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The economics of shipping decarbonisation: Carbon, production, and allocative efficiencies

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ABSTRACT

Existing shipping environmental regulations largely omit the economic dimension which, in turn, delays the industry's clean energy transition. This paper investigates the efficiency of global shipping on economic foundations. We apply a stochastic frontier analysis to assess the interactions between capital, operation, earnings, and transport work, both across all major shipping segments and at an individual-vessel level. The empirical results indicate that carbon efficiency of vessel types decreases with speed. Larger vessel types produce more carbon emissions for a given level of TC earnings and costs. At an individual vessel level, higher production efficiency is observed in vessels that are newer, spend more time at sea, have installed more energy saving technologies (ESTs), and belong to companies with stronger EST investment policy. Technical and operational inefficiencies raise the total cost of owning and operating a vessel by 7%, with market price dynamics and inefficient allocation of economic resources increasing it by 25%. An increase in fuel price of 38% or a reduction in speed of 13.5% does not severely affect a vessel's overall efficiency and total cost. Policy interventions need to be carefully designed in order not to negatively impact the overall efficiency of global shipping.

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, examining its economic efficiencies and how they can be affected by environmental regulations.

Maritime shipping facilitates more than 85% of international trade in goods and, at the same time, is responsible for approximately 2.1% of well-to-wake (WtW) GHG emissions (Clarksons' SIN, 2024). 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 GHG shipping emissions by or around 2050 (IMO, 2023). However, the significant technological, energy, and capital requirements for this transition, accompanied by high freight market volatility and cyclicality (Greenwood and Hanson, 2015), render it a hard-to-abate industry (Moutzouris et al., 2024).

Energy 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).

Nevertheless, those technical and operational measures do not account for the associated economic challenges faced by the key market stakeholders (i.e. ship owners and operators, financiers, charterers, and fuel producers) and, thus, fail to mobilise green investment. Namely, recent empirical evidence suggests that the income generated by greener vessels does not cover the required capital expenditure or, in other words, such investments generate insufficient returns (Petropoulos,

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2022; Moutzouris et al., 2024). As a result, the majority of shipowners either postpone their newbuilding investment decisions or invest in fossil oil-fuelled vessels to reduce the technological and regulatory uncertainty associated with the clean energy transition (Clarksons' SIN, 2024; Shi et al., 2026). Therefore, for shipowners to undertake – the riskier and more expensive greener investments – the economics of shipping energy efficiency need to be explicitly assessed and incorporated when developing environmental 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, International Maritime Organization, 2023). 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 (CO2) and economic variables (or, equivalently, production factors) such as the income generated by the 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 applies a stochastic frontier analysis (SFA), which can incorporate such production factors and evaluate the trade-offs between them. Specifically, to improve their fleet's energy efficiency, a shipowner can decide whether it is optimal to invest in either retrofitting an existing vessel (e.g. with energy saving technologies [ESTs]) or acquiring a clean(er) newbuilding one or/and implement operational improvements (e.g. speed reduction). As such, SFA allows to empirically assess cost minimisation and allocative efficiency decisions based on the trade-offs of the various production inputs of interest.

Accordingly, this paper relates 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.

We investigate the following questions: a) How do different shipping segments balance carbon emissions, economic costs, and income? b) How does energy used contribute to the production (transport) work of an individual vessel compared to other inputs? c) How do carbon mitigation strategies, such as slow steaming, influence the allocation of economic resources and total costs?

To answer those questions, this research first analyses the performance of each major shipping segment over the period 2021–2024 (i.e. each vessel type at an aggregate level), and then of specific vessels within two selected segments (i.e. each individual vessel within the two segments). Investigating at both levels provides a more holistic understanding of how energy efficiency and economic performance relate to each other in the shipping industry. Informed by our findings, 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 analyses various forms of economic efficiency in global shipping.

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

According to several review papers (Anderson et al., 2015; Barreiro et al., 2022; Jimenez et al., 2022), there exist two areas of research in relation to energy efficiency in shipping: one identifies the determinants of energy efficiency; the other investigates the barriers to the adoption of energy efficiency practices.

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%.

Cariou et al. (2019) find that slow steaming, energy saving technologies (ESTs), optimal routing, and efficient port operations led to a decrease in carbon emissions of containerships from 2007 to 2016. Lassesson and Andersson (2009) articulate how energy efficiency can be improved via ESTs such as better hull and propellor design, operation management such as slow steaming, and alternative fuels such as LNG. Lu et al. (2015) develop a semi-empirical model that enables voyage optimisation for energy-efficient shipping under various sea state and weather conditions. Nuchturee et al. (2020) review various energy efficient methods for all-electric ships, including integrated electric propulsion systems and renewable energy integration. Duan et al. (2023) analyse the relative importance of ship energy efficiency measures using a multi-level hierarchical model and expert interviews. They find that the most important factors are slow steaming, ESTs, and company management practices such as staff training, while route optimisation and the use of alternative fuels are considered relatively less important.

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 et al., 2018; Hansen et al., 2020).

Not many researchers have considered maritime economics and financial markets when analysing either energy or carbon efficiency in shipping. There are four 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 CO2 by 78.39% with a cost-effectiveness of $287.6/ton CO2. 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 CO2 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 second literature strand applies environmental economics on market-based measures, studying marginal abatement cost and carbon pricing. Longva et al. (2024) estimate the net present value (NPV) and emission reduction of energy efficiency measures, considering fuel prices, investment costs, and future fleet supply. They evaluate all ships above 400 gross tons and find that a marginal cost of 300 USD per ton of CO2 will enable net-zero emissions in 2050. Lagouvardou et al. (2023) estimate the carbon price required for various alternative fuels to offset their marginal abatement costs, using a Supramax bulker as a case study. Their analysis shows that adopting green liquid hydrogen would necessitate a carbon price of 243–704 USD per metric ton of CO2 equivalent. Oliveira et al. (2022) compare the marginal abatement costs of a number of ESTs and alternative fuel options. They find that measures with negative costs are implemented more frequently than those with positive costs.

The third strand incorporates econometric modelling to study the determinants or barriers to energy efficiency. Agnolucci et al. (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 2300 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 et al. (2020) study the determinants of energy efficiency investment for 6750 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.

The fourth strand studies the impact of geopolitical events on carbon dioxide emissions (CO2). Xu et al. (2025) analyse automatic identification system (AIS) data and find that, between 2021 and 2024, CO2 in Ukraine's Black Sea area decreased by 17.88% annually; meanwhile, those in Romania's and Turkey's Black Sea areas increased by 36.30% and 16.08%, respectively. Lyu et al. (2025) study AIS route records and one year after the start of the war in Ukraine, CO2 decreased by 5.8%, transport distances rose by 2.7%, and shipping volumes fell by 9.7%. Peng et al. (2024) analyse AIS data on containership rerouting around the Cape of Good Hope and find that the Red Sea Crisis led to a 25–75% increase in GHG emissions in 2024. Yue et al. (2024) employ complex network theory and estimate that the disruption of the Suez Canal in 2021 resulted in a 48.6% increase in total well-to-wake emissions.

Nevertheless, none of the above studies consider the energy efficiency or carbon efficiency measurement itself. Namely, they only apply technical and/or operational measurements of energy efficiency. Such measures include (a) the Energy Efficiency Design Index (EEDI) and the Energy Efficiency Existing Ship Index (EEXI), where CO2 is compared with the vessel's cargo capacity and reference speed; b) the Annual Efficiency Ratio (AER) and the Carbon Intensity Indicator (CII), where CO2 is compared with the vessel's cargo capacity and actual distance travelled; and c) the Energy Efficiency Operational Indicator (EEOI), where CO2 is compared with the actual cargo transported and distance travelled by the vessel.

As such, there is a significant gap in the literature – and practice alike – in accounting for vessels' economic performance when measuring energy efficiency. Focusing only on a physical-thermal measurement neglects key information on the economic factors associated with shipping decarbonisation, thereby presuming that decarbonisation will be either a self-driven process or an obligation to comply with policy. For instance, to minimise fuel consumption, shipowners face multiple choices, including investing in newer, more expensive, greener vessels (increase capital input), upgrading existing vessels (increase operation input), slow steaming (reduce energy input), etc. In line with production economic theories, an economic measurement allows to evaluate which vessel produces the lowest CO2 subject to costs and earnings. It is also essential to investigate the economic interactions between these inputs to quantify the losses and gains, the drivers of carbon efficiencies, and the degree of distortion in resource allocation. For example, economic measures could disentangle how higher fuel prices lead to lower fuel consumption and higher capital investment.

Data envelopment analysis (DEA) and SFA are two widely used methods incorporating production economic theories 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 ESTs 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 et al., 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 2.1% of WtW GHG emissions (Clarksons' SIN, 2024). 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 et al., 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 SFA. This measures efficiency relative to the frontier, i.e. it provides a relative measurement compared to the best practice on the frontier (Kumbhakar and Knox 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.

On the one hand, carbon efficiency is measured at vessel type level. The aim is to compare the carbon emissions of various vessel types (at an aggregate level for each type) with their economic revenue (output) and economic costs (inputs) and assess how carbon efficiency varies across types. This allows us to make industry and policy recommendations that can account for the characteristics of different vessel types. Note that this comparison could not be performed at an individual vessel level as the economic revenue data are only available at vessel type level.

On the other hand, production and cost efficiencies are estimated at individual vessel level. The objective is to assess the effects of varying input levels on a vessel's transport work and total cost. This “peer-to-peer” analysis (since individual vessels are of the same type) sheds light on how allocation of economic resources can affect the productivity and cost performance of a given vessel.

The vessel type and individual vessel analysis complement each other and enable us to investigate vessels' efficiency from a more holistic technoeconomic perspective.

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

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

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

To illustrate carbon efficiency, consider a simple model with only two inputs, CO2 and another input, such as capital. In Fig. 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.

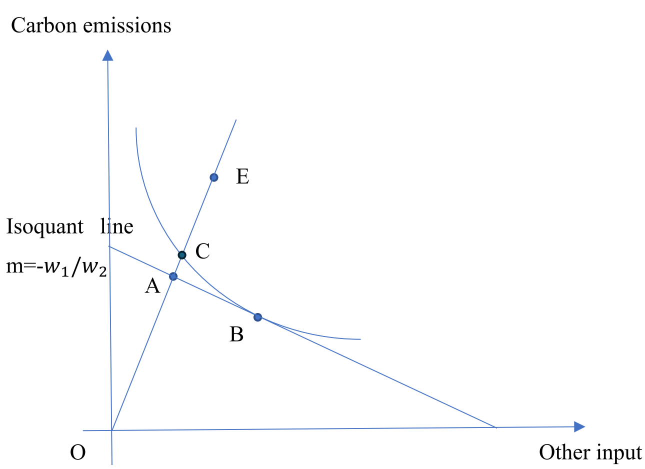

Fig. 1. Technical carbon efficiency and allocative carbon efficiency.

In general, 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 economic income generated (e.g. vessel earnings), or the vessel's transport work (expressed in ton-miles). When comparing vessel types, it is more accurate to use economic income as the output instead of transport work, since different types may operate on different routes, carry different commodities, and follow distinct trade patterns. This also allows to evaluate, from a shipping investor's perspective and across vessel types, how to maximise income while minimising CO2 and key costs. Conversely, when comparing individual vessels within the same segment, using transport work as the output provides higher accuracy and is less influenced by market fluctuations.

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. Energy is not included for two reasons. First, this will lead to invalid models, as the conversion factor from fuel to CO2 is nearly a constant, given that the current fleet predominantly uses fossil fuel oil.[1] Second, when a shipowner receives TC income, they do not pay for fuel/energy costs. Hence, the inputs in the production function comprise operation, capital, and CO2. Accordingly, carbon efficiency is measured as the relative CO2 given the vessel's outputs, operation, and capital inputs.

We begin by estimating the carbon efficiency of vessel types. Specifying a functional form for $CO2^*$ and assuming that the output corresponds to TC earnings, the technical carbon efficiency of Vessel Type *j* can be expressed as:

$$D(TC,K,OP) = \frac{CO2^*}{CO2_j} = \frac{f(TC,K,OP)}{CO2_j} \tag{4}$$

where *OP* is operation, *K* is capital, *CO2* is carbon emissions, and *TC* is time charter earnings.

Then, taking the natural logarithm on both sides of Eq. (4) and rearranging yields:

$$lnCO2_j = \ln[f(TC,K,OP)] - \ln[D(TC,K,OP)] \tag{5}$$

Incorporating a Cobb-Douglas production function, we obtain Eq. (6)[2]:

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

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

In SFA, the error term also includes a stochastic noise, v_j:

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

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

[1] In 2024, approximately 2% of the current global fleet of vessels were capable of using alternative fuels, representing around 8% by gross tonnage, with the vast majority still relying solely on oil-based fuels (Clarksons' SIN, 2024).

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

part, in line with Aigner et al. (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.

Next, we estimate the production efficiency and allocative efficiency of individual vessels. Vessels achieve production efficiency when maximising output subject to a given set of inputs (Eq. (2)). For a specific vessel i within a certain segment, the production function is expressed as:

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

Where E is energy, total seaborne trade (D^*V) is the actual distance travelled times the vessel's transport capacity. Due to unavailability of cargo utilisation rate data, we use the deadweight tonnage (DWT) of the vessel as a proxy for the actual cargo transported. This may overestimate the actual transport work as a vessel may either not be fully loaded in laden legs of their trips or may be sailing in ballast. Production efficiency can be written as:

$$ln(D^*V)_{it} = \beta_0 + \beta_1 lnOP_{it} + \beta_2 lnE_{it} + \beta_3 lnK_{it} + \delta_{it} + v_{it} \tag{9}$$

where δ_{it} is the technical production inefficiency. In contrast to u_{it} in Eq. (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. Eq. (11) shows cost efficiency with transport work as an output:

$$lnC_{it} = \gamma_0 + \gamma_1 ln(D^*V)_{it} + \gamma_2 lnLp_{it} + \gamma_3 lnFp_{it} + \gamma_2 lnKp_{it} - \theta_{it} + v_{it} \tag{10}$$

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 et al., 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 Knox Lovell (1979), Kopp et al. (1982) and Kumbhakar et al. (2015).

Consider minimising the total cost subject to the production function:

$$\min\ C = (\mathrm{Lp^*OP + Fp^*E + Kp^*K})$$

subject to

$$ln(D^*V)_{it} = \beta_0 + \beta_1 lnOP_i + \beta_2 lnE_i + \beta_3 lnK_i - u_i + v_i \tag{11}$$

The returns to scale, r, correspond to:

$$r = \beta_1 + \beta_2 + \beta_3 \tag{12}$$

The constraint minimisation yields:

$$f_E/f_L = Lp/Fp^*exp(\varepsilon_1) \tag{13}$$

$$f_K/f_L = Lp/Kp^*exp(\varepsilon_2) \tag{14}$$

$$f_K/f_E = Fp/Kp^*exp(\varepsilon_3) \tag{15}$$

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 Eq. (17) while ε_2' measures the input pair (capital, operation) in Eq. (18):

$$f_L/f_E = Fp/Lp^*exp(\varepsilon_1') \tag{16}$$

$$f_L/f_K = Kp/Lp^*exp(\varepsilon_2') \tag{17}$$

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

$$\varepsilon_1 = ln(\beta_2/\beta_1) - ln(Fp/Lp) - lnE + lnOP \tag{18}$$

$$\varepsilon_2 = ln(\beta_3/\beta_1) - ln(Kp/Lp) - lnK + lnOP \tag{19}$$

$$\varepsilon_3 = ln(\beta_3/\beta_2) - ln(Kp/Fp) - lnK + lnE \tag{20}$$

$$\varepsilon_1' = ln(\beta_1/\beta_2) - ln(Lp/Fp) - lnOP + lnE \tag{21}$$

$$\varepsilon_2' = ln(\beta_1/\beta_3) - ln(Lp/Kp) - lnOP + lnK \tag{22}$$

Following Kumbhakar et al. (2015), the effects of technical and allocative efficiencies on input demand can be estimated by solving the simultaneous equations obtained from Eq. (12), which yields Eqs. (24), (25), and (26):

$$\begin{aligned} lnOP = {} & \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) \\ & + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D^*V) + \frac{1}{r}(\beta_2\varepsilon_1' + \beta_3\varepsilon_2') \\ & - \frac{1}{r}(v-u) \end{aligned} \tag{23}$$

$$\begin{aligned} lnE = {} & \beta_2 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp \\ & + \beta_3 lnKp) - lnEp + \frac{1}{r}\ln(D^*V) + \frac{1}{r}(\beta_2\varepsilon_1' + \beta_3\varepsilon_2') - \varepsilon_1' - \frac{1}{r}(v-u) \end{aligned} \tag{24}$$

$$\begin{aligned} lnK = {} & \beta_3 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp \\ & + \beta_3 lnKp) - lnKp + \frac{1}{r}\ln(D^*V) + \frac{1}{r}(\beta_2\varepsilon_1 + \beta_3\varepsilon_2) - \varepsilon_2' - \frac{1}{r}(v-u) \end{aligned} \tag{25}$$

In Eqs. (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

$$\begin{aligned} lnOP^{none} = {} & \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp \\ & + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D^*V) \end{aligned} \tag{26}$$

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

$$\begin{aligned} lnOP^{te} = {} & \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp \\ & + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D^*V) - \frac{1}{r}(-u) \end{aligned} \tag{27}$$

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

$$lnOP^a = \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D^*V) + \frac{1}{r}(\beta_2\varepsilon_1' + \beta_3\varepsilon_2') \tag{28}$$

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

$$lnOP^{both} = \beta_1 - \frac{1}{r}(\beta_0 + \beta_1 ln\beta_1 + \beta_2 ln\beta_2 + \beta_3 ln\beta_3) + \frac{1}{r}(\beta_1 lnLp + \beta_2 lnFp + \beta_3 lnKp) - lnLp + \frac{1}{r}\ln(D^*V) + \frac{1}{r}(\beta_2\varepsilon_1' + \beta_3\varepsilon_2') - \frac{1}{r}(-u) \tag{29}$$

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:

$$c^{none} = Lp^*OP^{none} + Fp^*E^{none} + Kp^*K^{none} \tag{30}$$

$$c^{te} = Lp^*OP^{te} + Fp^*E^{te} + Kp^*K^{te} \tag{31}$$

$$c^{a} = Lp^*OP^{a} + Fp^*E^{a} + Kp^*K^{a} \tag{32}$$

$$c^{both} = Lp^*OP^{both} + Fp^*E^{both} + Kp^*K^{both} \tag{33}$$

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:

$$\text{Effects of technical efficiency on total cost}: \Delta c^{te} = c^{te} - c^{none} \tag{34}$$

$$\text{Effects of allocative efficiency on total cost}: \Delta c^{a} = c^{a} - c^{none} \tag{35}$$

Effects of both technical and allocative efficiencies on total cost:

$$\Delta c^{both} = c^{both} - c^{none} \tag{36}$$

4. Data

Data are obtained from Clarksons' Shipping Intelligence Network (Clarksons' SIN, 2024) and World Fleet Register (Clarksons' WFR, 2024). 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 592 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.[3]

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.

Table 1
Summary statistics for panel data for 12 vessel types from 2021 to 2024 (annual frequency).

	Min	Median	Mean	Max	s.d.
Newbuilding price (*$m*)	20.8	53.1	58.1	132.5	29.0
Operating expenses (*$/day*)	4617	6765	6772	9430	1321
Carbon emissions (*tons/day*)	52.3	95.8	106.9	230.7	51.6
Time charter earnings (*$/day*)	10,708	24,296	29,941	105,452	20,799
Number of crew	17.0	23.6	23.0	27.0	2.4
Loan rate (*%*)	2.7	2.8	2.8	3.1	0.2
Fuel price (*$/ton*)	526	535	588	756	98
Speed (*knots*)	10.9	11.5	12.1	16.1	1.5
Suez Canal transits (*DWT million*)	90.3	445.4	418.2	714.0	213.0
Port congestion (*% fleet DWT*)	29.3	30.0	30.1	31.0	0.7

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.

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 Sulphur Fuel Oil (VLSFO) from 13 major ports worldwide (Clarksons' SIN, 2024).[4] To control for speed and exogenous, geopolitical factors, three control variables are included. Speed refers to the actual average travel speed of the vessel type. Suez Canal transits and port congestion serve as a proxy for trade disruptions resulting from geopolitical events such as the Red Sea Crisis and the Russia-Ukraine war. Suez Canal transits are measured in terms of DWT. Port congestion is quantified by the average percentage of the fleet (in DWT terms) awaiting to load or unload cargo. 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. We have removed outliers – i.e. vessels that travel less than 2000 h per year at sea – to exclude vessels not actively in use. 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 typically result in lower OPEX.

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 (Crewell, 2025;

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

[4] 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.

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

	Min	Mean	Median	Max	s.d.
Age (*years*)	1	12	13	24	5
Distance (*NM*)	20,562	66,603	67,867	92,847	12,462
Deadweight tonnage *(DWT)*	178,438	246,334	208,000	403,919	72,270
Design speed (*knots*)	8	14.8	14.8	21.5	1.3
Time at sea (*day*)	84	235	243	325	50
Fuel consumption at design speed (*tons per day*)	28	70	64	120	22
Capital *($ m)*	10	75	60	2350	113
Operating expenses (*$/day*)	1480	4157	3809	9413	1428
Transport work (*million tons cargo * NM*)	6150	16,600	13,900	36,500	6650
Total fuel consumption (*thousand tons/year*)	140	395	352	857	150
Loan rate (*%*)	1.5	4.4	3.7	8.0	1.5
Wage (*$/year*)	24,120	39,367	34,198	82,637	13,228
Fuel price (*$/ton*)	494	545	494	620	62
Own EST	1.0	1.8	2.0	6.0	1.0
Other EST	0.3	1.7	1.7	3.9	0.5
Company size	2	111	33	1708	304

Notes: The total number of observations is 592. The individual vessels include Capesize bulk carriers and VLCCs.

Maritime Zone, 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 or not.

To control for technology and company capacity and strategy, three control variables have been added. "Own EST" is the number of ESTs[5] installed on the vessel. "Other EST" is the average number of ESTs installed on the other vessels owned by the same company. This variable indicates to what extent the company has a pro-sustainability management strategy. Company size is proxied by the number of vessels owned by the company – quartile dummies are used in the analysis to smoothen out outliers. 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 uses SFA to assess the carbon efficiency of vessel types. 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.

While Section 5.1 provides a comparison between vessel segments, Section 5.2 analyses within-segment variation. Namely, Section 5.2 performs SFA on individual vessels in the two biggest segments, i.e. Capesize bulk carriers and VLCCs. The analysis controls for factors related to vessel technology, company strategy, and company capacity. As such, Section 5.2 focuses on a static analysis of the current fleet. Accordingly, Section 5.3 investigates potential effects on vessels' carbon efficiency in case further stricter decarbonisation regulations enter into force in the future (for instance, regulations requiring the use of green (er) alternative fuels or/and slow steaming).

The prevalent measures of energy and carbon efficiency compare the energy consumed and, in turn, the CO2 emitted with the vessel's design or actual transport work. Fig. A1 in Appendix A illustrates 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 actual 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.

However, the above measures do not consider any economic dynamics. Figs. A2 and A3 in Appendix A demonstrate the vessel earnings per ton of CO2 by vessel type. 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. Nevertheless, this measure also has shortcomings. First, since earnings vary significantly over the years, it is unreliable to estimate efficiency based on those. Second, the measure does not consider other inputs, such as capital and operation. To address those limitations, we use SFA, where TC earnings are compared with CO2, as well as capital and operation costs. As such, fluctuations due to market conditions can be partially mitigated since corresponding costs will likely increase (decrease) following an increase (decrease) in earnings. The SFA also incorporates an economic function where various inputs produce an output.

Furthermore, SFA allows to control for vessel- and company-specific effects – such as vessel technology and company capability, respectively – when measuring efficiency. For instance, subject to eco status, the earnings per ton of CO2 vary across a range of vessel types (Figs. A4 and A5 in Appendix A). The 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 mechanism may have heterogeneous effects on the various shipping sectors.

5.1. *Stochastic frontier analysis by vessel type*

This subsection applies SFA to analyse the carbon efficiency of different vessel types from 2021 to 2024. Table A1 in Appendix A presents the size and category of these vessel types.

We begin by estimating the carbon efficiency using Eq. (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). By accounting for capital and operation inputs in economic terms, this approach mitigates potential significant fluctuations in TC earnings and reduces estimation bias. Three control variables, "speed", "Suez", and "congestion", have been added to

[5] ESTs include air lubrication system, ballast water management system, bow enhancement, exhaust gas economiser high voltage shore connection, hull fin, propeller boss cap fin, propeller duct, rudder bulb, and waste heat recovery.

Table 3
Carbon efficiency of vessel types.

	(1)	(2)	(3)
	Dependent variable: ln(CO2)		
Efficiency trend[a]	Increase	Increase	Increase
Time effect	No	No	Yes
Distribution	Half normal	Half normal	Half normal
(Intercept)	3.19***	3.22***	1.31
ln(K)	0.97	1.09***	0.84***
ln(OP)	−0.41	−0.29***	0.1
ln(TC)	0.09	−0.07	−0.12**
(Z intercept)	−0.004	−0.09	−1.75***
Congestion	0.001		
Suez		0.0004	
Speed			0.16***
Time			0.004
Sigma Squared	0.07	0.07***	0.02***
Gamma	0.98*	0.99***	0.99***
log likelihood	21.09***	22.55***	36.59***
Mean efficiency	0.81	0.82	0.79

Note: significance levels: 0.01 '***' 0.05 '**' 0.1 '*'. The total number of observations is 48.
[a] A wide range of models with various efficiency trends, time effects, and distribution patterns have been examined. The three best models based on the diagnostic test results (sigma squared, gamma, and log likelihood) are presented in Table 3. The rest are available from the authors upon request.

control for differences across vessel types in terms of sailing speed, geopolitical disruptions around the Suez Canal, and port congestion, respectively.

Table 3 displays the results from three representative models which vary depending on the control variables and the inclusion of a time trend. Sigma squared in 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.

According to Table 3, the mean efficiency across all vessel types is around 80%, suggesting that there is potential to reduce CO2 by 20% on average subject to given levels of capital (newbuilding price), operation (crew plus maintenance and upgrades), and TC earnings.

Model (1) controls for the effects of port congestion; the results suggest that port congestion does not possess significant explanatory power. When accounting for the effects of the Red Sea Crisis and the related Suez Canal geopolitical disruptions (Model (2)) or speed increase (Model (3)), capital is positively associated with carbon efficiency. Namely, the longer route around the Cape of Good Hope or the increase in speed leads to lower carbon efficiency due to higher CO2, ceteris paribus. However, operating a more capital-intensive vessel can mitigate the CO2 increase. In all models, the effects of operation and TC earnings are either not significant or much smaller in magnitude compared to capital.

While the "Suez" variable is not significant, the vessel's speed significantly negatively affects carbon efficiency (n.b. a positive sign indicates a negative effect on carbon efficiency, and vice versa). Due to the cubic relationship between speed and fuel consumption, an increase in speed causes a disproportionately higher increase in CO2, resulting in lower carbon efficiency. Finally, there is no evidence that the overall carbon efficiency has improved or deteriorated over time as the time variable is insignificant.

Our findings are largely consistent with the existing literature and confirm related conclusions from an economic perspective. Previous studies have shown that energy efficiency is affected by vessel speed (Lassesson and Andersson, 2009; Acciaro and McKinnon, 2015; Rehmatulla and Smith, 2015b; Duan et al., 2023); this is in line with our findings. However, different from our finding that carbon efficiency is not related to Suez Canal transits, the literature has found that rerouting from the Suez Canal to the Cape of Good Hope leads to higher carbon emissions (Peng et al., 2024; Yue et al., 2024). Our results highlight the complexities of relative carbon efficiency: while absolute CO2 may increase due to factors such as geopolitical disruptions, relative efficiency can remain stable when emissions are assessed against economic inputs and outputs. While traditional relative metrics of carbon efficiency – such as CII, which measure transport work per ton of CO2 – are inappropriate for policymaking, we find that economic relative metrics – such as earnings per ton of CO2 – are also unsuitable. None of these measures aim to minimise the absolute volume of CO2. Therefore, carbon pricing should consider the absolute values of CO2 and the actual cargo transported between two places.

Fig. 2 disaggregates the carbon efficiency results by vessel type and year, with the minimum carbon efficiency score being 0 and the highest 1.

Namely, Fig. 2 examines carbon efficiency from a ship owner's perspective.[6] Subject to TC income and investments in capital and operation, it ranks vessel types based on their CO2 emissions. In other words, the carbon efficiency measurement compares a vessel type's carbon emissions with its economic costs and generated income. However, there are intrinsic variations in vessel types which result in different carbon efficiency frontiers. First, containerships are less carbon efficient than bulk carriers and tankers. This may be explained by the fact that containerships emit relatively more CO2 due to higher speeds as they typically carry time-sensitive cargoes. 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 and costs.

Future environmental regulations should consider the differences in carbon efficiency across vessel types. Our results are in line with IMO's Net-zero Framework (IMO, International Maritime Organization, 2025b), which proposes that the GHG emission intensity targets vary by vessel type and size. The regulation proportionately reduces the profitability of certain unsustainable vessel types and sizes, thereby mitigating adverse impacts on trade in specific commodities.

5.2. 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 592 Capesize bulk carriers and VLCCs in 2023. The dependent variable is transport work capacity (D*V), which corresponds to the actual distance travelled by the vessel times its DWT.[7]

The production efficiency is estimated based on Eq. (9). Incorporating individual-vessel data in this subsection allows us to control for additional variables, including vessel age ("Age"), time sailing at sea ("Time"), the number of ESTs ("own EST"), ESTs on other vessels within the same company ("other EST"), company size, and a dummy variable to distinguish between the Capesize and VLCC sectors. Company size is measured by three quartile dummies: "Size 1" represents the largest 25% companies, "Size 2" represents the next 25%, and "Size 3" represents the following 25%. The remaining 25% serve as the reference group. This enables more thorough investigation and interpretation of the findings.

Accordingly, five representative models that differ in terms of the

[6] The validity of the results in Fig. 2 is subject to measurement errors. For instance: (a) TC earnings might not fully represent the revenue of shipowners since some shipowners operate their own vessels; (b) capital is measured as newbuilding price, but some shipowners purchase vessels in the second-hand market.

[7] We cannot consider the actual cargo utilisation rate due to data limitations.

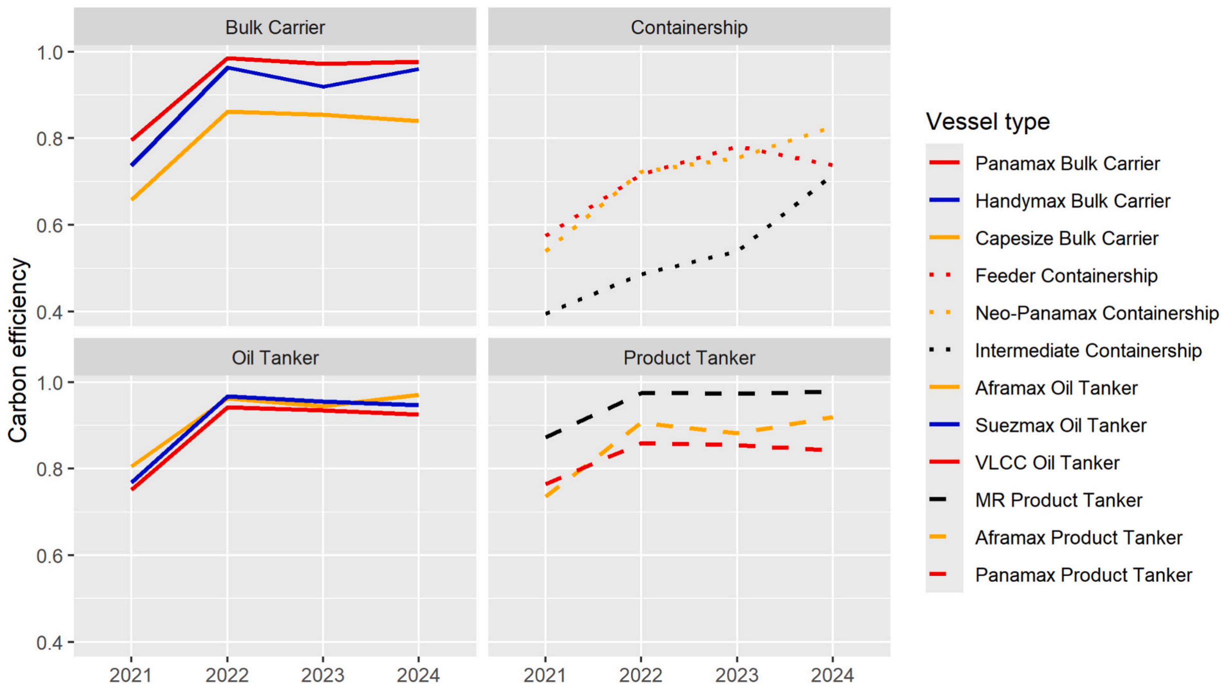

Fig. 2. Carbon efficiency by vessel type and year.

Table 4
Production efficiency of individual vessels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: ln(D*V)					
ln(OP)	0.04**	0.02	0.05**	0.04*	0.01	0.04**
ln(E)	0.72***	0.73***	0.7***	0.72***	0.73***	0.71***
ln(K)	0.13***	0.14***	0.13***	0.13***	0.14***	0.13***
Constant	11.85***	11.62***	12.17***	11.83***	11.6***	12.09***
Age	0.24***		0.27***	0.25***		0.28***
Own EST	−0.76***	−1.08***	−0.59***	−0.77***	−1.12***	−0.60***
Other EST		−0.94**	−0.27		−0.86*	−0.23
Capesize (dummy)		−0.10	0.86**			0.96**
Size1				−0.42	−0.29	−0.23
Size2				−0.20	−0.53	−0.30
Size3				−0.08	−0.25	−0.09
U sigma	0.08***	0.07***	0.09***	0.08***	0.07***	0.09***
V sigma	0.15***	0.16***	0.15***	0.15***	0.16***	0.15***
Log likelihood	212***	198***	215***	213	198***	216***
Returns to scale	0.89	0.85	0.84	0.85	0.85	0.82
Mean efficiency	0.91	0.93	0.90	0.91	0.90	0.90

Note: significance levels: 0.01 '***' 0.05 '**' 0.1 '*'. The total number of observations is 592. All models assume exponential distribution for the inefficiency term. We present the inefficiency effect (U sigma) and the stochastic noise (V sigma). The returns to scale are estimated through Eq. (12).

incorporated control variables have been estimated (Table 4).[8] 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. The residuals of the models are presented in Section A.3 in Appendix A.

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.

Table 4 implies that higher fuel consumption, capital expenditure, and OPEX are associated with higher annual transport work of each vessel. In particular, the returns to scale are less than one, indicating that doubling the inputs may result in less than double the output.

The signs of the control variables are in line with economic theory. Namely, higher production efficiency is achieved by younger vessels and vessels equipped with more ESTs. The number of ESTs enhances production efficiency because upgrading and retrofitting the existing fleet substantially improves vessels' energy use and emissions outcomes. Additionally, a vessel's production efficiency is positively associated with the number of ESTs installed on other vessels within the same

[8] All models assume that the inefficiency term follows an exponential distribution. Table A2 (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.

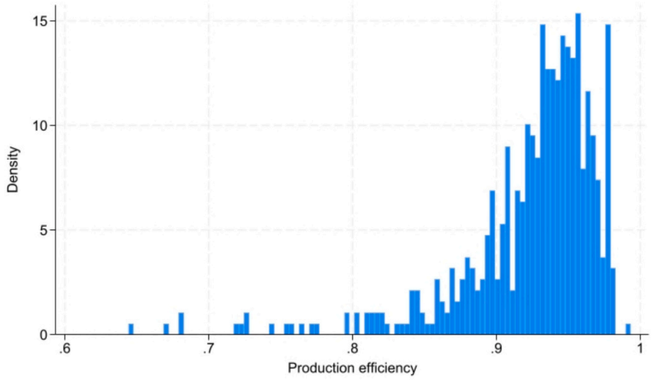

Fig. 3. Histogram of production efficiency of individual vessels.

company, suggesting that a company's pro-sustainability fleet management strategy may exert positive influence. Furthermore, production efficiency does differ significantly between the two vessel types, and company size is not a significant determinant either.

Our findings are consistent with the literature in both engineering and management fields. Prior engineering studies suggest that energy efficiency is influenced by vessel size, vessel age, routing, and ESTs installed (Lassesson and Andersson, 2009; Acciaro and McKinnon, 2015; Cariou et al., 2019; Longarela-Ares et al., 2020; Duan et al., 2023). Moreover, the adoption of energy efficiency measures is closely linked to management strategy (Jafarzadeh and Utne, 2014; Rehmatulla and Smith, 2015b; Johnson and Andersson, 2016; Dewan et al., 2018; Hansen et al., 2020; Duan et al., 2023). To the best of our knowledge, no previous study has offered empirical evidence on the factors influencing energy efficiency from an economic perspective.

Fig. 3 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 80% and 98%. Additional policy measures might be required to improve vessels' performance subject to their emissions.

To further investigate the performance of vessels, Eqs. (34)–(36) 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 the vessel(s) on the efficient frontier. The respective results suggest that the average vessel overuses operation, energy, and capital by around 9%. 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.

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

	Technical inefficiency	Allocative inefficiency	Both inefficiencies
Operation	8.9%	108.6%	127.4%
Energy	8.8%	−42.8%	−37.7%
Capital	8.7%	466.7%	512.9%

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

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 109%. 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 467%. 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 shown in Fig. A4 in Appendix A, vessels have significantly improved economic performance relative to their CO2: for Capesizes, the eco figure is \$401/ton CO2 against \$280/ton CO2 for the non-eco one; for VLCCs, \$420/ton CO2 and \$278/ton CO2, respectively. However, this does not seem sufficient to justify, in purely financial terms, the significant excess investment required (Petropoulos, 2022; Jia et al., 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, International Maritime Organization, 2023).

The energy allocative inefficiency of −38% (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 0–38% increase, this would not severely impact vessels' output, other things being equal. In Section 5.3, 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).

To explore how the technical, allocative, and both inefficiencies affect the annualised cost of financing and running a vessel, Fig. 4 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.

The relatively flat plot of technical inefficiency in Fig. 4 suggests that its effect on the total cost is similar across vessels. In contrast, the

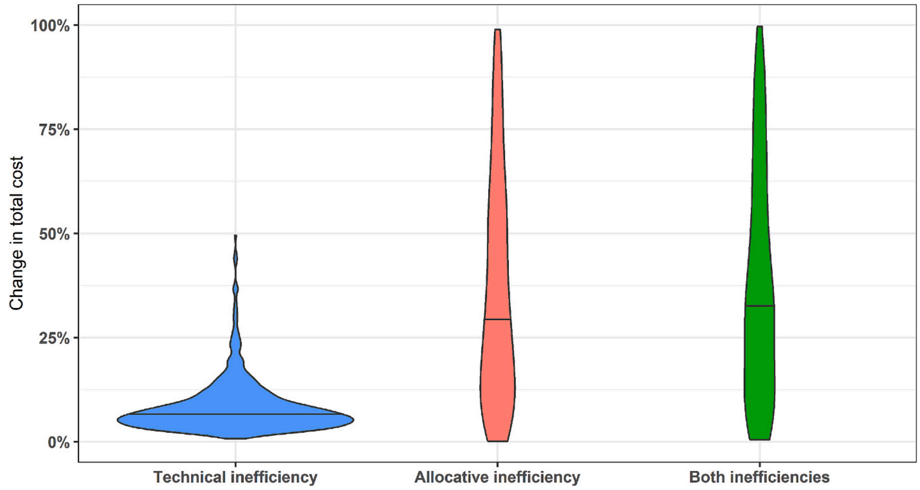

Fig. 4. Change in total cost of an individual vessel.
Notes: the wider the plot for a given y, the more observations correspond to that value. The line in the middle denotes the median value. Outliers, i.e. observations above 100%, have been removed.

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 7% and 29%, respectively. The median in the violin plot of the combined inefficiencies is around 32%, 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.

5.3. Sensitivity analysis on individual vessels

In this subsection, we run sensitivity analysis to investigate the effects of changes in fuel price and speed on vessels' technical efficiency, allocative efficiency, and total cost. Appendix B includes sensitivity analyses with respect to the loan rate (cost of capital) and wage (cost of operation).

First, we investigate how fuel price changes affect the efficiencies of individual Capesize and VLCC vessels. As shown in Table B1 in Appendix B, the fuel price in the benchmark analysis ranges from 494 to 620 \$/ton, with a mean and median of 549 and 494 \$/ton, respectively. In the sensitivity analysis, the price is varied in increments of 100 \$/ton.

Fig. 5 presents the effects of allocative inefficiency on input demand when changing the fuel price (the benchmark results are summarised in Table 5).

Fig. 5 shows that, as fuel price increases, energy becomes slightly more underused. Meanwhile, capital's overuse significantly decreases, and operation's overuse steeply increases. There is a disproportional change in energy and operation because vessels are limited (by their design and already installed engines and ESTs) on how much they can instantaneously reduce their energy use, despite a large increase in fuel price. Instead, shipowners can drastically improve the energy efficiency of their vessels by increasing expenses on maintenance and technological upgrades such as installing ETSs (to minimise energy use and, in turn, cost). As fuel price increases by more than \$300 per ton, input misallocation becomes more severe. 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, severely distort the allocative efficiency of inputs and hinder the profitability from shipping operations.

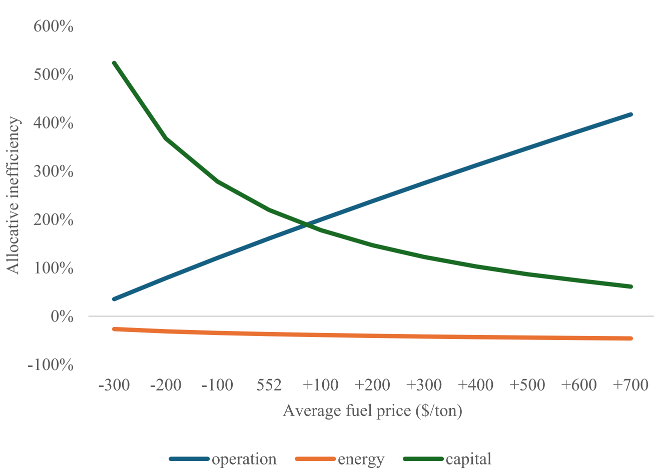

Fig. 5. The effects of allocative inefficiency on input demand by varying the fuel price.

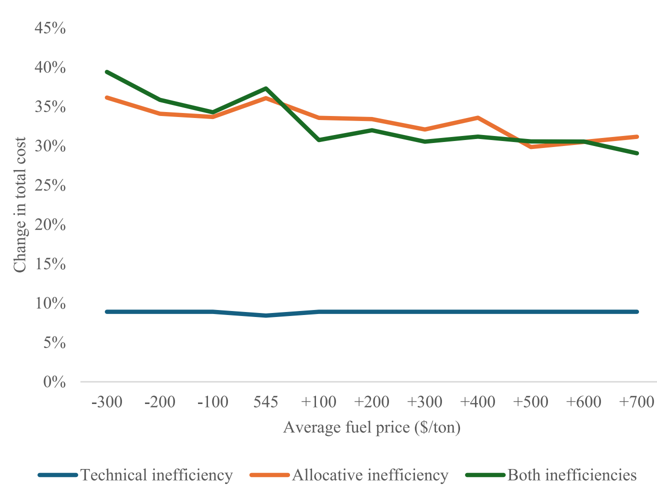

Fig. 6. Changes in total cost by varying the fuel price.

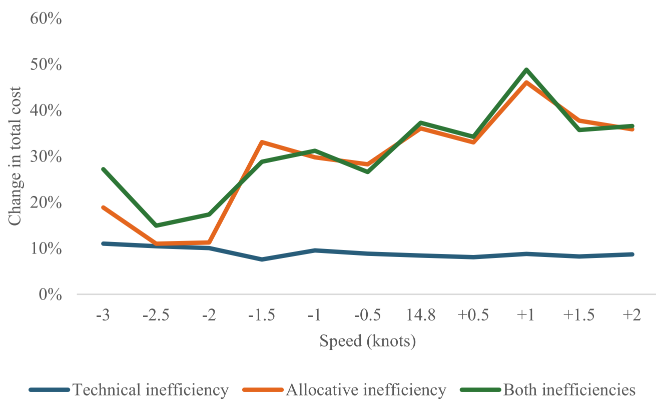

Fig. 7. Changes in total cost by varying the speed.

Fig. 6 presents the effects of technical, allocative, and both inefficiencies on the vessel's total cost with respect to different fuel prices. As fuel price does not affect technical efficiency, there is no change in the impact of technical inefficiency on total cost. Allocative inefficiency and both inefficiencies combined gradually go down, i.e. the effects on the vessel's total cost decrease. This can be explained by the fact that, an increase in fuel price may mobilise greener investment to improve energy efficiency and, thus, it may eventually reduce the total cost.

The sensitivity analyses results (Figs. 5 and 6) suggest that an increase in fuel price of up to 38% 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 ESTs. Indicatively, the price of LNG – which is a transitional and not a zero/near-zero fuel – in 2024 has been 17% higher on average compared to the fuel oil equivalent (Clarksons' SIN, 2024)[9]; thus, within the acceptable range mentioned above. However, currently, biofuels and zero/near-zero fuels (e.g. green ammonia, green methanol) have more than 38% higher prices than oil (IMO, International Maritime Organization, 2025a; S&P Global, 2025). Long-term strategic planning is required, such as carbon pricing for the use of fossil fuels and monetary incentives (subsidies) for the use of zero/near-zero fuels. Without supportive measures for the operators of greener-fuelled vessels, the net-zero transition will not be able to take place in line with the Paris Agreement and the IMO's timelines. Furthermore, it can significantly affect the well-functioning of the shipping fleet and the financial health of companies, especially small and medium enterprises.

Our findings address an important gap in the literature. Engineering studies have shown that the use of alternative fuels is a key determinant of energy and carbon efficiency (Lassesson and Andersson, 2009; Nuchturee et al., 2020). Economic studies have estimated the marginal abatement costs of adopting alternative fuels to be around 250–700 USD per ton of CO2 (Lagouvardou et al., 2023; Longva et al., 2024). Our estimation is slightly lower, at approximately 200 USD per ton,[10] a level that does not severely affect vessel productivity. This difference arises because our study accounts for the way fuel prices influence both capital investment and operating expenses, which together shape total costs. From a production economics perspective, our estimation incorporates the interaction between input factors and their joint impact on total production and costs.

We then examine the effects of sailing speed on vessels' efficiencies. In the benchmark case, all vessels are assumed to sail at their design speed (Table B2 in Appendix B). Accordingly, the actual speed is varied from three knots below the design speed to two knots above it. For a given change in speed, fuel consumption is estimated according to the cubic rule (Adland et al., 2020; Wu, 2020). Since speed and fuel consumption are used as inputs in the technical and allocative inefficiency estimates, we test how the total cost varies in relation to changes in both variables.

Fig. 7 presents the effects of technical, allocative, and both inefficiencies combined on total cost as vessel speed varies. The impact of technical inefficiency on total cost remains similar to the benchmark case shown in Fig. 4. However, the impacts of allocative and combined inefficiencies first decrease, as speed approaches two knots below the design speed, before rising and declining again at lower speeds. Due to the cubic rule mentioned above, fuel consumption decreases when the speed falls by 2.5 knots below its design speed (approximately 17%). This, in turn, brings the total costs of the vessel close to optimal levels from an allocative efficiency perspective. When speed is reduced by more than 17%, however, the effective supply of the fleet significantly declines, indicating less efficient utilisation of capital and operation. This finding is important in its own right, from both industry and policy perspectives, as a widely discussed short-term measure to reduce shipping emissions has been the so-called “slow steaming” of vessels.

The current decarbonisation pathway requires significant capital investment in low-carbon technologies (Klaßen 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. The 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 EST installation. 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 Fig. 4 imply that this underinvestment can be more effectively addressed with economic measures that can optimise the resource allocation of shipping companies rather than with only purely technical improvements.

Appropriate economic measures and resource allocation are crucial in facilitating the transition towards net zero (Coulomb et al., 2021; Oehmke and Opp, 2024; Mengesha and Roy, 2025). In the shipping context, previous literature estimates the costs for slow steaming (Ammar, 2018) or the carbon price needed for adopting alternative fuels and ESTs (Oliveira et al., 2022; Lagouvardou et al., 2023; Longva et al., 2024). Adding to the literature, this study identifies the potential effects that environmental regulations can have on vessels' productivity, shipping costs, and resource allocation. Our results show that an increase in fuel price of over 38% could severely distort the allocative efficiency of capital investment and operation. Slow steaming of over 17% may seriously reduce allocative efficiency as well as increase the overall costs. Regulatory interventions can improve the carbon efficiency of vessels but need to be applied with careful consideration.

There are certain limitations in the above analysis. First, a relative efficiency measurement, such as SFA, is different from the absolute value of CO2. The overall CO2 could be increasing but the carbon efficiency might remain stable. For instance, recent geopolitical disruptions have resulted in longer voyage distance for certain trades which, in turn, causes more CO2. The relative measurements, including both the IMO's short-term measures (AER, EEOI, and CII) and our measurement, account for both the increase in distance and CO2. For example, as the Red Sea crisis increases both distance and CO2, the relative measure does not change as much as the absolute one (i.e. the CO2 values per se). Future studies could combine both relative efficiency indicators and absolute emission figures, offering a complete perspective that accounts not only for per-unit performance but also for the total emissions of the sector and the factors driving them.

Second, the analysis on vessel types is based on microeconomic

[9] 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.

[10] 38% of fuel price: 552 USD/ton * 38% ≈ 200 USD/ton

foundations, comparing monetary values and CO2. The actual physical-thermal carbon efficiency of a vessel type can be predetermined by additional factors, such as trade routes and patterns, port infrastructure, commodity flows, cargo utilisation rates, and the time-sensitivity of the cargo. In addition, the model cannot fully consider the impact of macroeconomic conditions on vessels' efficiency.

Third, this paper cannot fully test or verify the validity of the proposed economic measure of shipping energy efficiency, as it is the first to develop a theoretical economic model in this context. The proposed method should be compared with other economic measures in future research. It remains uncertain whether this method can ultimately serve as a standard.

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. This paper assesses the carbon, production, and allocative efficiencies on economic foundations, and analyses the impact of fuel price, speed, wage and interest rate changes on these efficiencies. The findings can be of significant value to shipowners and operators, capital providers, charterers, and regulators alike.

This research aims to address this gap by examining the carbon, production, 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, as well as for 592 individual Capesize bulk carriers and VLCCs, including sensitivity analyses with respect to changes in the fuel price, speed, wage, and loan rate. SFA enables the estimation of carbon efficiency on economic foundations, where carbon emissions are regressed on vessel's capital expenditure, operating expenditure, and earnings. It also measures vessels' allocative efficiency, which compares 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 CO2 emitted and earned USD 295.1 per ton of CO2 emitted over the period 2021–2024. Vessels with electronic eco engines have 27–54% higher earnings per ton of CO2 than conventional ones. Larger vessels are overall more carbon efficient in transporting goods while smaller ones in generating revenue, suggesting that it is inappropriate to apply a simple linear model for carbon pricing.

From a financial perspective, our carbon efficiency measurement compares the carbon emissions of various vessel types given their earnings, capital, and operating expenses. Different shipping segments vary in how they balance carbon emissions, economic costs, and income. Vessel types with higher carbon efficiency are observed among those operating at lower speeds, while port congestion and the volume of Suez Canal transits do not have a significant impact. Policymakers should note that relative profitability per ton of CO2 may remain constant even as absolute CO2 increase, indicating that carbon pricing should not be implemented solely on a "per ton of CO2" basis.

The transport work of an individual vessel is significantly positively related to energy used, as well as to operating costs and capital investment. As expected, higher production efficiency is observed in younger vessels, vessels spending more time at sea, and vessels with more ESTs. It is also found that production efficiency is positively related with a company's pro-sustainability strategy, measured by the number of ESTs installed on other vessels within the same company. Technical inefficiency increases the energy use, operation, and capital by around 8%. The technical and allocative inefficiencies combined increase the owning and operating costs for the median vessel by roughly 25%.

Allocating economic resources appropriately can play the most important role in reducing 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 GHG pricing mechanisms would raise the fuel costs, within a range of 0–38% increases, this would not severely impact vessels' transport work, other things being equal. Capital is overused, indicating that the excess capital expenditure needed to comply with the increasingly strict environmental regulations does not generate sufficient return to shipowners. Moreover, our sensitivity analyses shows that slow steaming of up to 13.5% could effectively improve the production efficiency and reduce overall costs.

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. These findings have strong implications for the industry, as they imply that investing in certain vessel types, installing ESTs, and renewing the fleet might optimise the economic-sustainability profile of a company. They also yield significant policy recommendations regarding the introduction of economic measures. Policymakers should consider stricter environmental regulations to accelerate the energy transition of the shipping industry. However, the scope of such measures is limited without adequate rewards and subsidies, which are essential to prevent undermining the production and allocative efficiency of vessels and to ensure that overall costs do not rise sharply.

CRediT authorship contribution statement

Yao Shi: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ioannis C. Moutzouris:** Writing – original draft, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Copilot in order to proofread. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Appendix A. Appendix

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		8000-16,999
	Intermediate		3000-7999
	Feeder		100–2999
Bulk carrier	Capesize	180,000	
	Panamax	76,000	
	Handymax	60,000	
	Handysize	35,000	

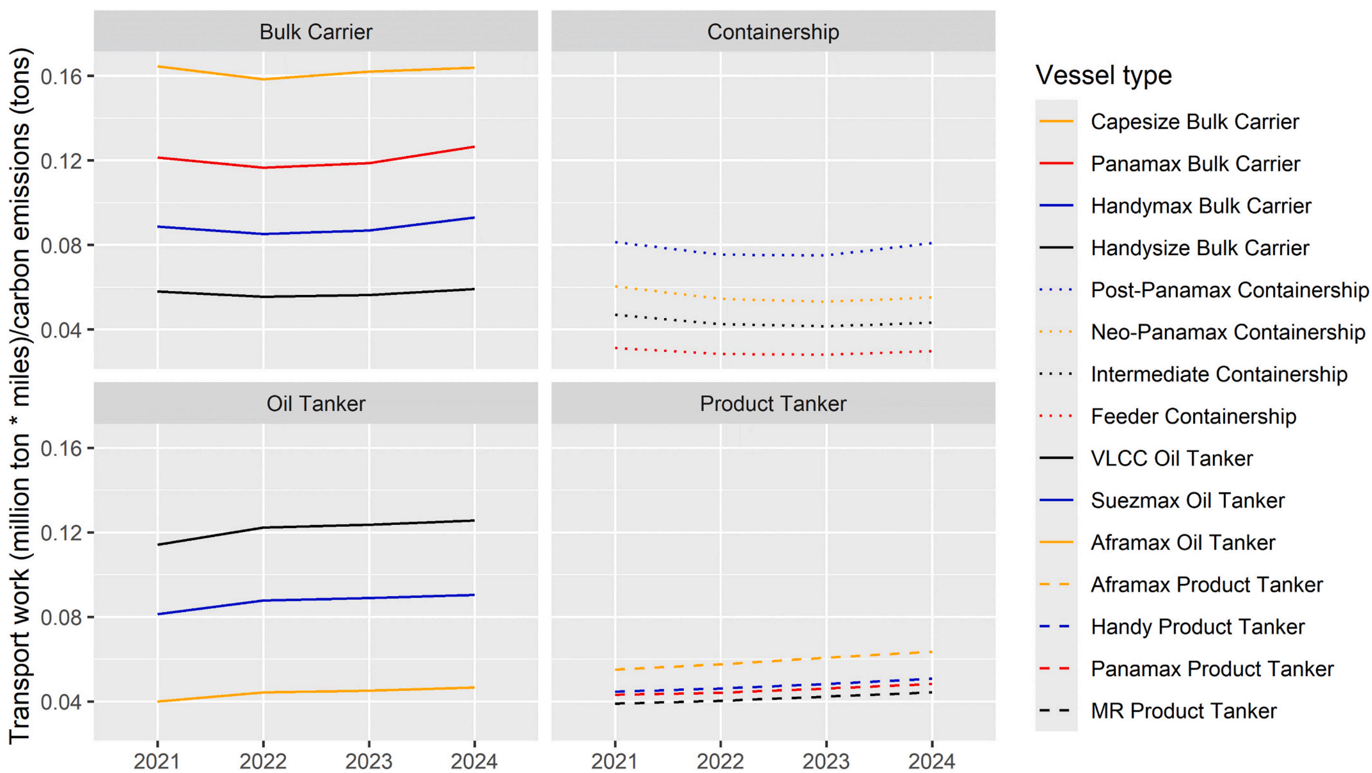

Fig. A1. Transport work per ton of carbon emissions by vessel type (D*V/CO2). Note: D is distance, V is deadweight.

According to Fig. A1, 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 (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.

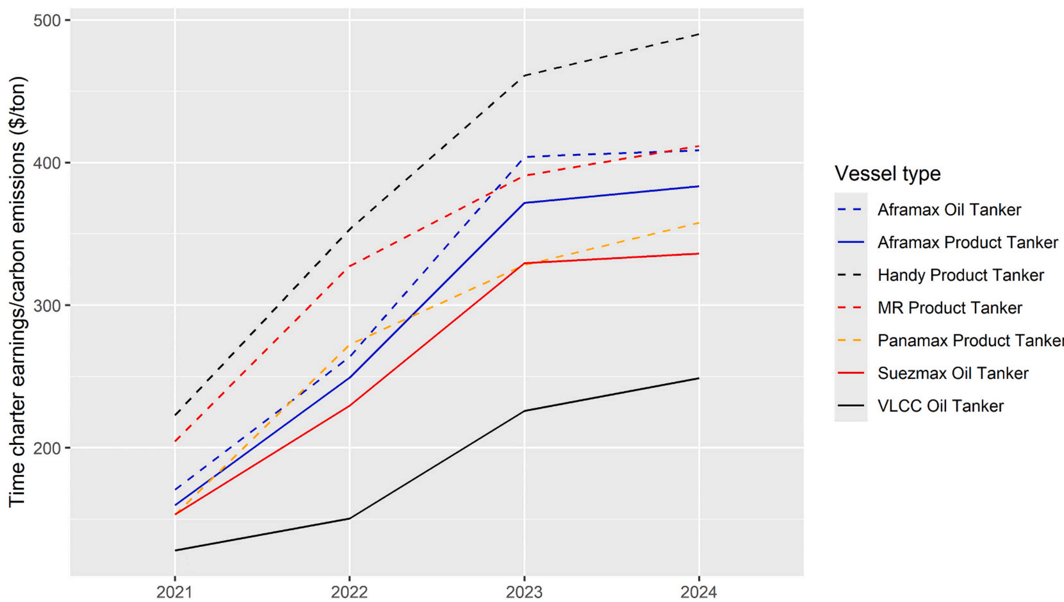

Fig. A2. Time charter earnings per ton of carbon emissions of tankers.

Fig. A2 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 (Fig. A3), 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 (Fig. A3). 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.

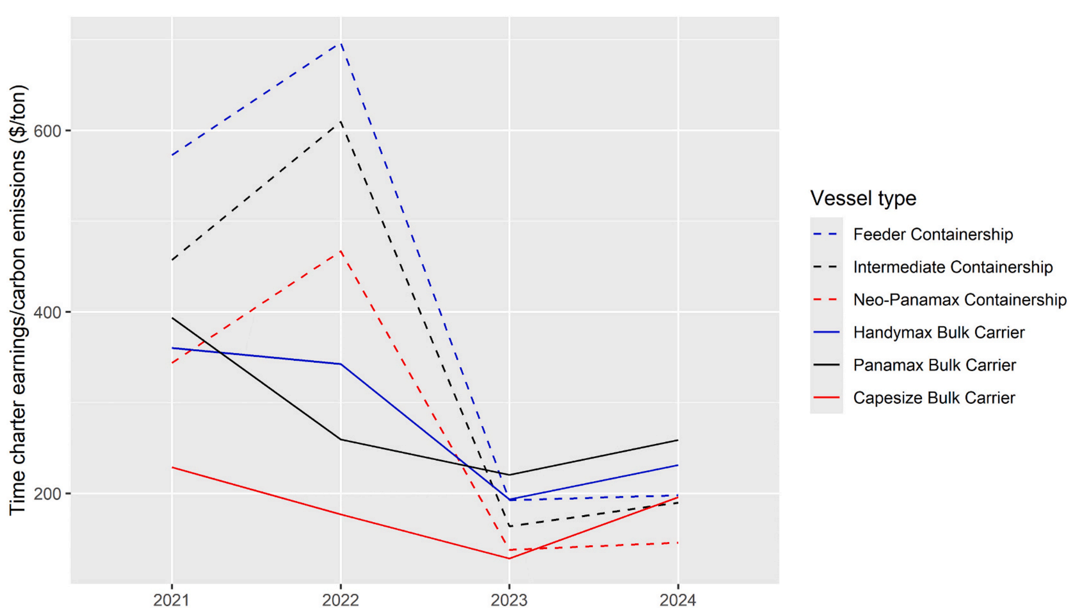

Fig. A3. Time charter earnings per ton of carbon emissions of bulk carriers and containerships.

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.

The economic measurement of carbon efficiency (Figs. A2 and A3) reveals some interesting differences from the traditional one (which is based on transport work per carbon emissions) (Fig. A1). 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.

Fig. A4 compares the net earnings per ton of CO2 between eco-engine vessels and conventional-engine ones for various vessel types. In contrast to the previous analysis for which the relevant data are not available, we now use net earnings instead of TC earnings as they capture more accurately the shipowner's/operator's inflows. Namely, those correspond to the respective TC earnings minus the fuel, port, canal, and EU ETS (if any) costs.

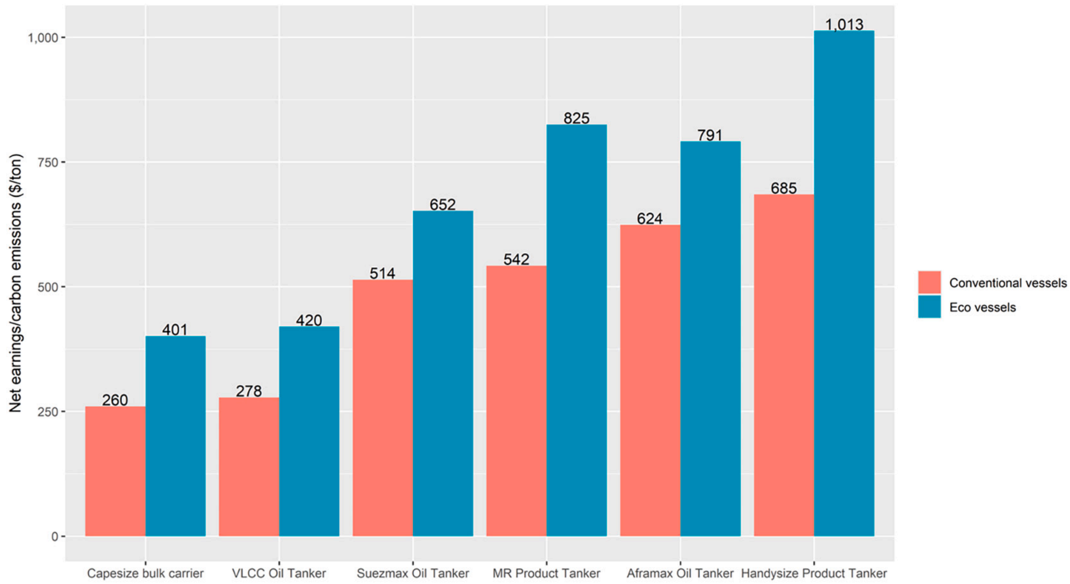

Fig. A4. Net earnings per ton of carbon emissions by built year. Note: The carbon emissions values are obtained by taking the average of the carbon intensity from LPG, LNG, LSFO, and HSFO. "eco vessel" refers to all ships with a 2-stroke engine which have an electronically controlled fuel injection system. 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.

Fig. A5 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 Fig. A4, where only eco against non-eco vessels are compared.

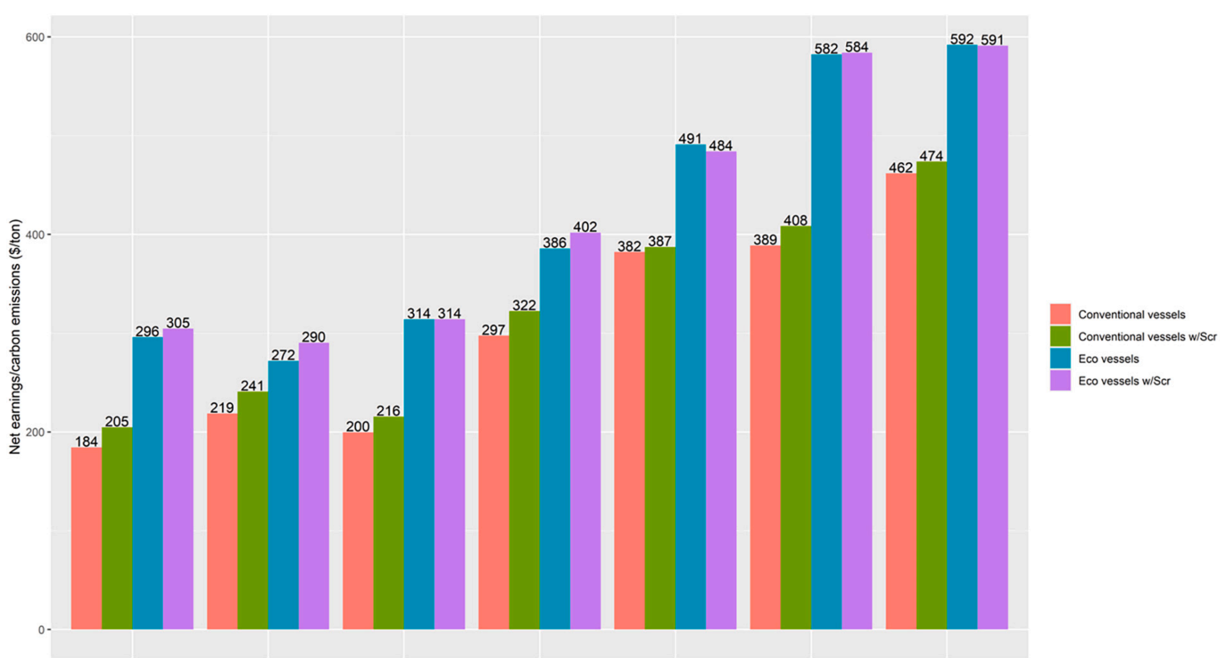

Fig. A5. Net earnings per ton of carbon emissions by eco and scrubber status.

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. Additional models of production efficiency

Table A2 shows three models with various assumptions on the distribution of the inefficiency term.

Table A2
Production efficiency of individual vessels: Additional models.

	(1)	(2)	(3)
	Dependent variable: ln(D*V)		
Distribution	Half normal	Truncated normal	Exponential
Intercept	11.34***	11.28***	11.28***
ln(OP)	−0.01	−0.01	−0.01
ln(E)	0.76***	0.76***	0.76***
ln(K)	0.14***	0.14***	0.14***
Mu		−5.91	
U sigma	0.12*	0.63	0.06**
V sigma	0.16***	0.17***	0.17***
Lambda	0.71***	3.76	0.38***
Log likelihood	180***	180***	180***

Note: significance levels: 0.01 '***' 0.05 '**' 0.1 '*'. The total number of observations is 592 vessels.

A.3. Distributions of residuals

Figs. A6-A11 show the distributions of the residuals of the five models in Table 4. The residuals comprise both noise and inefficiency term. As expected, all the residuals are left skewed, confirming the existence of production inefficiencies. No extreme outliers are present, demonstrating that traditional distribution forms, such as an exponential distribution, are valid for fitting the inefficiency term.

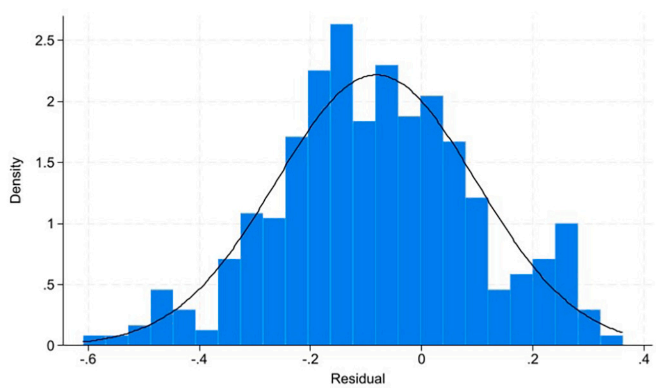

Fig. A6. Distribution of residuals in Model (1).

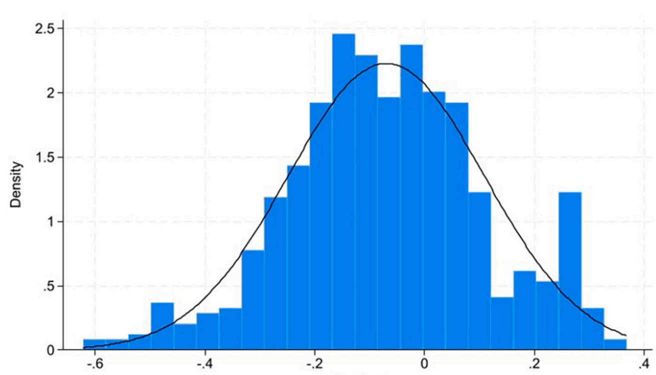

Fig. A7. Distribution of residuals in Model (2).

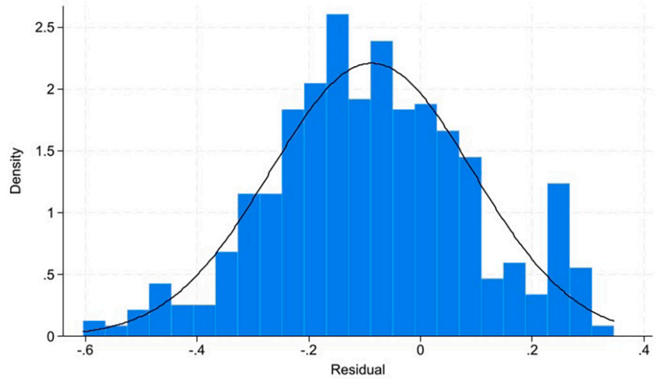

Fig. A8. Distribution of residuals in Model (3).

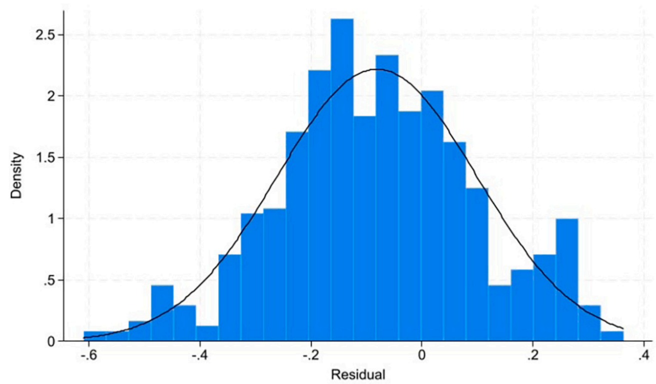

Fig. A9. Distribution of residuals in Model (4).

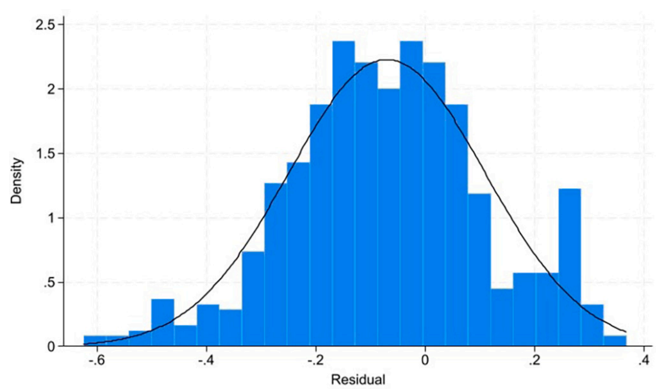

Fig. A10. Distribution of residuals in Model (5).

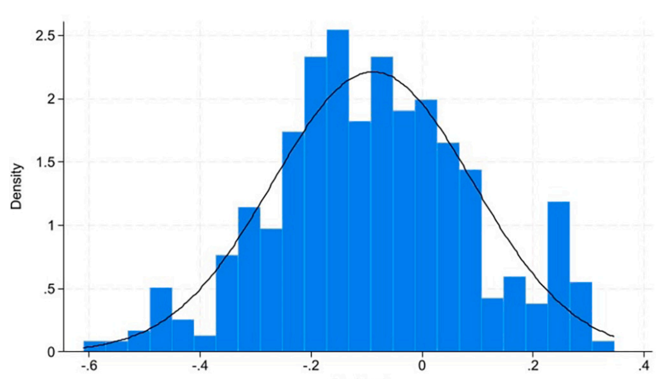

Fig. A11. Distribution of residuals in Model (6).

Appendix B. Sensitivity analysis

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

B.1. Fuel price

Table B1
Sensitivity analysis of individual vessels by varying the fuel price.

Fuel price ($/ton)	Min	Mean	Median	Max	s.d.
Initial	494	549	494	620	62
Sensitivity Analysis 1	394	449	394	520	62
Sensitivity Analysis 2	294	349	294	420	62
Sensitivity Analysis 3	194	249	194	320	62
Sensitivity Analysis 4	594	649	594	720	62
Sensitivity Analysis 5	694	749	694	820	62
Sensitivity Analysis 6	794	849	794	920	62
Sensitivity Analysis 7	894	949	894	1020	62
Sensitivity Analysis 8	994	1049	994	1120	62
Sensitivity Analysis 9	1094	1149	1094	1220	62

B.2. Speed

Table B2
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	374	338	857	167
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	338	306	777	151
Sensitivity Analysis 2:					
Design speed – 1 knot	7.0	13.8	13.8	20.5	1.3
Total fuel consumption (thousand tons)	1.6	304	275	701	137
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	272	247	630	123
Sensitivity Analysis 4:					
Design speed – 2 knots	6.0	12.8	12.8	19.5	1.3
Total fuel consumption (thousand tons)	1.3	243	221	565	111
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	216	196	505	100
Sensitivity Analysis 6:					
Design speed – 3 knots	5.0	11.8	11.8	18.5	1.3
Total fuel consumption (thousand tons)	1.0	191	173	466	89
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	414	374	944	183
Sensitivity Analysis 8:					
Design speed +1 knot	9.0	15.8	15.8	22.5	1.3
Total fuel consumption (thousand tons)	2.3	455	413	1035	201
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	500	453	1133	220
Sensitivity Analysis 10:					
Design speed +2 knots	10.0	16.8	16.8	23.5	1.3
Total fuel consumption (thousand tons)	2.7	547	496	1237	240

Note: the number of observations is 575, due to missing data of design speed.

B.3. Wage

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 4 and 5. Table B3 summarises the respective wage in each sensitivity analysis.

Table B3
Sensitivity analysis of individual vessels by varying the wage.

Wage ($/year)	Min	Mean	Median	Max	s.d.
Initial	24,120	39,367	34,198	82,637	13,228
Sensitivity Analysis 1	22,120	37,367	32,198	80,637	13,228
Sensitivity Analysis 2	20,120	35,367	30,198	78,637	13,228
Sensitivity Analysis 3	18,120	33,367	28,198	76,637	13,228
Sensitivity Analysis 4	16,120	31,367	26,198	74,637	13,228
Sensitivity Analysis 5	14,120	29,367	24,198	72,637	13,228
Sensitivity Analysis 6	26,120	41,367	36,198	84,637	13,228
Sensitivity Analysis 7	28,120	43,367	38,198	86,637	13,228
Sensitivity Analysis 8	30,120	45,367	40,198	88,637	13,228
Sensitivity Analysis 9	32,120	47,367	42,198	90,637	13,228
Sensitivity Analysis 10	34,120	49,367	44,198	92,637	13,228

Fig. B1 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 109% to 62%. Meanwhile, the overuse of capital roughly triples but energy use remains underused and overall unaffected by wage changes. When the wage decreases, capital becomes less overused. 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.

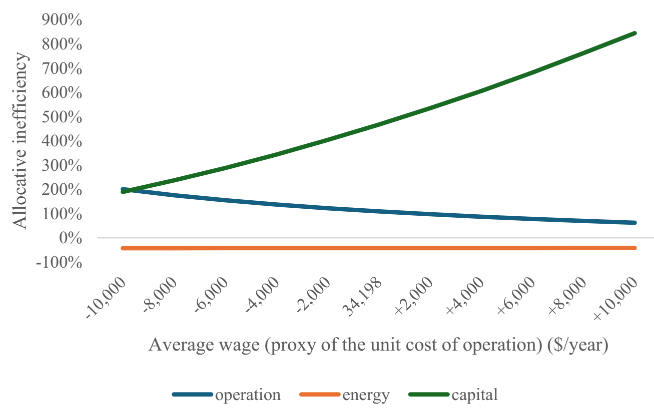

Fig. B1. The effects of allocative inefficiency on input demand by varying the wage.

Fig. B2 presents the effects of the technical, allocative, and both inefficiencies combined on the total cost when the wage is varied.

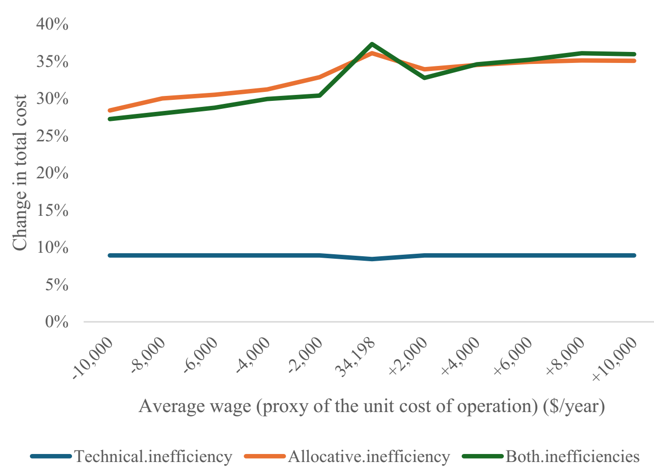

Fig. B2. Changes in total cost by varying the wage.

As shown in Fig. B2, the blue line remains 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 lines are sensitive to wage changes. 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. Loan rate

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 increases them by 1% (Table B4). The loan rate is not decreased because the initial values are at a historical low from 2011 to 2014.

Table B4
Sensitivity analysis of individual vessels by varying the loan rate.

Loan rate (%)	Min	Mean	Median	Max	s.d.
Initial	1.5	4.4	3.7	8.0	1.5
Sensitivity Analysis 1	2.5	5.4	4.7	9.0	1.5
Sensitivity Analysis 2	3.5	6.4	5.7	10.0	1.5
…					
Sensitivity Analysis 6	7.5	10.4	9.7	14.0	1.5

Note: An exponential distribution of the error term is assumed, with vessel age and sailing time incorporated 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. Fig. B3 summarises the effects of allocative inefficiency on the input demand for operation, energy, and capital when the loan rate increases. 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.

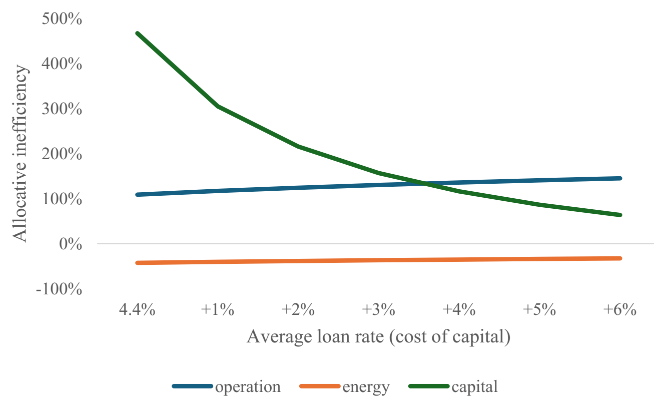

Fig. B3. The effects of allocative inefficiency on input demand by varying the loan rate. Note: all models assume an exponential distribution of the error term.

When the loan rate increases by 6%, the allocative inefficiency of capital decreases from (an overuse of) around 304% to (an underuse of) circa 63%. Equivalently, capital is less overused if the loan rate gets lower. 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.

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

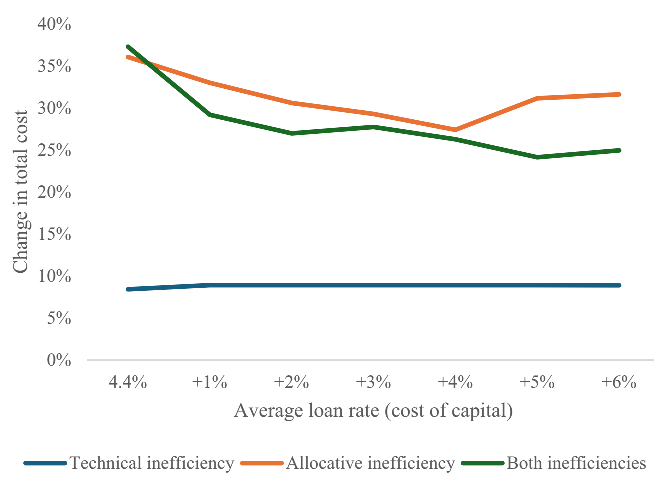

Fig. B4. Changes in total cost by varying the loan rate.

As the loan rate increases, the impact of technical inefficiency on total cost remains unchanged. Thus, as expected, the loan rate does not affect the technical performance of the vessel. However, when the loan rate increases, the impact of allocative inefficiency on total costdeclines (i.e. the red line goes down). Namely, the results suggest that when the rate becomes higher, it improves the allocative efficiency by reducing the overinvestment in vessels and, in turn, the overuse of capital.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2026.109280.

Data availability

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.

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