleaning system [EGCS]) to those without one, i.e. eco with scrubber versus eco and non-eco with scrubber versus non-eco. This aims to complement the analysis for Figure 4, where only eco against non-eco vessels are compared.

Figure A1: Net earnings per ton of carbon emissions by eco and scrubber status



The results suggest that installing a scrubber does not have a large impact on vessels' net earnings per ton of CO2. This is because scrubbers do not reduce CO2 but only sulphur emissions (the marginal differences are because scrubber-fitted vessels receive a slightly higher TC rate).

A.2 Production efficiency and cost efficiency of vessel types

Table A2 summarises the regression results for the production efficiency, based on Equation (10) and three model specifications. In contrast to the carbon efficiency estimation, this is an output-oriented SFA, where the dependent variable is transport work (D*V), and the independent ones are the capital, operation, and CO2 inputs (CO2 is considered an input as it is directly related to energy consumption). As shown in Equation (1), this model estimates by how much transport work can be increased subject to the current input levels.

Table A2: Production efficiency of vessel types

	(1)	(2)	(3)
		Dependent variable: ln(D*V)	
Efficiency trend	Increase	Increase	Increase
Time effect	Yes	No	Yes
Distribution	Truncated normal	Half normal	Half normal
Intercept	-12.44***	-6.64***	1.00***
ln(K)	-0.53	-0.06	0.54
ln(OP)	2.39**	0.35***	0.95**
ln(CO2)	1.39	1.33***	0.90
Mu	0.0005		0.68
Time	0.11		
Sigma Sq.	0.41	0.58**	0.997
Gamma	0.95	0.997***	0.74
log likelihood	11.94***	55.68***	11.93***
Mean efficiency	0.51	0.60	0.51

*Note: significance levels: 0.01 '***' 0.05 '**' 0.1 '*'. The total number of observations is 56.*

The goodness of fit statistics suggest that Model (2) is the best performing one. Operation and CO2 are both significantly positively associated with transport work while capital is not. The economic analysis of the findings is included in the main text.

Table A3 summarises the regression results for the cost efficiency, based on Equation (11). In line with Stopford (2008), the total cost is approximated by the sum of capital expenditure, operational expenses (OPEX) and energy cost. The independent variables consist of the respective input prices – i.e., loan rate (cost of capital), wage (unit cost of OPEX) and fuel price (cost of energy) – and the vessel's output, measured through its transport work.

Based on the significance of the time trend and the goodness of fit statistics, Model (3) is the most appropriate specification. The loan rate and wage are both strongly positively associated with the total cost. These are rather fixed costs that the shipowner needs to pay on a continuous basis and, thus, substantially affect the total cost. Hence, their respective coefficients are positive and rather large in magnitude. Transport work is also positively related to the total costs as, the more cargo the vessel transports over longer distances, the higher the variable costs, i.e., voyage costs such as fuel expenses, port charges, and canal dues.

While the negative sign of fuel price might seem counterintuitive, a possible explanation is that, when fuel prices are high, ship operators place significant emphasis on the optimisation of operations and on reducing fuel expenses unless operating the vessel yields a profit. In addition, high fuel prices can influence the decision to lay up a vessel. For instance, in bad freight market conditions where voyage costs might exceed the freight revenue, it is common market practice to lay up an old and less efficient vessel instead of commercially operating it and realising losses. Note that the coefficient of fuel costs is significantly smaller in absolute terms than the one of loan rate. This is in line with the fact that the capital needed to invest in a vessel is much larger in magnitude and is considered a fixed cost as opposed to fuel expenses.

Table A3: Cost efficiency of vessel types

	(1)	(2)	(3)
	Dependent variable: ln(total cost)		
Inefficiency trend	Increase	Increase	Increase
Time effect	No	No	Yes
Distribution	Half normal	Truncated normal	Truncated normal
Intercept	12.24***	-7.45***	-16.83***
ln(loan rate)	6.05***	5.6***	4.25***
ln(wage)	0.83	-0.69***	1.55***
ln(fuel price)	-1.33***	-0.95***	-0.7***
ln(D*V)	0.45***	0.69***	0.41***
Mu		0.77***	0.54***
Time			-0.3***
Sigma Sq.	0.13	0.16***	0.08***
Gamma	0.82	0.95***	0.9***
ln likelihood	9.75***	23.15***	37.31***
Mean efficiency	0.76	0.42	0.66

*Note: significance levels: 0.01 '***' 0.05 '**' 0.1 '*'. The total number of observations is 56.*

A.3 Additional models of production efficiency

Table A4 shows three models with various assumptions on the distribution of the inefficiency term.

Table A4: Production efficiency of individual vessels: Additional models

	(1)	(2)	(3)
		Dependent variable: ln(D*V)	
Distribution	Half normal	Truncated normal	Exponential
Intercept	9.12***	9.21***	9.21***
ln(OP)	0.02	0.02	0.02
ln(E)	0.94***	0.93***	0.93***
ln(K)	0.13***	0.13***	0.13***
Mu		-105	
U sigma	0.01	2.82	0.08***
V sigma	0.20***	0.19***	0.19***
Lambda	0.03	15.14**	0.40***
Log likelihood	124***	124***	124***

*Note: significance levels: 0.01 '***' 0.05 '**' 0.1 '*'. The total number of observations is 664 vessels.*

Appendix B: Sensitivity analysis

Appendix B presents sensitivity analysis results for alternative values of key model parameters as loan rate (Section B.1), fuel price (Section B.2), wage (Section B.3), and speed (Section B.4).

B.1 Loan rate

First, we vary the loan rate (cost of capital) corresponding to the vessel type dataset (Table 1), while keeping all other variables constant. The initial loan rates range from 2.7% to 3.1%, and 1% is added to it for each sensitivity analysis (Table B1).

Table B1: Sensitivity analysis of vessel types by varying the loan rate

Loan rate (%)	Min	Median	Mean	Max	s.d.
Initial	2.7	2.9	2.9	3.1	0.15
Sensitivity Analysis 1	3.7	3.9	3.9	4.1	0.15
Sensitivity Analysis 2	4.7	4.9	4.9	5.1	0.15
…					
Sensitivity Analysis 12	14.7	15.9	15.9	15.1	0.15

As the loan rate is only incorporated in the cost efficiency estimation, the results checked for robustness relate to Table A3 and Figure 8. The best model of each sensitivity analysis is selected; coincidentally, they all include a time effect, a declining trend and a truncated normal distribution for the error term. All the coefficients are significant at either the 95% or 99% confidence level. The results of the coefficients, time effects and mean efficiencies are presented in Figure B1. From left to right, the loan rate increases by 1% in each model, and there are twelve sensitivity analyses in total. The coefficients of the loan rate are on the right y-axis and everything else on the left one.

The coefficients of the loan rate increase as the rate rises since, the more expensive capital becomes, the more it contributes to total cost. However, the fact that the coefficients of the other variables, the time effect and the mean efficiency remain relatively stable, shows the robustness of the model and the associated results. This is further confirmed by Figure B2, where the cost efficiencies across the 15 vessel types remain stable despite the change in the loan rate.

Figure B1: Coefficients of the cost efficiency models by varying the loan rate

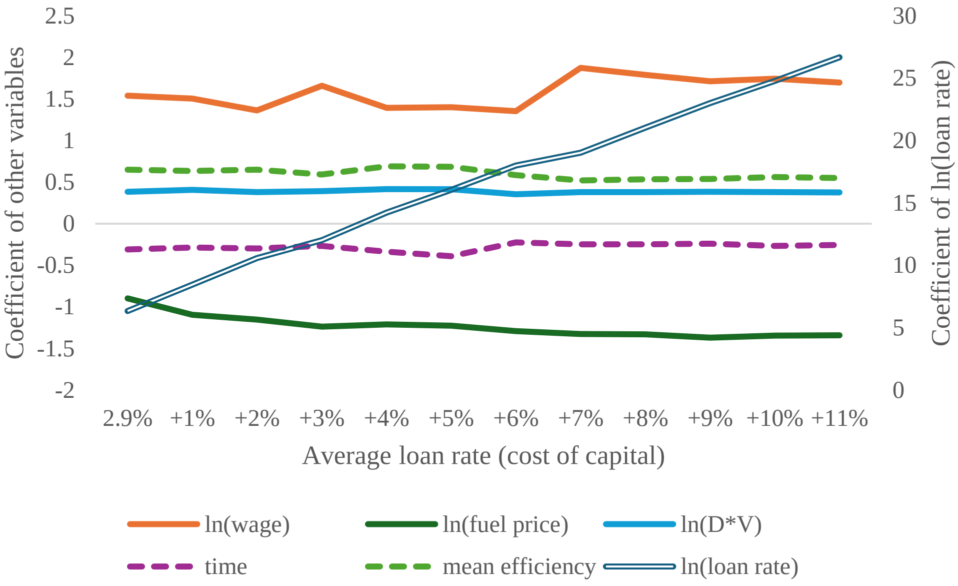
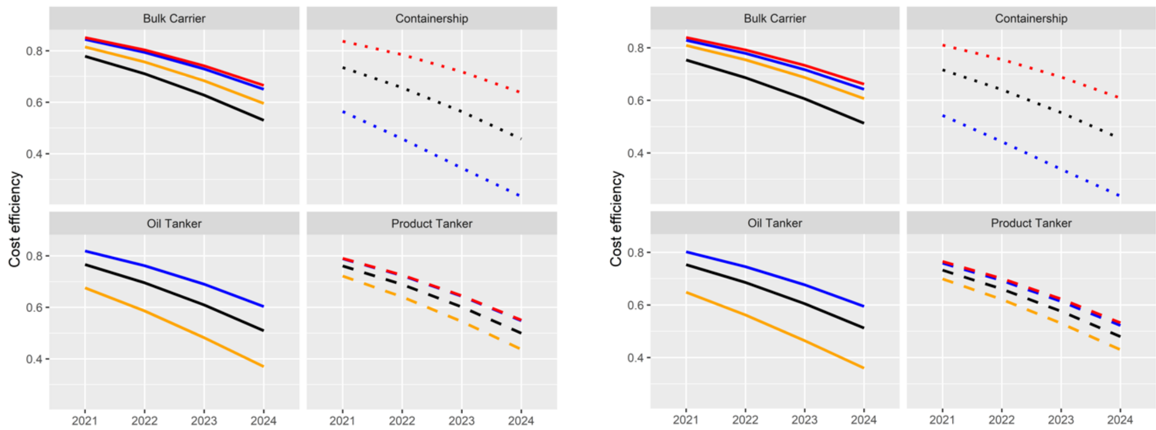


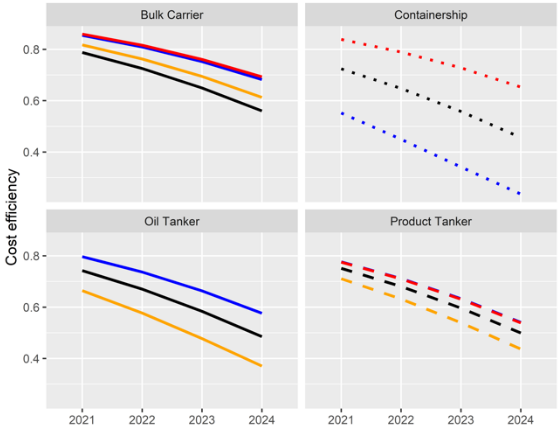
Figure B2: Cost efficiency of vessel type by varying the loan rate



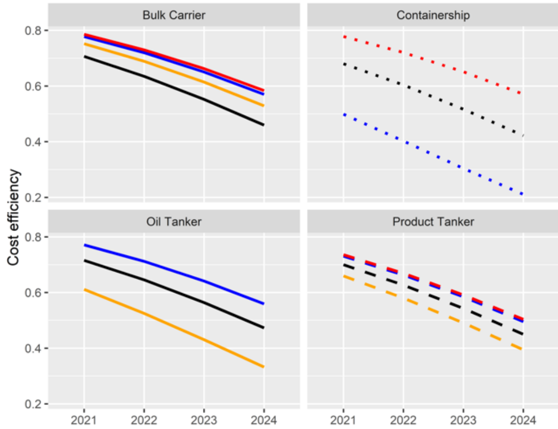
Loan rate + 1% Loan rate + 2%

(to be continued)

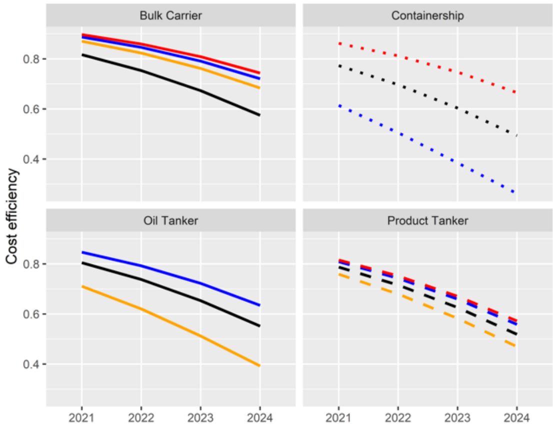
(continued)



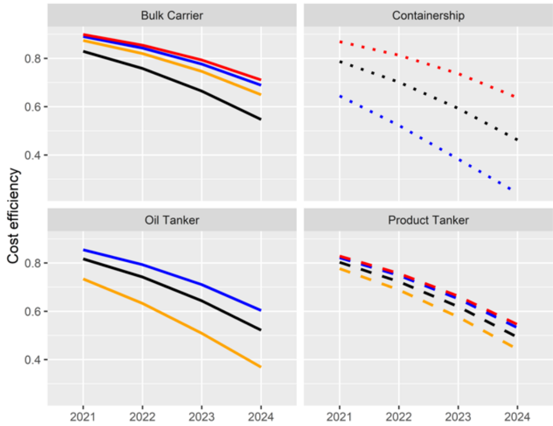
Loan rate + 3%



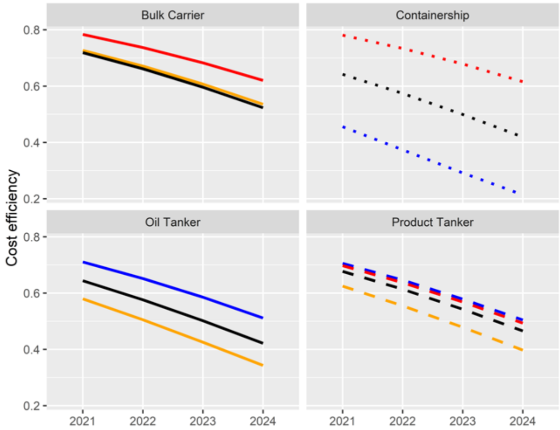
Loan rate + 4%



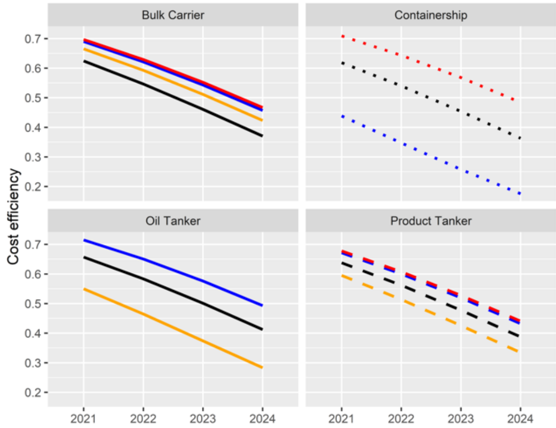
Loan rate + 5%



Loan rate + 6%

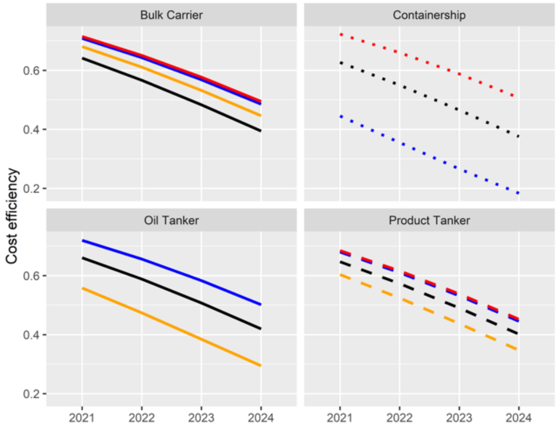


Loan rate + 7%

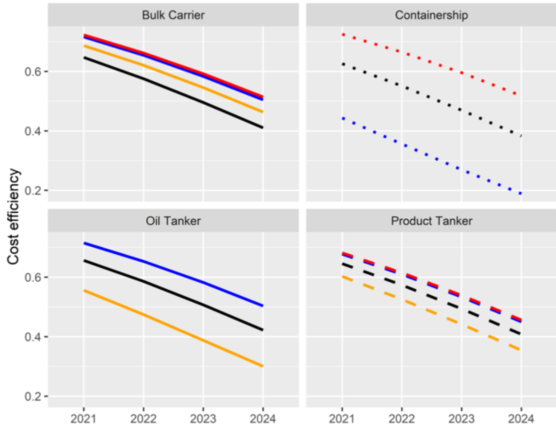


Loan rate + 8%

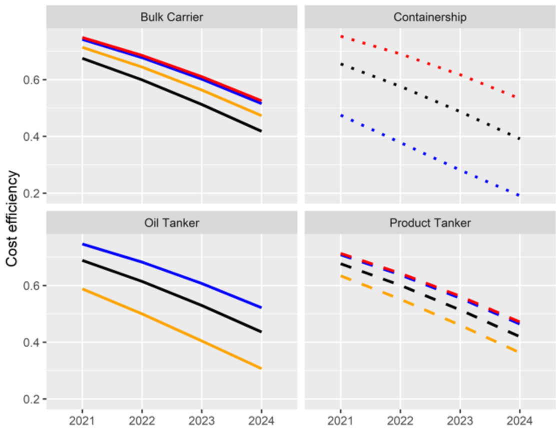
(continued)



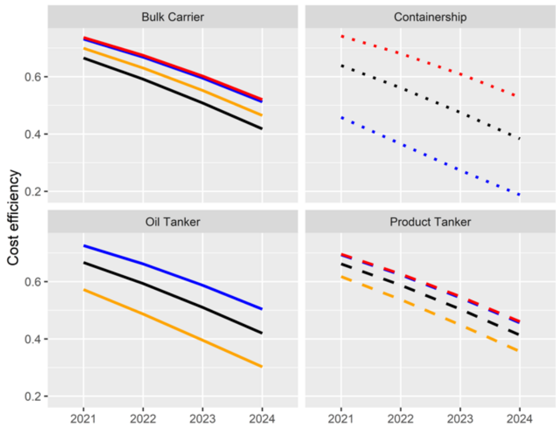
Loan rate + 9%



Loan rate + 10%



Loan rate + 11%



Loan rate + 12%

Second, we vary the loan rate (cost of capital) corresponding to the individual vessel dataset (Table 2), while keeping all other variables constant. The initial loan rates range from 1.5% to 8.0%, and each of the seven sensitivity analyses adds 1% to them (Table B2). The loan rate is not decreased because the initial values are at a historical low from 2011 to 2014.

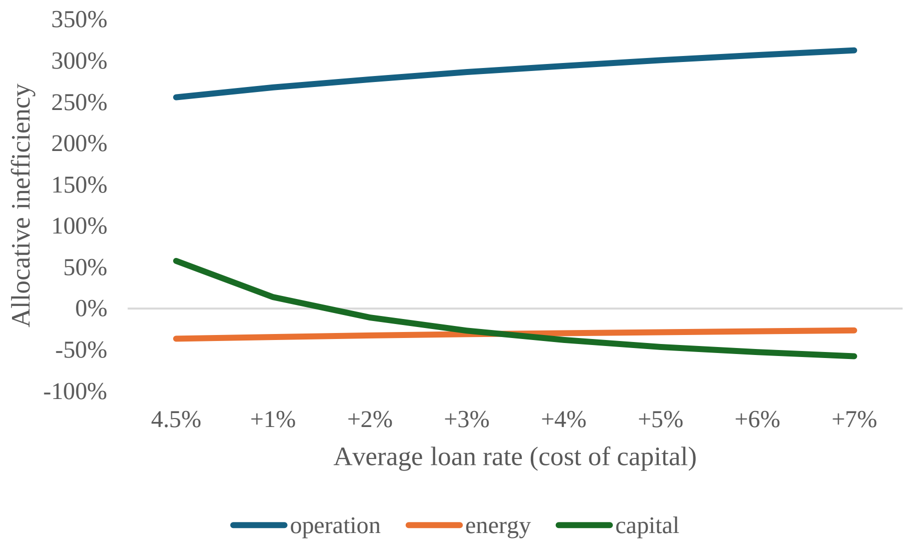
Table B2: Sensitivity analysis of individual vessels by varying the loan rate

Loan rate (%)	Min	Mean	Median	Max	s.d.
Initial	1.5	4.5	3.9	8.0	1.6
Sensitivity Analysis 1	2.5	5.5	4.9	9.0	1.6
Sensitivity Analysis 2	3.5	6.5	5.9	10.0	1.6
…					
Sensitivity Analysis 7	8.5	11.5	10.9	15.0	1.6

As the loan rate is solely used in the allocative efficiency estimation, the results checked for robustness relate to Table 4 and Figure 10. An exponential distribution of the error term is assumed along with vessel age and time travelled as control variables since this specification provides the best goodness of fit.

The main results in Table 4 suggest that, while allocative inefficiency decreases the demand for energy, it increases the demand for operation and capital. In other words, energy is underused but both operation and capital are overused. Figure B3 summarises the effects of allocative inefficiency on the input demand for operation, energy, and capital when the loan rate is increased. The sensitivity analysis first re-estimates the optimal input demand given the new rate and then compares each vessel's input demand with the optimal level via SFA. In doing so, we incorporate own-price and cross-price elasticities and estimate how allocative efficiency adjusts according to the new set of inputs.

Figure B3: The effects of allocative inefficiency on input demand by varying the loan rate

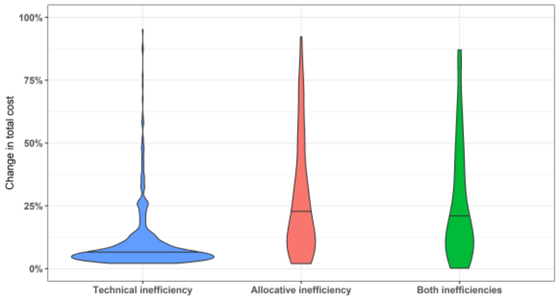


Note: all models assume an exponential distribution of the error term.

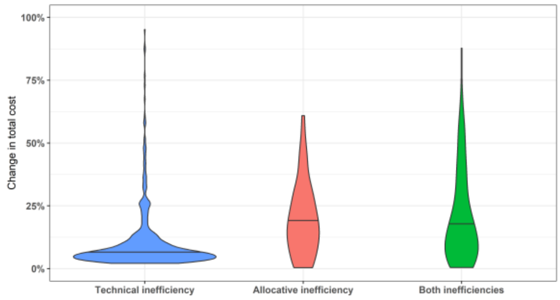
When the loan rate increases by 7%, the allocative inefficiency of capital decreases from (an overuse of) around 60% to (an underuse of) circa -60%. Equivalently, capital is overused if the loan rate is low but underused when it is high. Furthermore, the rise in the cost of capital slightly increases the overuse of operation and decreases the underuse of energy. However, the changes in the allocative inefficiency of operation and energy are much smaller compared to that of capital, which proves the robustness of the model.

Figure B4 presents the effects of the technical, allocative, and both inefficiencies combined on the total cost when the loan rate is increased.

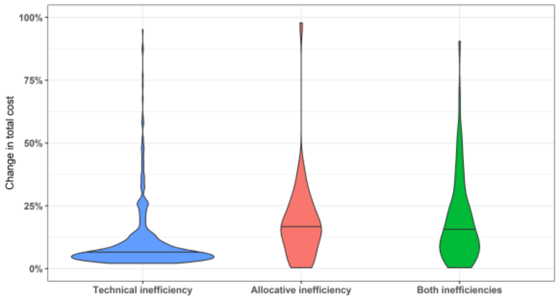
Figure B4: Change in total cost by varying the loan rate



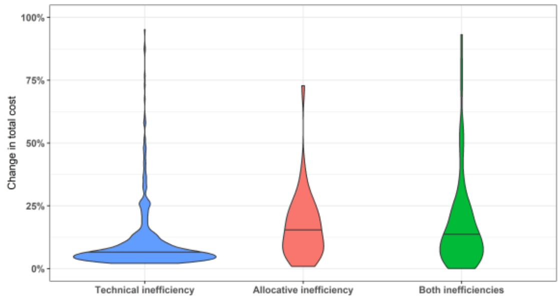
Loan rate + 1%



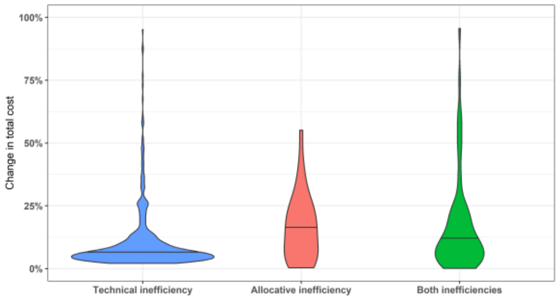
Loan rate + 2%



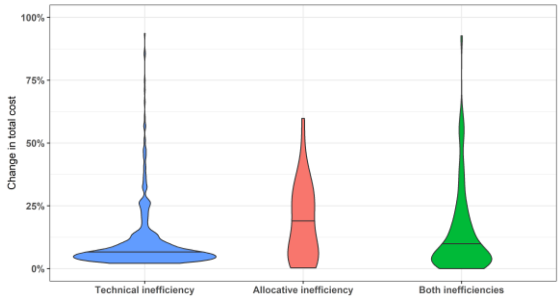
Loan rate + 3%



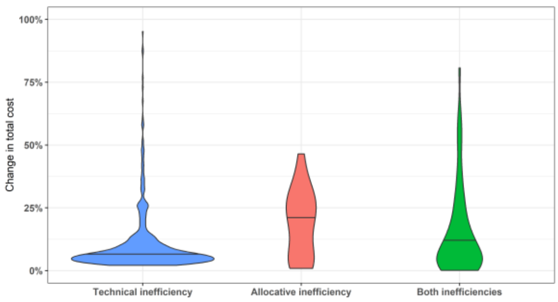
Loan rate + 4%



Loan rate + 5%



Loan rate + 6%



Loan rate + 7%

The shapes of all plots in Figure B4 look overall similar to the respective ones in Figure 10, which confirms the robustness of the model. As the loan rate increases, the blue violin plot remains unchanged. Thus, as expected, the loan rate does not affect the technical performance of the vessel. However, when the loan rate increases, the allocative inefficiency first declines (i.e., the red plot widens and the median decreases) and then rises (i.e. the red plot becomes thinner and the median increases). Namely, the results suggest that a higher loan rate can improve the allocative efficiency by reducing the overinvestment in vessels and, in turn, the overuse of capital. However, when the rate becomes too high, the excess capital costs result in capital inefficiency.

B.2 Fuel price

We now examine the sensitivity of the results to changes in fuel price. The fuel price in the initial analysis for the different vessel types ranges from 526 to 756 $/ton, with a mean and median of 535 and 588 $/ton, respectively. In Table B3, the price is varied in increments of 100 $/ton.

Table B3: Sensitivity analysis of vessel types by varying the fuel price

Fuel price ($/ton)	Min	Mean	Median	Max	s.d.
Initial	526	535	588	756	113
Sensitivity Analysis 1	426	435	488	656	113
Sensitivity Analysis 2	326	335	388	556	113
Sensitivity Analysis 3	226	235	288	456	113
Sensitivity Analysis 4	626	635	688	856	113
Sensitivity Analysis 5	726	735	788	956	113
Sensitivity Analysis 6	826	835	888	1,056	113
Sensitivity Analysis 7	926	935	988	1,156	113
Sensitivity Analysis 8	1,026	1,035	1,088	1,256	113
Sensitivity Analysis 9	1,126	1,135	1,188	1,356	113

As fuel price is used in the cost efficiency model (Table A3 and Figure 8), Figure B5 presents the model's coefficients based on the new prices. Figure B6 illustrates the cost efficiency by vessel type with the new prices.

In the initial estimation, cost efficiency and fuel price exhibit a negative relationship. Figure B5 suggests that the coefficient of fuel price remains negative and relatively stable up to 400

$/ton increases but fluctuates significantly with further changes. At this point, also the coefficient of the loan rate and the mean efficiency vary substantially. This indicates that a very high fuel price not only increases the total vessel cost but also significantly alters its cost efficiency. These could have a negative impact on shipping supply, especially during market downturns. The large swings in coefficients and mean efficiency in Figure B6 confirm that the cost efficiency across the various shipping sectors fluctuates dramatically when the fuel price increases by more $400 per ton. On the other hand, the coefficient of the wage is rather stable. This is line with economic theory as a vessel's OPEX are not affected by fuel price changes.

Figure B5: Coefficients of the cost efficiency models by varying the fuel price

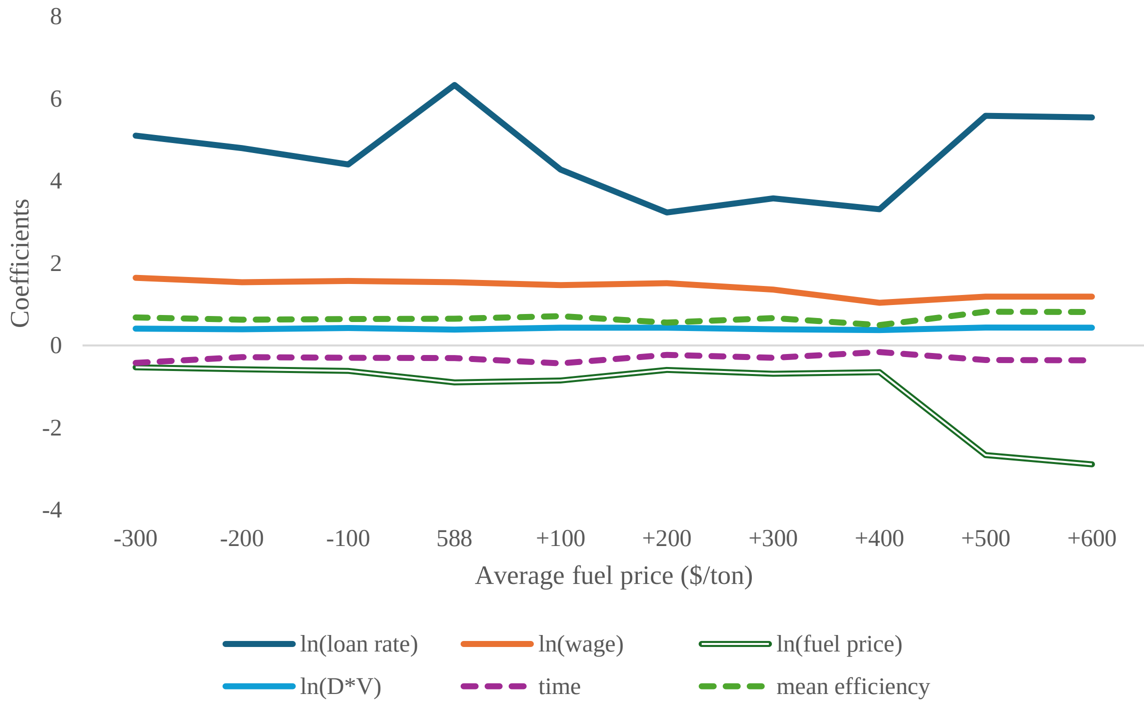
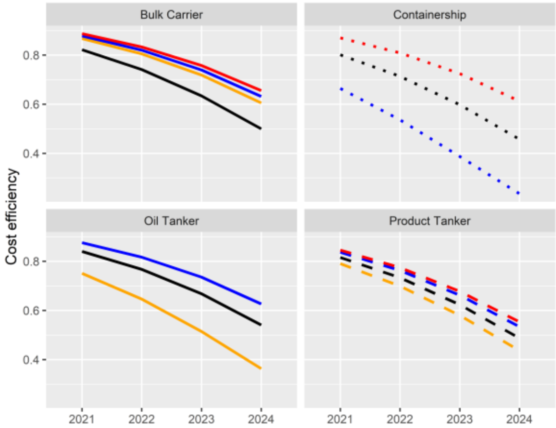
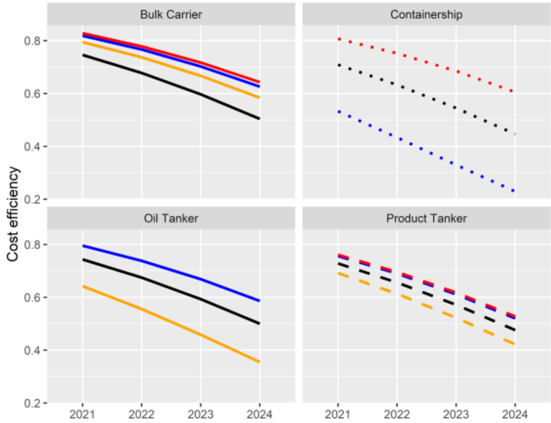


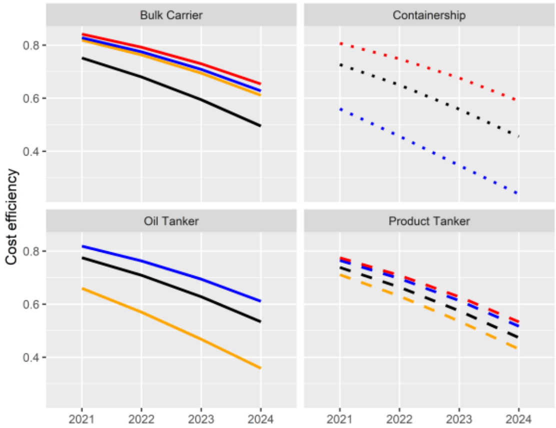
Figure B6: Cost efficiency of vessel type by varying the fuel price



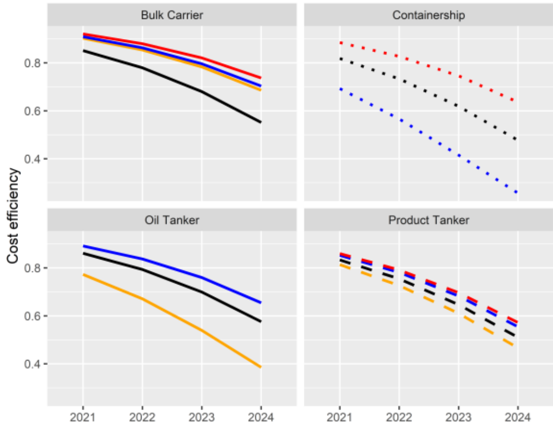
Fuel price – 300 $/ton



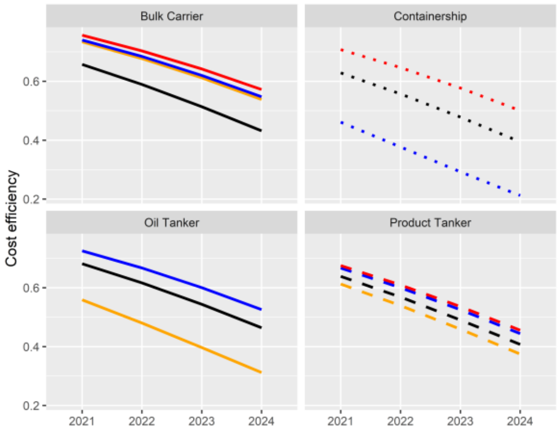
Fuel price – 200 $/ton



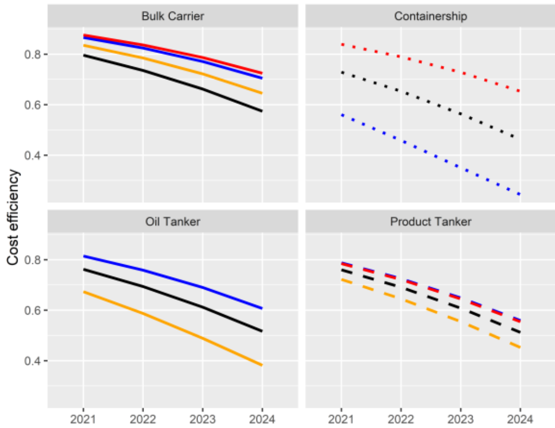
Fuel price – 100 $/ton



Fuel price + 100 $/ton



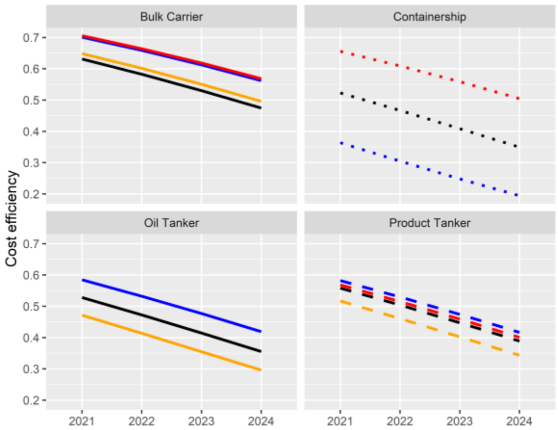
Fuel price + 200 $/ton



Fuel price + 300 $/ton

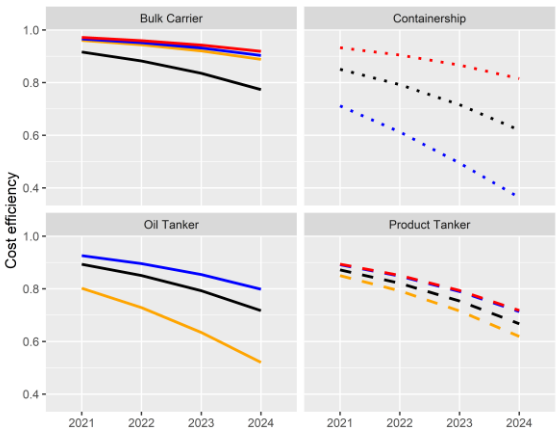
(to be continued)

(continued)



Fuel price + 400 $/ton

Fuel price + 500 $/ton



Fuel price + 600 $/ton

We then investigate how fuel price changes affect the efficiencies of individual Capesize and VLCC vessels. The fuel price in the initial analysis ranges from 494 to 620 $/ton, with a mean and median of 552 and 494 $/ton, respectively. In Table B4, the price is varied in increments of 100 $/ton.

Table B4: Sensitivity analysis of individual vessels by varying the fuel price

Fuel price ($/ton)	Min	Mean	Median	Max	s.d.
Initial	494	552	494	620	63
Sensitivity Analysis 1	394	452	394	520	63
Sensitivity Analysis 2	294	352	294	420	63
Sensitivity Analysis 3	194	252	194	320	63
Sensitivity Analysis 4	594	652	594	720	63
Sensitivity Analysis 5	694	752	694	820	63
Sensitivity Analysis 6	794	852	794	920	63
Sensitivity Analysis 7	894	952	894	1,020	63
Sensitivity Analysis 8	994	1,052	994	1,120	63
Sensitivity Analysis 9	1,094	1,152	1,094	1,220	63

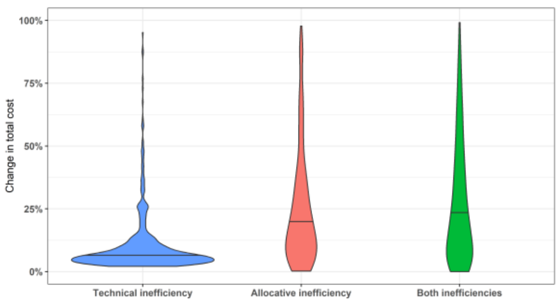
Figure B7 presents the effects of allocative inefficiency on input demand when changing the fuel price (the initial results are summarised in Table 5 of the main text).

Figure B7: The effects of allocative inefficiency on input demand by varying the fuel price

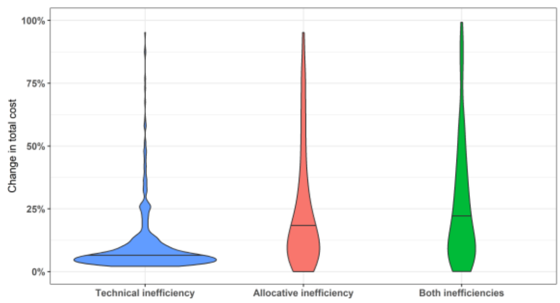
Figure B7 shows that, as fuel price increases, energy becomes slightly more underused. Meanwhile, capital's overuse significantly decreases until it becomes slightly underused; operation's overuse steeply increases. There is a disproportional change in energy and operation, because it is difficult for vessels to reduce energy use despite a large increase in fuel price, but much easier to dramatically increase expenses on maintenance and upgrades to minimise energy cost. As fuel price increases by more than $300 per ton, we can see that input misallocation becomes more severe. This is in line with the findings from Figures B5 and B6 where an increase in fuel price of over $400 leads to severe fluctuations in cost efficiency. In conclusion, an increase of over 50% in fuel price may, on the one hand, facilitate green investment in vessels with higher OPEX but, on the other hand, hinder the stability of shipping supply.

Figure B8 presents the effects of technical, allocative, and both inefficiencies on a vessel's total cost with respect to different fuel prices. As fuel price increases, the red and green violin plots first become thinner and then wider, i.e., the effects on total cost first decrease and then increase. This can be explained by the fact that, a relatively small increase in fuel price worsens the allocative inefficiency which drives up the total cost; however, a sharp increase in fuel price may mobilise greener investment to improve energy efficiency and, thus, it may even reduce the total cost.

Figure B8: Change in total cost by varying the fuel price



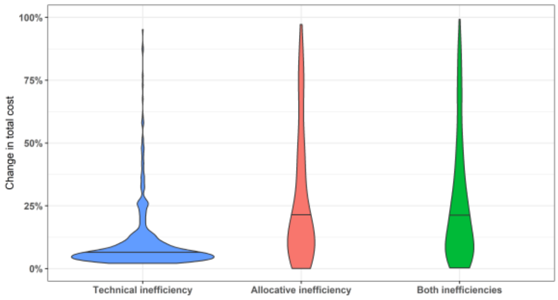
Fuel price – 300 $/ton



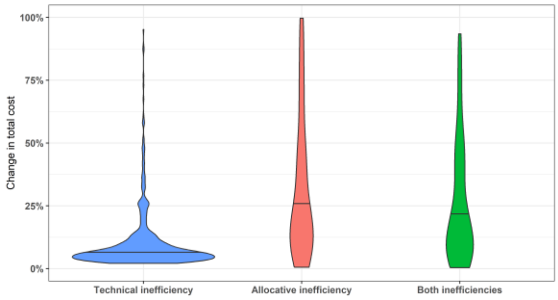
Fuel price – 200 $/ton

(to be continued)

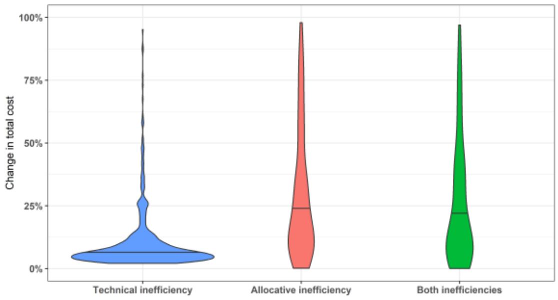
(continued)



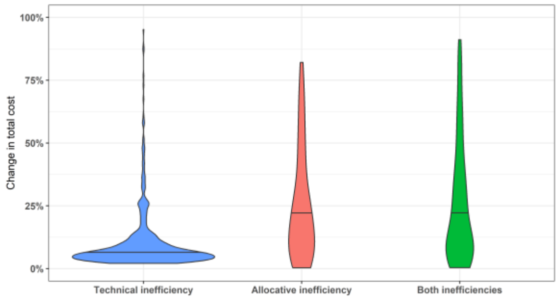
Fuel price – 100 $/ton



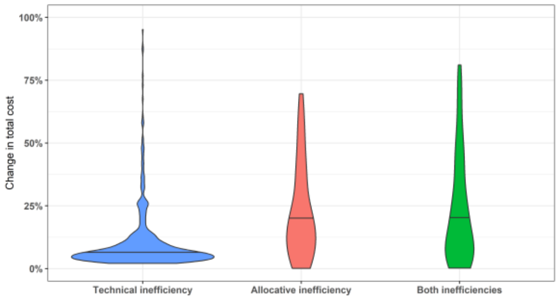
Fuel price + 100 $/ton



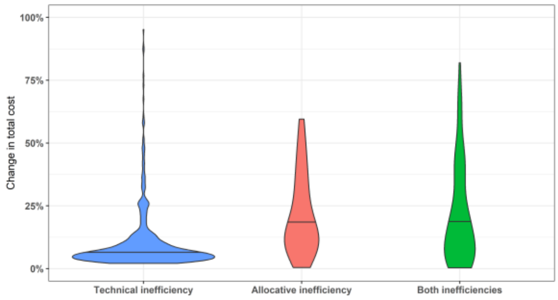
Fuel price + 200 $/ton



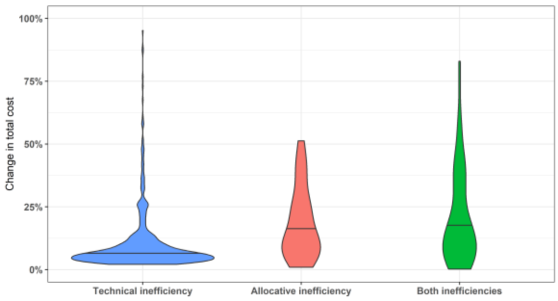
Fuel price + 300 $/ton



Fuel price + 400 $/ton



Fuel price + 500 $/ton



Fuel price + 600 $/ton

B.3 Wage

Next, we vary the wage (cost of operation) corresponding to the individual vessel dataset (Table 2). As the wage is solely used in the allocative efficiency estimation, the results checked for robustness relate to Tables 5 and 10. Table B5 summarises the respective wage in each sensitivity analysis.

Table B5: Sensitivity analysis of individual vessels by varying the wage

Wage ($/year)	Min	Mean	Median	Max	s.d.
Initial	24,120	39,824	34,198	82,637	12,239
Sensitivity Analysis 1	22,120	37,824	32,198	80,637	12,239
Sensitivity Analysis 2	20,120	35,824	30,198	78,637	12,239
Sensitivity Analysis 3	18,120	33,824	28,198	76,637	12,239
Sensitivity Analysis 4	16,120	31,824	26,198	74,637	12,239
Sensitivity Analysis 5	14,120	29,824	24,198	72,637	12,239
Sensitivity Analysis 6	26,120	41,824	36,198	84,637	12,239
Sensitivity Analysis 7	28,120	43,824	38,198	86,637	12,239
Sensitivity Analysis 8	30,120	45,824	40,198	88,637	12,239
Sensitivity Analysis 9	32,120	47,824	42,198	90,637	12,239
Sensitivity Analysis 10	34,120	49,824	44,198	92,637	12,239

Figure B9 shows that the overuse of operation decreases when the wage increases. Specifically, when the wage increases by $10,000 per year, the overuse of operation decreases from around 260% to 180%. Meanwhile, the overuse of capital roughly triples but energy use remains underused and overall unaffected by wage changes. When the wage decreases by more than ca. $8,000 per year though, capital becomes underused. This may be explained by the fact that, when the wage is rather low and the overuse of operation increases, it would require more capital expenditure for more vessels to operate.

Figure B9: The effects of allocative inefficiency on input demand by varying the wage

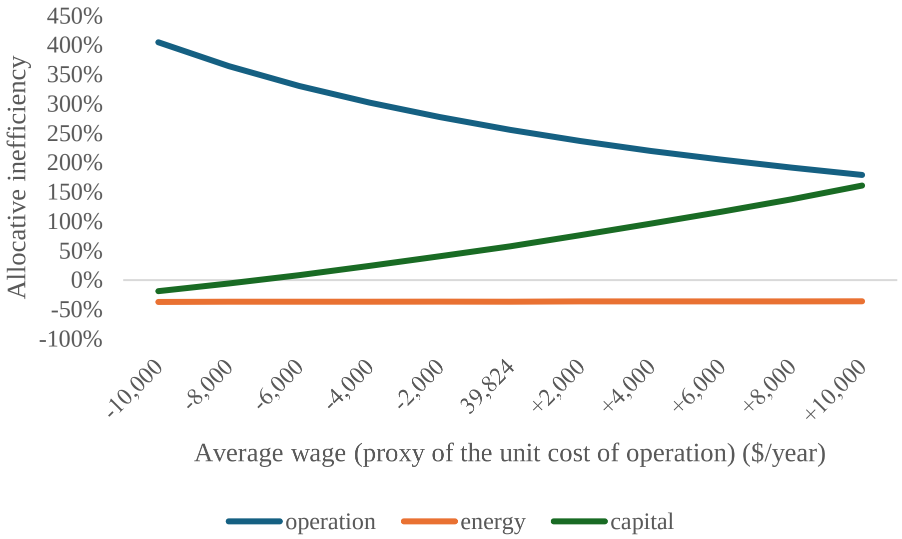
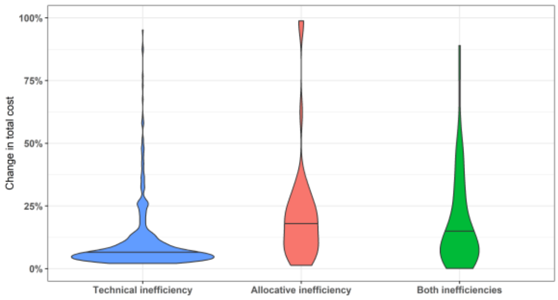
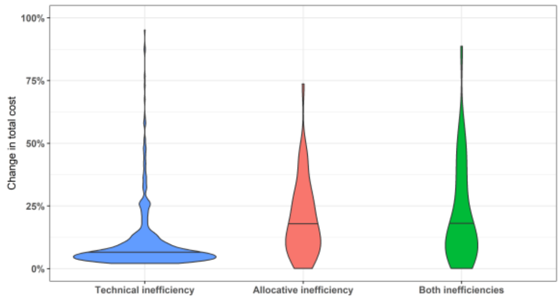


Figure B6 presents the effects of the technical, allocative, and both inefficiencies combined on the total cost when the wage is varied.

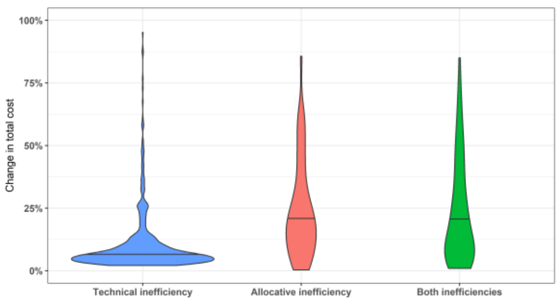
Figure B10: Change in total cost by varying the wage



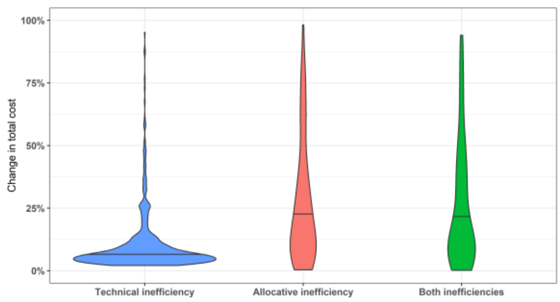
Wage – 10,000 $/year



Wage – 8,000 $/year



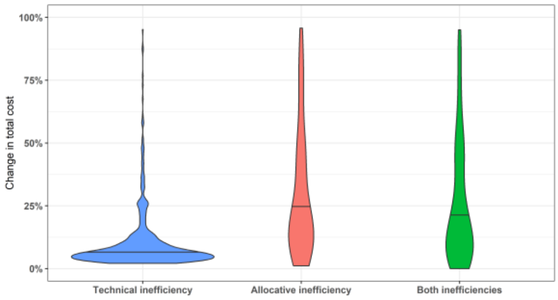
Wage – 6,000 $/year



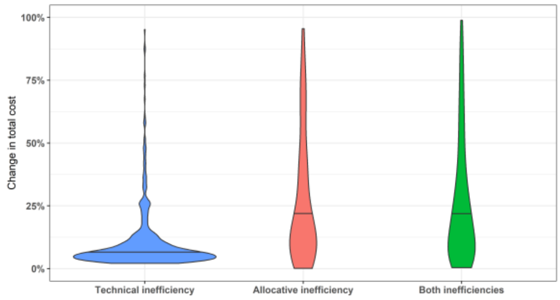
Wage – 4,000 $/year

(to be continued)

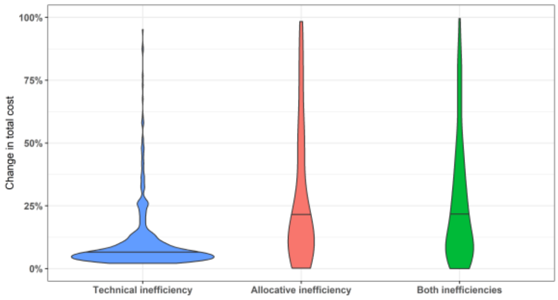
(continued)



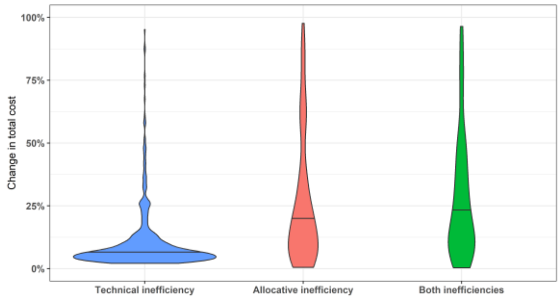
Wage – 2,000 $/year



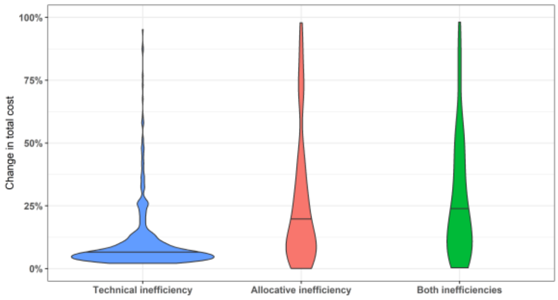
Wage + 2,000 $/year



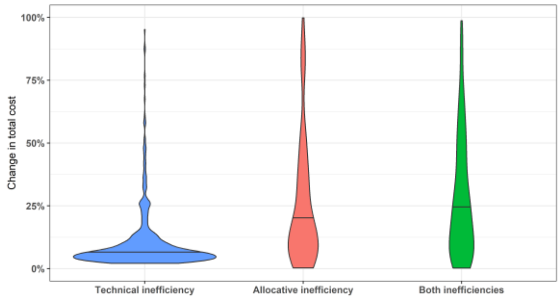
Wage + 4,000 $/year



Wage + 6,000 $/year



Wage + 8,000 $/year



Wage + 10,000 $/year

As shown in Figure B6, the blue violin plots remain the same irrespective of the wage level. This is because the wage does not affect the technical and operational efficiency of the vessel. However, the red and green plots are sensitive to wage changes. When it increases, they become narrower with more values distributed at the higher end. That is, when the wage is higher, the negative effects of allocative inefficiency on the total cost become higher, and vice versa. A potential explanation is that, as operation is overused, a higher wage will result in less investment in vessel maintenance and upgrades (as the number of crew cannot decrease), causing higher inefficiency and total costs.

B.4 Speed

Finally, we examine the effects of the sailing speed on the vessels' efficiencies – in the benchmark case, all vessels are assumed to sail at their design speed (Table B4). For a given change in speed, the fuel consumption is estimated according to the cubic rule (Adland, Cariou and Wolff, 2020; Wu, 2020).

Table B6 Sensitivity analysis of individual vessels by varying the speed

	Min	Mean	Median	Max	s.d.
Initial					
Design speed (knots)	8.0	14.8	14.8	21.5	1.3
Total fuel consumption (thousand tons)	1.9	371	343	857	165
Sensitivity Analysis 1:					
Design speed – 0.5 knot	7.5	14.3	14.3	21.0	1.3
Total fuel consumption (thousand tons)	1.7	335	305	777	150
Sensitivity Analysis 2:					
Design speed – 1 knot	7.0	13.8	13.8	20.5	1.3
Total fuel consumption (thousand tons)	1.6	301	274	701	135
Sensitivity Analysis 3:					
Design speed – 1.5 knot	6.5	13.3	13.3	20.0	1.3
Total fuel consumption (thousand tons)	1.4	269	246	630	122
Sensitivity Analysis 4:					
Design speed – 2 knots	6.0	12.8	12.8	19.5	1.3
Total fuel consumption (thousand tons)	1.3	240	220	565	110
Sensitivity Analysis 5:					
Design speed – 2.5 knots	5.5	12.3	12.3	19.0	1.3
Total fuel consumption (thousand tons)	1.1	213	195	505	98
Sensitivity Analysis 6:					
Design speed – 3 knots	5.0	11.8	11.8	18.5	1.3
Total fuel consumption (thousand tons)	1.0	189	173	466	88
Sensitivity Analysis 7:					
Design speed + 0.5 knots	8.5	15.3	15.3	22.0	1.3
Total fuel consumption (thousand tons)	2.1	410	371	944	182

(to be continued)

(continued)					
Sensitivity Analysis 8:					
Design speed + 1 knot	9.0	15.8	15.8	22.5	1.3
Total fuel consumption (thousand tons)	2.3	451	409	1035	200
Sensitivity Analysis 9:					
Design speed + 1.5 knot	9.5	16.3	16.3	23.0	1.3
Total fuel consumption (thousand tons)	2.5	496	449	1133	218
Sensitivity Analysis 10:					
Design speed + 2 knots	10.0	16.8	16.8	23.5	1.3
Total fuel consumption (thousand tons)	2.7	543	493	1237	239

Since the speed and fuel consumption are used in the technical and allocative inefficiency estimates, the robustness of both to those changes is tested (Table 4 and Figure 10). Figure B11 presents the effects of technical inefficiency on the input demand of operation, energy, and capital when speed is varied.

Figure B11 The effects of technical inefficiency on input demand by varying the speed

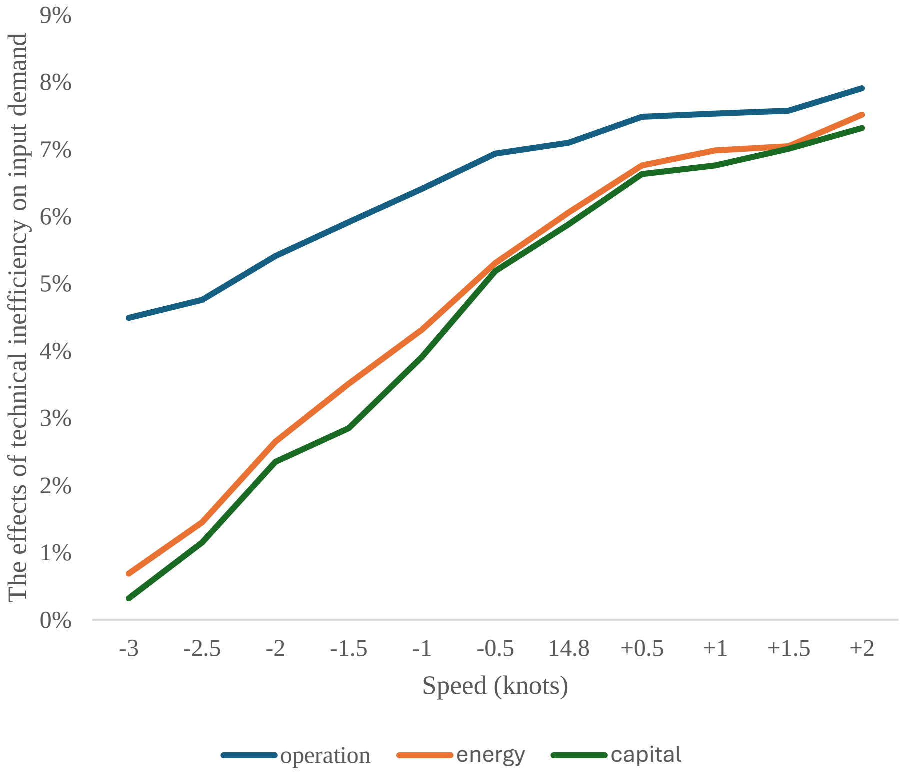


Figure B11 shows that, as speed increases, the technical inefficiencies of all inputs increase, especially of energy and capital. As speed decreases below the design level, the technical inefficiencies of energy and capital steeply decrease towards zero. Due to the cubic rule mentioned above, fuel consumption and, thus, CO2 rapidly decrease when the speed falls. This, in turn, brings the energy costs of the vessel close to the optimal levels from a technical efficiency perspective. Furthermore, when the vessel's speed decreases, the effective supply of the fleet is reduced which suggests that capital is more efficiently utilised. This finding is important in its own right, from both a ship operators' and a policy perspective, as a widely discussed measure to reduce shipping emissions in the short run has been the so-called "slow steaming" of vessels.

Figure B12 illustrates the effects of allocative inefficiency on the input demand of operation, energy and capital when speed is varied. As speed decreases, operation becomes relatively more overused and energy more underused, while capital becomes less overused. This is in line with the analysis of Figure B7.

Figure B12: The effects of allocative inefficiency on input demand by varying the speed

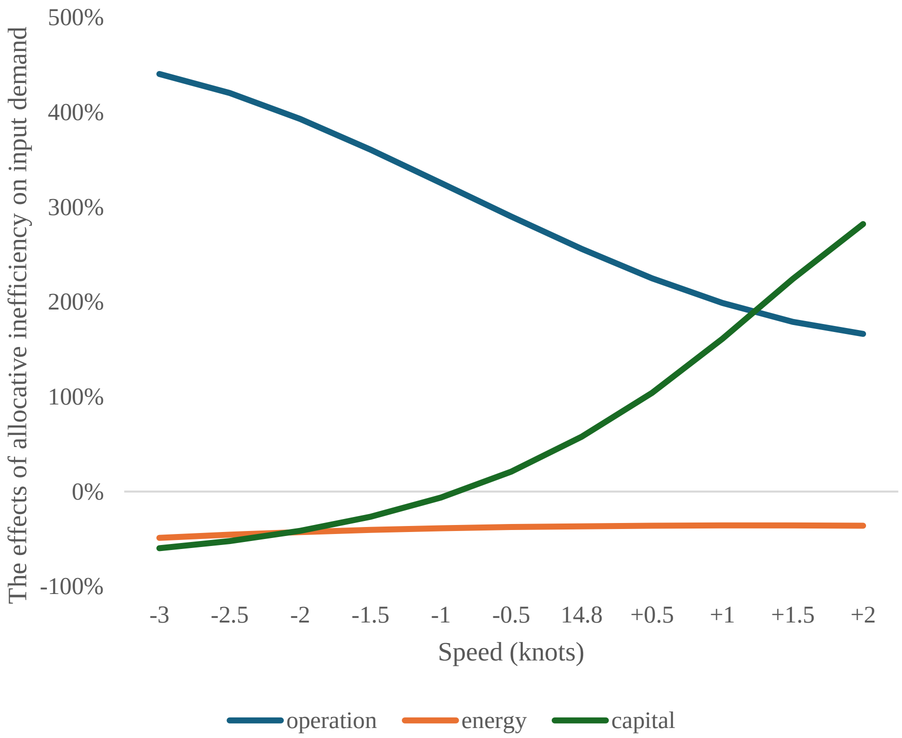
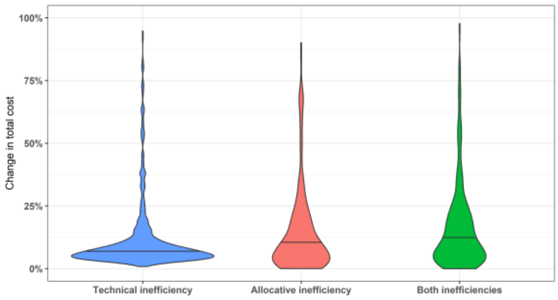
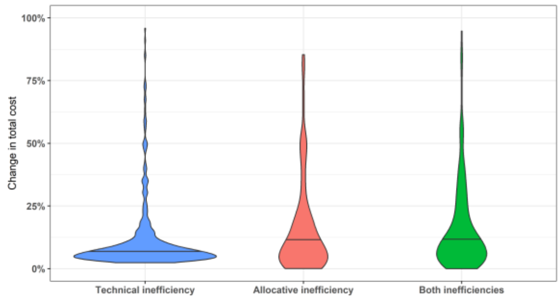


Figure B13 presents the effects of technical, allocative, and both inefficiencies combined on the total cost when the speed is varied. The blue plots remain similar to the original one in Figure 10, but the red and green plots become wider as speed decreases, indicating that the allocative inefficiency significantly increases the total costs across vessels.

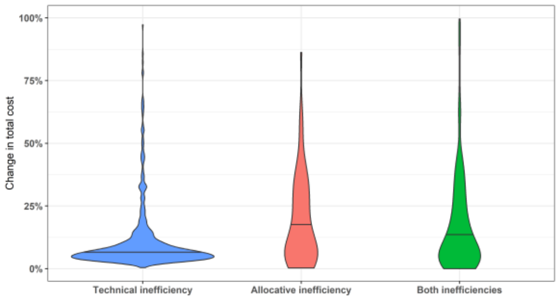
Figure B13 Change in total cost by varying the speed



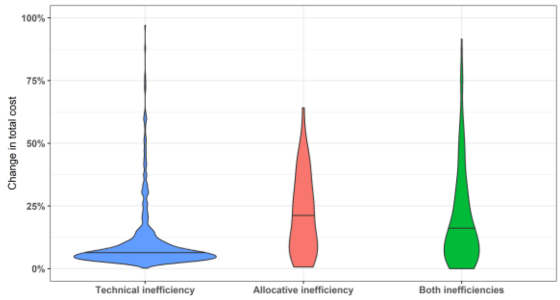
Deigned speed – 3 knots



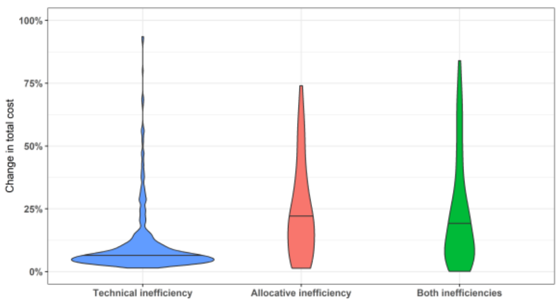
Design speed – 2.5 knots



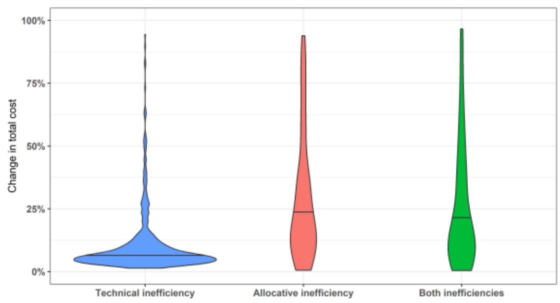
Design speed – 2 knots



Design speed – 1.5 knots



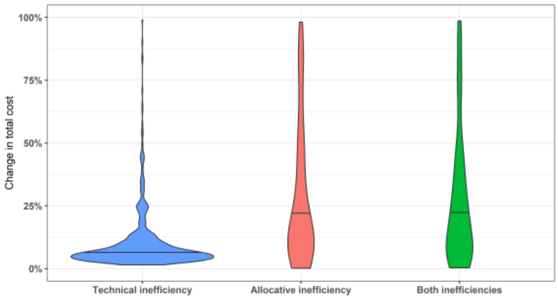
Design speed – 1 knot



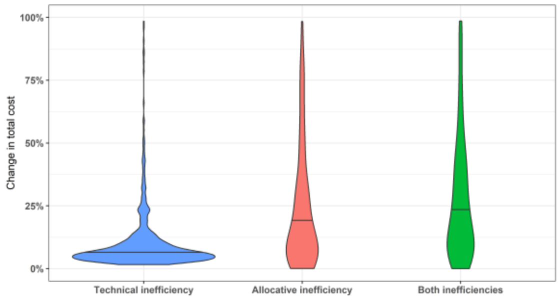
Design speed – 0.5 knot

(to be continued)

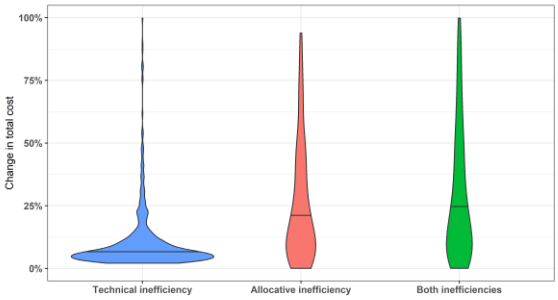
(continued)



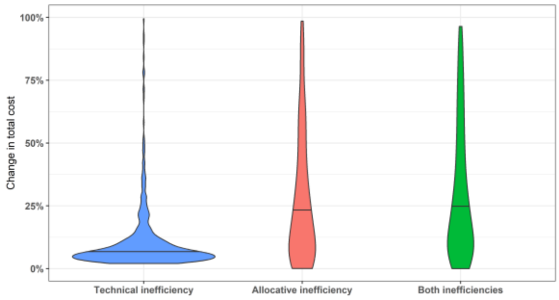
Design speed + 0.5 knot



Design speed + 1 knot



Design speed + 1.5 knots



Design speed + 2 knots