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Approach and Initial Findings in Modeling Future Seaborne Trade and Its Impact on Energy Demand

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Abstract

International shipping contributes approximately 3% of global carbon dioxide (CO_2) emissions, prompting the International Maritime Organization (IMO) to aim for net-zero shipping greenhouse gas (GHG) emissions by 2050 to mitigate climate change. Shipping is a critical link between countries for transporting goods, and its future advancements will hinge primarily on customer demand for goods and regional growth trends. This study has a dual objective. First, this work seeks to establish a methodological framework for forecasting the trajectory of future global trade. Second, it aims to utilize the estimated future seaborne trade to understand the impact on energy demand in the shipping sector across three scenarios. The results indicate that compared with 22 billion tons in 2021, the global seaborne trade is projected to reach 44 billion tons in 2050, encompassing both intra- and intercountry cargo movements. This situation corresponds to an energy demand of 10.11 mboe/d in 2050 under the business-as-usual (BAU) scenario. However, applying the energy efficiency (EE) and sustainable development (SD) scenarios results in reduced energy demands of 7.55 mboe/d and 6.10 mboe/d, respectively. Under the BAU scenario, energy demand is expected to increase by 73% by 2050 compared with the 2021 level, with an average annual growth rate of 1.89%. Conversely, the EE scenario projects a total energy demand increase of 30%, translating to an average annual growth rate of 0.91%, and the SD scenario indicates only a 5% increase in energy demand, with an average annual growth rate of 0.17%. This finding suggests that SD efforts could reduce energy demand by approximately 40%, whereas EE measures might lead to a reduction of approximately 25% compared with the BAU scenario.

1.0 Introduction

In today's increasingly interconnected world, governments and various organizations are actively developing new regulations concerning carbon dioxide (CO_2) emissions from maritime transportation. Ships predominantly rely on fossil fuels, such as heavy fuel oil (HFO). Given the widespread use of HFO in the shipping sector, significant emissions are released into the atmosphere. Consequently, research endeavors are concentrating on forecasting fuel consumption, enhancing energy efficiency (EE), and determining the requisite measures for cleaner fuels within this industry.

In 2020, fossil fuels accounted for approximately 83% of total energy demand worldwide (Holechek et al. 2022). However, despite their high energy yield and cost effectiveness, the utilization of these fuels for energy production has had significant environmental repercussions, including contributing to climate change through airborne emissions (Vidadili et al. 2017).

Extensive research conducted over the past two decades has thoroughly examined the environmental impact of shipping emissions. These studies have consistently highlighted the detrimental effects of these emissions on both human health and the environment (Cullinane and Bergqvist 2014; Dulebenets 2016; Psaraftis and Kontovas 2013; Wang et al. 2019). Specifically, severe pollution in coastal cities is compounded by the statistic that 70% of global ship emissions take place within 400 km of coastal regions (Corbett et al. 2007). Durmusoglu, Aksoy, and Denizs (2016) demonstrate that emissions from shipping and seaports lead to approximately 19,000 cases of lung cancer annually. Moreover, these pollutants are responsible for approximately 60,000 deaths annually from various diseases triggered by seaport or shipping emissions.

The IMO plays a pivotal role in regulating ship-generated air pollution, regularly issuing regulations and reports focused on estimating emissions, implementing emission reduction technologies, etc. The International Convention for the Prevention of Pollution from Ships (MARPOL) serves as the primary international agreement addressing ship pollution, with MARPOL Annex VI specifically targeting exhaust emission reduction. Recently, the IMO adopted an updated strategy aimed at curbing greenhouse gas (GHG) emissions from international shipping, with a target of achieving net-zero GHG emissions in international shipping by 2050 (IMO Press Briefing 2023). This target represents a significant advancement from the initial strategy adopted in 2018, which aimed for at least a 50% reduction in GHG emissions (IMO 2018). To realize this ambitious goal, attention must be paid to addressing the following four key elements:

1. Ship operation management
2. New ship design
3. Alternative fuels
4. Carbon capture

Both (1) and (2) involve enhancing efficiency through the implementation of obligatory technical measures such as the EE design index (EEDI) and operational measures such as the ship EE management plan (SEEMP) to increase the EE of ships.

According to a 2020 report from the IMO, ships emitted an average of 1,003 million tons of CO_2 between 2012 and 2018, accounting for approximately 3% of global CO_2 emissions. Without intervention, shipping emissions could rise by 90% to 130% by 2050 (IMO 2020). One of the key drivers of this increase has been the increase in average ship size (UNCTAD 2015). Consequently,

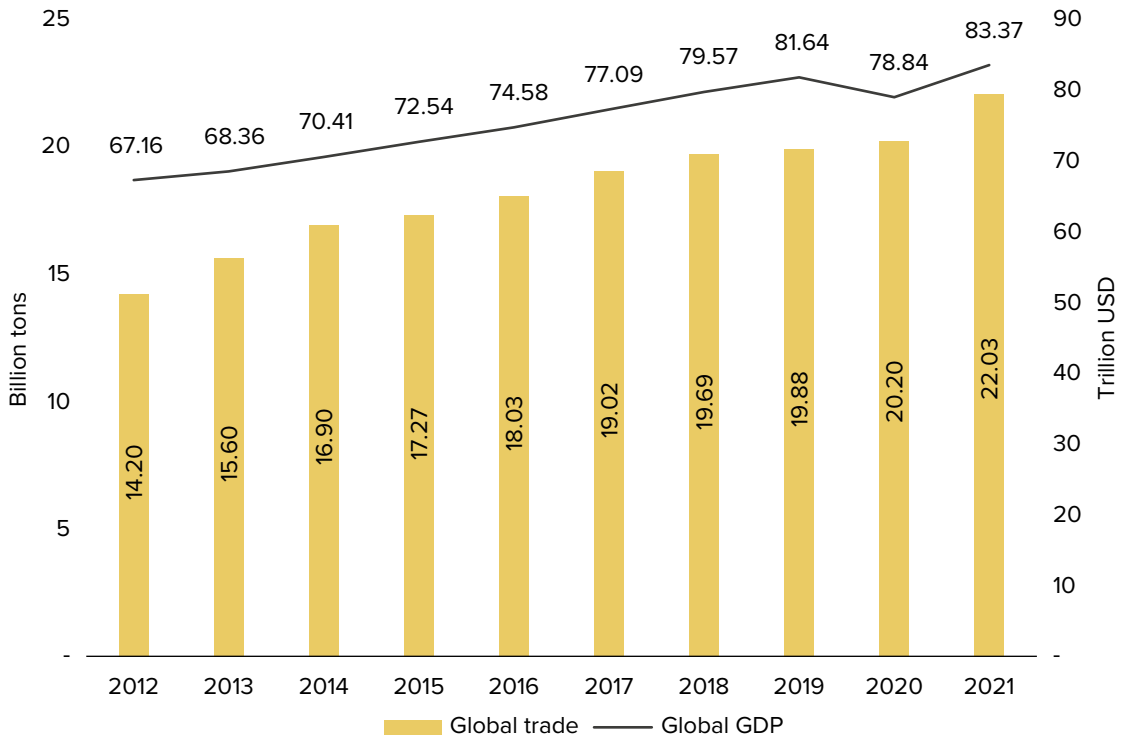
the rising energy demand and resulting emissions pose increasingly severe challenges. Therefore, accurate predictions of fuel consumption have become important and crucial. However, having an approximate idea of future fuel consumption can assist ship owners and operators in implementing measures such as route optimization or alternative energy-saving techniques to reach the IMO target.

Research indicates that there is ongoing expansion in global seaborne trade, driving sustained economic progress worldwide. Over the past decade, the global gross domestic product (GDP) in nominal terms has increased by 2.43%, accompanied by a population growth rate of 1% annually (authors' analysis on the basis of data from the S&P Market Intelligence Network [MINT] 2023; Oxford Economics 2022).

Figure 1 illustrates the historical trend of global trade (including domestic trade) and GDP in nominal terms from 2012 to 2021. The data reveal that in 2020, amid the COVID-19 pandemic, there was a notable decline in GDP of 3.4% compared with the level observed in 2019, and significant trade growth was not evident.

In this study, our objective is to utilize a statistical demand-side model to forecast future seaborne trade and subsequent energy demand in maritime transport on a global scale, considering key factors such as GDP and population, which significantly influence global trade. Understanding future

Figure 1. Trajectory of world GDP and trade, including domestic trade between 2012 and 2021.



Source: Authors' analysis using the MINT (2023) dataset.

global exports can provide insights into future fuel consumption.

The remainder of this study unfolds as follows. Section 2 presents a concise overview of the relevant literature, while Section 3 delves into a comprehensive analysis of seaborne dynamics from 2012 to 2021. The methodological details and data are outlined in Section 4, followed by a presentation of the experimental results, including future seaborne trade projections and their implications for energy demand and discussions, in Section 5. Finally, Section 6 offers concluding remarks.

2.0 Literature Review

Sea transport accounts for more than 80% of global trade by volume and more than 70% by value (UNCTAD 2017). Approximately 94% of the global fleet[1] is dedicated to transporting these trade volumes, with the remainder fulfilling diverse roles, such as passenger transportation (UNCTAD 2016). International trade by sea expanded annually at a rate of 5.9% between the 1950s and 2000s (Behar and Venables 2011; Hummels 2007).

Forecasting the growth of global trade presents a challenge because of the multitude of influencing factors and their intricate connections (Walsh, Mander, and Larkin 2017). Seaborne trade, being a derived demand, relies not only on economic growth but also on various transport-related drivers and trade patterns. The demand for commodities evolves with the emergence of new products and shifts in consumer behavior, potentially rendering current markets obsolete. Moreover, technological advancements in the maritime sector can alter transport costs and their significance compared with other trade barriers, adding to the uncertainty of future scenarios. Given the complexity and uncertainty surrounding the evolution of maritime transport demand, predicting long-term sectoral CO_2 emissions remains challenging. Scenarios depicting future seaborne trade serve as valuable tools for understanding prospective energy demands, aiding policymakers in navigating the discourse on decarbonizing the shipping industry.

Fontagné and Fouré (2013) employ a global economic model to project world trade volume up to 2035, initially focusing on observed trade elasticities to income, highlighting the significance of GDP. Their scenarios incorporate various drivers, such as national economic growth, demographics, and trade policies. The projected growth in the global trade volume ranges from 1.3 to 4.3 times by 2035 compared to 2012 levels. Similarly, Chateâu et al. (2014) utilize a comparable methodology to explore longer-term perspectives until 2060, considering scenarios reflecting different degrees of trade liberalization, from regionalization to multilateralism. These scenarios result in annual increases of 3.6% and 3.8% in global exports, potentially leading to a quadrupling of trade by 2050 compared with 2012 levels. Sharmina et al. (2017) estimate future energy demand by examining global energy decarbonization scenarios and anticipate a significant decline in fossil fuel usage by 2050, which is unlikely to be solely compensated for by an increase in clean energy trade; they project that the global oil demand could rise to 434 exajoules per year by 2050, which translates to 194 million barrels of oil equivalent per day.

In addition to academic research, Lloyd's Register (Smith et al. 2014) introduces three divergent scenarios for 2030, taking into account the influence of critical variables such as population, economy, and natural resources on trade. The outcomes are outlined for the following four primary ship categories: dry bulk, crude, other wet bulk, and containers. Projections suggest that by 2030, trade is expected to rise approximately 1.15 to 2.8 times compared with 2010 levels, varying according to ship type and scenario.

With a notable increase in trade, energy demand within the shipping sector is expected to correspondingly rise, leading to an increase in GHG emissions. In 2023, the IMO, the United Nations body responsible for regulating the environmental aspects of international shipping, introduced strategies aimed at achieving near-zero emissions by 2050.

[1] Measured in deadweight units.

Over the past decade, the IMO has implemented various measures to mitigate shipping-related GHG emissions. One significant example is its EEDI policy, which also incorporates carbon intensity regulations. This policy sets CO_2 emission standards (gCO_2/t-nm) for newly built ships after 2012, mandating an increase in the efficiency of new vessels (Transport and Environment 2018). Additionally, the IMO recently introduced the EE existing ship index (EEXI) to improve the EE of existing ships. On the operational front, the IMO has enforced the SEEMP policy, which is an operational measure designed to increase a ship's EE in a cost-effective manner and offers a practical framework for ship operators to monitor fleet efficiency via the EE operational indicator (EEOI) (IMO 2020). In 2021, a rating scheme based on a mandatory carbon intensity indicator (CII) was approved to reinforce the SEEMP.

This resolution has imposed both regulatory and financial constraints on maritime shipping to reduce its energy consumption and environmental footprint. For example, the EEDI is a technical regulation intended to encourage the use of energy-efficient equipment and engines in the design of new ships, with the goal of reducing emissions. The EEDI sets a minimum standard for EE per ton-km from the outset of the design process, allowing shipbuilders the freedom to incorporate diverse innovative technologies as long as they meet this efficiency requirement. This situation has spurred researchers and industry professionals to explore various pathways through which to increase vessel EE, thereby reducing fuel usage and ultimately mitigating harmful emissions, contributing to the sector's decarbonization. The literature offers numerous studies on mitigation measures for decarbonizing the shipping sector. Eide et al. (2011) and Hoffmann, Eide, and Endresen (2012) examine the effectiveness of 25 mitigation measures, evaluating their cost performance versus CO_2 emission reduction. Heitmann and Peterson (2014) and Lindstad et al. (2015) also assess these measures and their potential impact on global GHG emissions, whereas Bouman et al. (2017) conduct a study on mitigation strategies for reducing GHG emissions.

The shipping sector serves as a critical link for trade flows across global regions and is thus susceptible to regional policy changes. Additionally, advancements in technology and the transition to alternative marine fuels will coincide with similar developments in other energy-consuming sectors. Therefore, to better grasp the feasibility of the IMO's 2050 target, it is imperative to analyze and evaluate how trade and energy demand in shipping may evolve over time.

3.0 Seaborne Trade Dynamics: 2012-2021

3.1 Global Trade

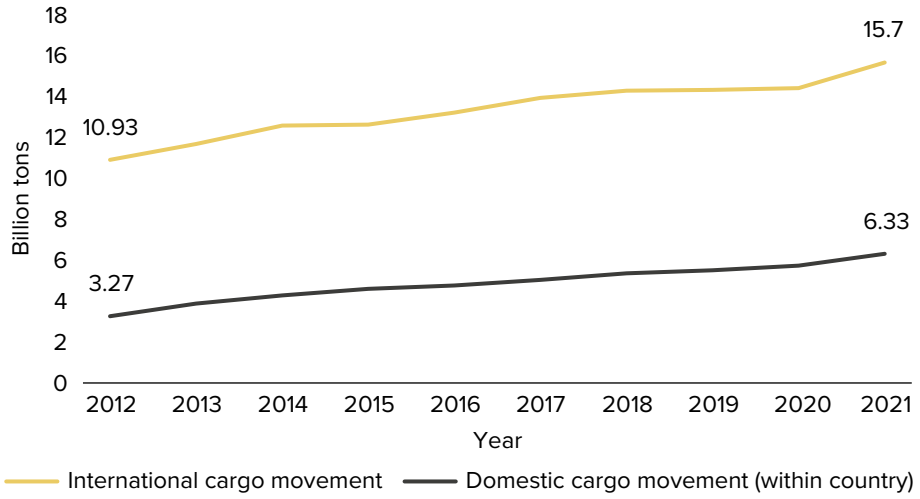
This section examines the dynamics of international seaborne trade, with a focus on the period between 2012 and 2021, presented by regions globally. Over the last decade, global seaborne trade volume has grown by approximately 4.10% annually, excluding domestic shipping within countries. When domestic shipping is included, the growth rate increases to 5% (authors' analysis). However, there was a decline of approximately 2.21% in 2019 and 1.91% in 2020 compared with 2018, excluding domestic cargo movement (see Figure 2). This decrease is likely attributable to the impacts of COVID-19. Nevertheless, trade growth rebounded to prepandemic levels, with the highest increase observed in 2021. When considering domestic cargo movement, there was a decline of approximately 2.52% in 2019 and 1.89% in 2020 compared with 2018 levels, yet trade rebounded to pre-COVID-19 levels in 2021 (see Figure 2).

3.2 Current World GDP, Population and Trade in 2021

According to the available MINT dataset, the global population in 2021 was 7.2 billion, with Other Asia having the largest population of approximately 2.6 billion (see Figure 3), followed by Organisation for Economic Co-operation and Development (OECD) Asia Oceania, with a population of approximately 1.7 billion in the same year. In terms of GDP, the world's GDP is approximately US$84 trillion, with OECD America exhibiting the highest GDP at US$23.6 trillion, followed closely by OECD Asia Oceania, at US$23.4 trillion (see Figure 4).

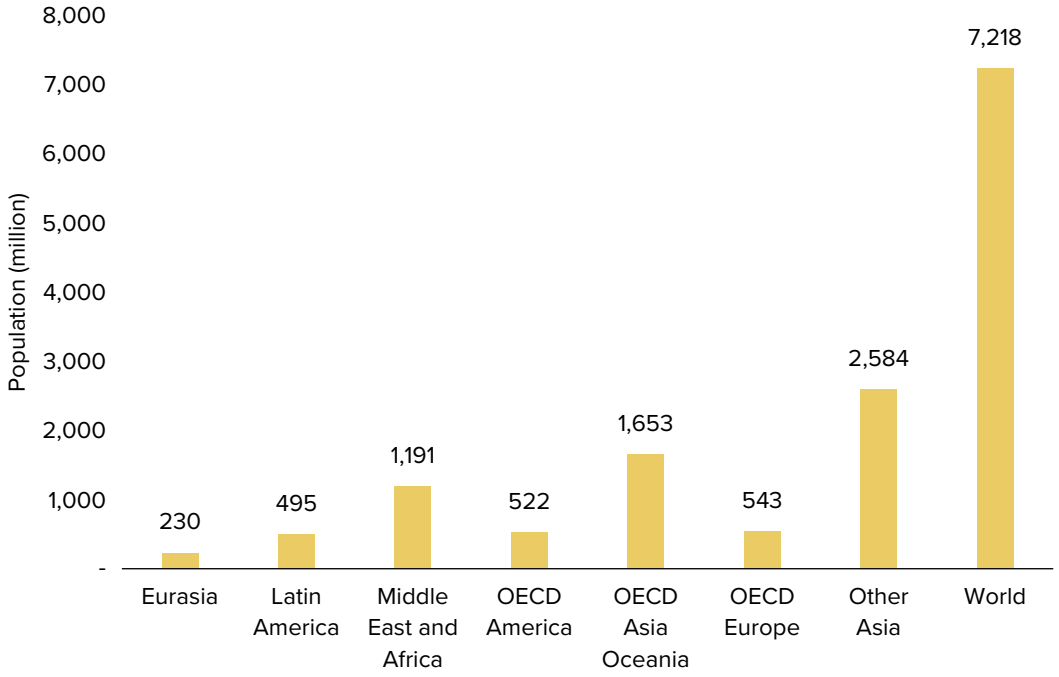
In 2021, OECD Asia Oceania accounted for the highest volume of seaborne trade, representing approximately 22.6% of total trade. The Middle East and Africa accounted for the second-highest share of global trade, accounting for approximately 19.8%, whereas OECD America accounted for approximately 9.7%.

Figure 2. Global seaborne trade and domestic cargo movement (2012-2021).



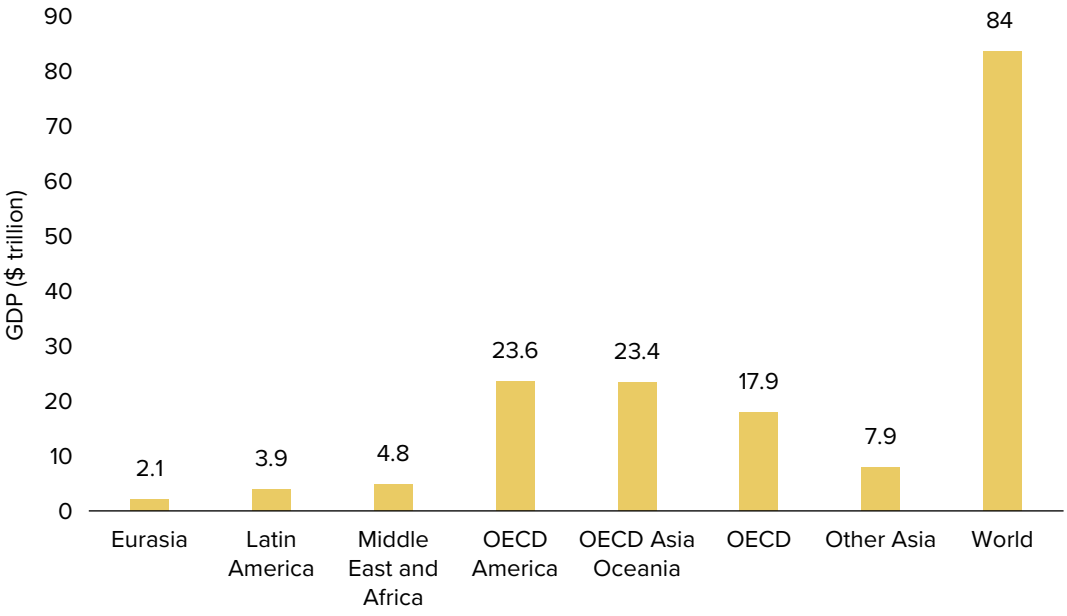
Source: Authors' analysis using the MINT (2023) dataset.

Figure 3. World population in 2021.



Source: Authors' analysis using MINT (2023) dataset.

Figure 4. World GDP in 2021.

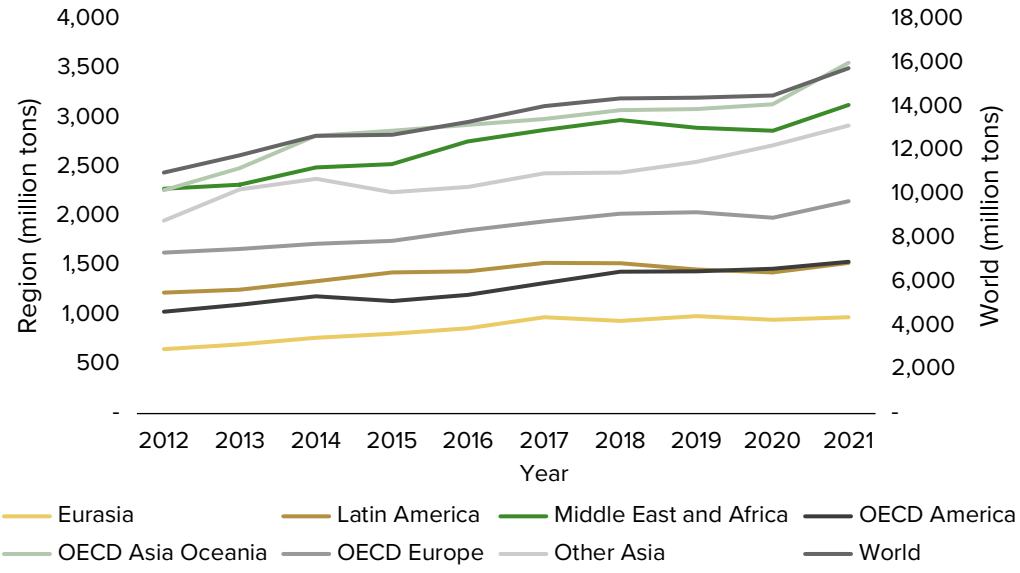


Source: Authors' analysis using the MINT (2023) dataset.

Eurasia shared the least trade with the world, accounting for 6.1% of the total. Other Asia, which include India, held the third-largest share of global trade, accounting for 18.5% (Figure 5).

Figure 5 also depicts the trends in global trade alongside average annual growth rates. The data indicate a 4.1% growth in world trade from 2012 to 2021. Among regions, OECD Asia Oceania had the highest volume of trade, while the highest average annual growth was observed in OECD Europe, at 5.2%, with Latin America experiencing the lowest growth rate, at 2.5%.

Figure 5. Trends in world trade by region excluding within-country cargo movement.



Source: Authors' analysis using the MINT (2023) dataset.

4.0 Data and Methodology

4.1 Data Sources

The bulk of the data utilized in this study were sourced from the MINT database developed by S&P Global (2022), spanning the period from 2011 to 2021 and encompassing data from 159 countries. To assess world seaborne trade, we grouped countries into seven regions, with the number of countries in each region, based on our categorization and data availability, as follows:

1. Eurasia: 12 countries
2. Latin America: 36 countries
3. Middle East and Africa: 51 countries
4. OECD America: 7 countries
5. OECD Asia Oceania: 5 countries
6. OECD Europe: 19 countries
7. Other Asia: 29 countries

For a detailed breakdown of all countries within each region, please refer to Table A in the Appendix, which provides a comprehensive list of countries by their respective regions on a global scale. However, this database offers comprehensive coverage, encompassing nearly every vessel engaged in international shipping globally, along with information on their origins and destinations. The data were aggregated annually and categorized by vessel type. The data include various components, such as origin and destination country, vessel and cargo type, cargo size, vessel capacity, distance traveled, ton-miles delivered, total fuel consumption, and average ship speed. Additionally, GDP and population data by country were obtained from Oxford Economics, incorporating forecasted figures up to 2050.

For this study, we used the following components from the MINT dataset, the description of which was given by S&P Global:

- Origin departure year: The year of the vessel's departure from the origin port/anchorage country.
- Country of origin: The country of the port/anchorage where the vessel commenced its voyage.
- Destination country: The country of the port/anchorage where the vessel completed its voyage. Note that transit points (for bunkering and canals) were ignored as best as possible (e.g., a vessel with an origin in Brazil with a transit bunkering calling at Singapore completing its voyage in China had its destination country as China rather than as Singapore.
- Cargo size: Cargo size refers to the total cargo weight, in metric tons, of laden vessels making voyages during the aggregated period. It is calculated based on the vessel's draught value at the discharge port, as vessels are often not fully loaded with cargo. The reason for this is that vessels are very often not fully loaded with cargo. The tons per centimeter immersed (TPCI) value of each vessel is used to compare the arrival draught to the maximum draught of the vessel to calculate the estimated cargo size. This calculated tonnage is then subtracted from the maximum capacity tonnage. An estimated bunker fuel tonnage is then subtracted from that value, resulting in the estimated cargo size. The MINT database uses the following equation to calculate the cargo size:

  Cargo size = maximum capacity tonnage – ((maximum draught – arrival draught) × TPCI) – Estimated bunker fuel onboard

The TPCI for any draught is the mass that must be loaded or discharged to change a ship's mean draught in saltwater by one centimeter. The TPCI varies with draught and water density.

4.2 Data Processing and Structuring

To construct the dynamic panel data models, we organized the data into origin-destination (O-D) pairs, which were categorized by region. When running the model with region-to-region O-D pairs, we aggregated the values of all the variables used by region.

To facilitate forecasting, we assigned O-D pairs up to 2050. We used the 2018 O-D pairs as our reference from 2022 to 2050. This choice is supported by the following factors: the availability of comprehensive data for 2018, the establishment of a robust historical baseline for analysis, and the need for ongoing consistency to track changes over time. Additionally, the disruptive effects of the COVID-19 pandemic in 2019 and 2020 make 2018 a more stable and representative reference point for long-term forecasting.

4.3 Variables Used in the Model

In the model, we employed the following variables to estimate the coefficients and forecast the future trend in exports:

- Export (dependent variable)
- GDP of the destination region
- GDP per capita of the region of the origin
- Number of routes (NR) from the origin region (as a proxy of connectivity)
- 2021 as a dummy

Table 1 describes the details of the variables.

As the data were processed by region, GDP and population were aggregated accordingly at the regional level. To calculate exports, cargo sizes were summed by country within specific regions to obtain the total cargo size of those regions. These calculations were applied separately for both origin and destination regions.

Table 1. Description of the variables used in the model.

Variable	Type of variable	Abbreviation	Units	Description
Exports	Dependent	EX	Metric tons	Cargo size including container, dry bulk, general cargo, tanker, and others
GDP of the destination region	Independent	GDP_D	USD	Total GDP of the destination region in USD
GDP per capita of the origin region	Independent	GDPCAP_O	USD	GDP per capita of origin region in USD
Number of routes	Independent	NR	Number	Number of voyages from origin to destination (proxy of connectivity)
Dummy	Independent	Y2021D	[0, 1]	Captures the shock in global exports

Tanker includes chemical, product, liquefied natural gas (LNG), liquefied petroleum gas (LPG), and crude.

The NR was determined on the basis of the country of origin and then aggregated by region to obtain the total NR for region-to-region O-D pairs, representing the proxy of connectivity. For example, we assessed how many destination countries were connected to seaborne trade from a country of origin. Consequently, the connected destination countries represented the NR for the country of origin. The NR for each country within a particular region was subsequently summed to determine the total NR for that region.

After all countries were consolidated by region, the final dataset comprised 539 data points[2]. This sample incorporated inter- and intraregional cargo movements to encompass the entirety of cargo movement, enabling the estimation of corresponding future energy demand.

4.4 Model Specifications

We utilized a dynamic panel data model, recognized as a potent econometric technique for forecasting (Liu, Moon, and Schorfheide 2020; Arkadievich et al. 2008). This approach offers several advantages. First, it allows for the identification of and addresses unobservable and constant heterogeneity within panel data (Coakley, Fuertes, and Smith 2006; Wintoki, Linck, and Netter 2012). Second, the dynamic panel data model is specifically tailored for handling smaller time series datasets, thereby mitigating bias (Santos, and Barrios 2011; Bruno 2005a; Maket, Szakálné Kanó, and Vas 2023). Finally, these models provide a flexible framework for analyzing multiple endogenous variables, offering advantages over static models (Li et al. 2021).

Nickell (1981) noted that the least squares dummy variable (LSDV) estimator yields inconsistent results when estimating the parameters of a first-order autoregressive panel data model with finite time (T) and numerous cross-sectional units (N). As alternatives to the LSDV, various instrumental variable (IV) and generalized method of moments (GMM) estimators have been proposed in the econometric literature (Kiviet 1995; Abonazel 2017; Gujarati 2003). Anderson and Hsiao (1982) suggested an IV estimator by transforming the model into first differences to mitigate unobserved individual heterogeneity. Arellano and Bond (1991) proposed a GMM estimator for the first-differenced model, which, relying on a larger number of internal instruments, is more efficient than is Anderson and Hsiao's model. However, Blundell and Bond (1998) reported that with highly persistent data, first-differenced IV or GMM estimators may suffer from severe small-sample bias due to weak instruments. To address these challenges, a system GMM estimator with first-differenced instruments for the equation in levels and instruments in levels for the first-differenced equation was suggested as a solution (Bruno 2005a).

Bruno (2004) argued that IV-GMM estimators can maintain consistency when the cross-sectional units (N) are large, but the results may be significantly biased with small sample sizes. Nickel (1981) noted that the LSDV estimator has a smaller variance in large samples, albeit inconsistent, than do IV-GMM methods. This observation is supported by studies by Judson and Owen (1999) and Kiviet (2005). While the LSDV may achieve consistency in large samples with an adequate number of periods (T), it may exhibit greater variance than may IV-GMM estimators in small samples with highly persistent data (Bun and Kiviet 2003).

Thus, to address issues such as potential endogeneity, serial correlation, and short-panel bias,

[2] Seven regions over 11 years (7*7*11=539).

we utilize the methods of Kiviet (1995) and Bruno (2005b), known as the (bias)-corrected LSDVC. On the basis of rigorous research conducted by Flannery and Hankins (2013), Bun and Carree (2005), and Judson and Owen (1999), the LSDVC method emerges as a superior alternative to ordinary least squares (OLS), fixed effects, and GMM methods. Other dynamic methods may result in information loss because of their failure to address bias correction in the panel data (Growitsch and Stronzik 2009). Flannery and Hankins (2013) demonstrated that the LSDVC method is particularly effective for short time series data. The bias-corrected LSDVC estimator, as proposed by Kiviet (1995), mitigates the bias potential due to the small sample size. While the LSDVC method is not mainly proposed for endogenous regressors, Flannery and Hankins (2013) mentioned that "we find this to be true, but the damage is limited to the estimated coefficients on the endogenous variables: LSDVC remains accurate for the lagged dependent variable and exogenous regressors". This means that any bias introduced by endogenous variables is minimal when the LSDVC approach is applied. Moreover, Flannery and Hankins (2013) asserted that the LSDVC estimator is among the best precise estimators in the presence of second-order serial correlation. Therefore, we conclude that it is preferable to use the LSDVC estimator over IV and GMM estimators for our analysis.

Furthermore, the LSDVC estimator provides efficient and robust estimates compared with other dynamic estimators, such as GMM estimators, which tend to exhibit higher root mean square errors (RMSEs) and less bias. Specifically, the LSDVC method performs better when the sample of cross-sectional units is small (Bruno 2005a). Accordingly, the model specification becomes the following:

$$ln_EX_{it} = \gamma^{*}(ln_EX_{i,t-1}) + \beta_1^{*}(ln_GDP_D_{it}) + \beta_2^{*}(ln_GDPCAP_O_{it}) + \beta_3^{*}(NR_{it}) + \beta_4^{*}(Y2021D) + \mu_i + \varepsilon_{it},\ i = 1,\ldots,N;\ t = 1,\ldots\ldots T. \quad (1)$$

In the equation, *ln_EX* represents the dependent variable, denoting seaborne exports presented in logarithmic form. $EX_{i,t-1}$, a lagged dependent variable, is included among the regressors to account for the dynamic aspect of seaborne exports. The primary variable of interest, *ln_GDP_D*, represents the GDP of destination countries expressed in natural log terms, whereas *ln_GDPCAP_O* indicates the GDP per capita of the countries of origin, also expressed in natural log terms. The per capita GDP reflects the "income effect" (Moudud-Ul-Huq 2019). The variable NR denotes the NR from countries of origin, whereas Y2021D serves as a dummy variable capturing systemic shocks to global exports. The error term encompasses the O-D specific effect (μ_i) and the white noise error term (ε_{it}) with variance (δ_ε^2). The time span of the selected variables extends from 2011 to 2021.

This study employs a novel Stata routine called *xtlsdvc*, which applies the LSDVC methodology on the basis of the theoretical approximation formulas outlined in Bruno (2005b). This routine also estimates a bootstrap variance-covariance matrix for the corrected estimator.

5.0 Results and Discussion

Table 2 presents the results after applying a bias-correction method. Our analysis focuses on the impact of demand-side inputs, destination country GDP, and country of origin GDP per capita. The GDP of the destination country is indicative of expenditure affordability, thereby affecting both export and production levels. We hypothesize that an increase in destination country GDP leads to greater exports from origin countries. Conversely, the GDP per capita of countries of origin reflects their production capacity, influencing export levels after meeting domestic demand. Additionally, we include the NR as a control variable indicating the proxy of connectivity, which may influence the outcomes.

The diverse characteristics across regions in terms of population and GDP are noted in Figures 3 and 4. To capture this diversity, we need to quantify the fixed effects for each O-D pair because forecasting after applying the LSDVC via the xtlasdvc routine is underestimated because the fixed effects are not captured. Table B (presented in the Appendix) displays the fixed effects for each O-D pair.

5.1 Econometric Analysis: LSDVC Dynamic Regression Model

We transition to a dynamic regression model. Equation (1) is computed via the bias-corrected LSDVC method. As mentioned, Flannery and Hankins (2013) discovered that LSDVC estimates remain robust, irrespective of whether the initial coefficient matrix is estimated through difference GMM or system GMM. The Stata command xtlsdvc reports bootstrap standard errors. Notably, LSDVC estimation automatically incorporates the lagged measure of the dependent variable.

All the variables of interest are significant in the anticipated direction (Table 2).

5.2 Current and Future Global Exports

Global population growth is decelerating, with the global population projected to reach 9.7 billion

Table 2. LSDVC dynamic regression estimation results with bias correction.

Variable	Coef.	Bootstrapped std. err.	Z	P > |z|	95% conf. interval	
					Lower	Upper
ln_EX_{t-1}	0.2123	0.0267	7.94	0.000	0.1595	0.2641
ln_GDP_D	**0.4988**	**0.1088**	**4.58**	**0.000**	**0.2855**	**0.7121**
ln_GDPCAP_O	**0.2753**	**0.1066**	**2.58**	**0.010**	**0.0664**	**0.4843**
NR	0.0005	0.0005	1.05	0.294	–0.0005	0.0015
Y2021D	0.0485	0.0222	2.18	0.029	0.0049	0.0920
Observations	441					
Number of groups	49					

Source: Authors' analysis using the MINT dataset (2023).

people by 2050 (UNCTAD 2023). Economic expansion is expected to persist, with the global economy expected to reach US$300 trillion by 2050, boasting an average growth rate of 2.5% from 2019 to 2050 (DNV 2022). Historically, trade demand has surged due to GDP and population growth, along with advancements in living standards. The overall demand for maritime trade dictates the extent of maritime energy consumption and corresponding GHG emissions, potentially mitigated by EE improvements driven by targets set by international organizations such as the IMO for the shipping sector.

Using a gravity model[3], the IMO forecasts that global maritime trade could increase by 40% to 115% by 2050 compared with 2020 levels (IMO 2020). The fuel composition of the shipping sector, primarily HFO, has remained largely unchanged over the years because of the challenges inherent in finding greener and commercially feasible fuels for shipping (IMO 2014, 2020). Without mitigation measures, GHG emissions from shipping could increase by 50% to 250% by 2050 (IMO 2020). The increase in both population and wealth drives increased consumption, resulting in increased demand for goods and, subsequently, increased energy consumption unless offset by significant efficiency enhancements.

International trade has gained significant prominence, with a growing portion of GDP allocated to both exports and imports. Understanding the global patterns of exports and imports is particularly vital for all nations. The accurate estimation and forecasting of these trends are pivotal for shaping future policies and fostering development on a global scale.

As shown in Figure 6, OECD Asia Oceania presents the highest annual growth rate of 7.0% (compound annual growth rate) over the past decade, with Latin America showing the lowest growth rate of 2.6%. OECD Asia Oceania comprises China, Japan, South Korea, Australia, and New Zealand, with China's presence potentially exerting a significant influence on global trade. OECD America, encompassing the U.S. and Canada, among countries, secures the second-highest growth, at 5.4%, whereas Other Asia ranks third, with a growth rate of 5.2%, driven primarily by countries such as India, Malaysia, Indonesia, Thailand, and Vietnam.

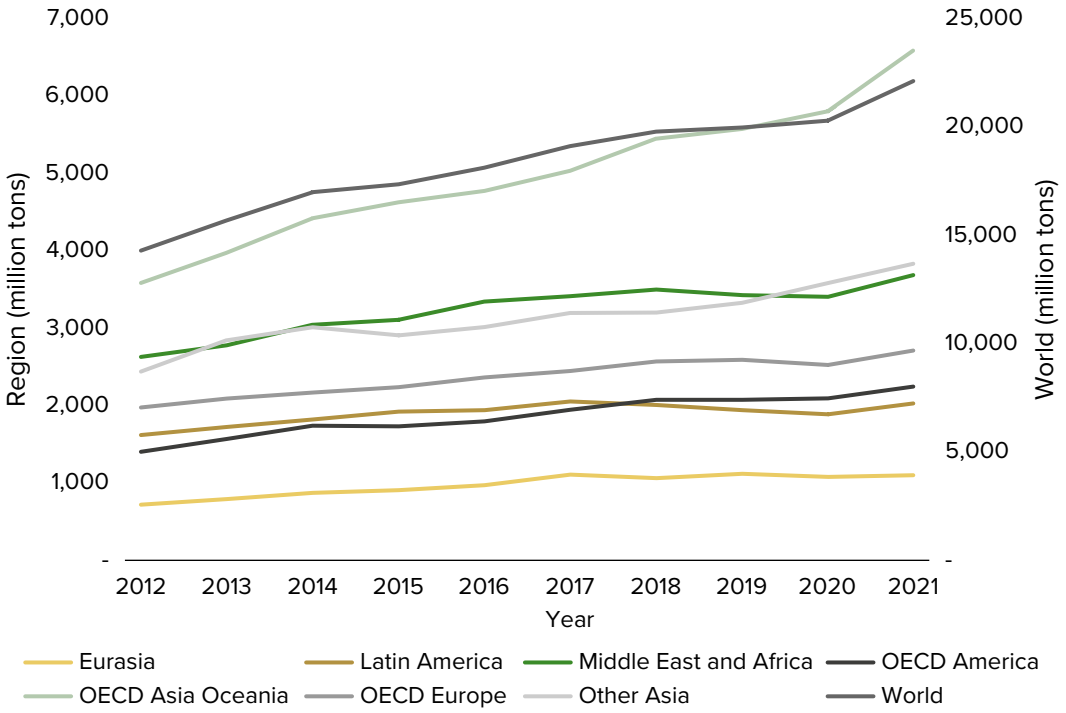
Utilizing the coefficients outlined in Table 2, we estimate future global exports up to 2050 (see Table 3). The overall growth in exports is anticipated to reach 2.4% globally, with Other Asia expected to lead with a growth rate of 3.5%, and OECD Europe projected to have the lowest growth, at 1.5%, among all regions worldwide (authors' analysis). OECD Asia Oceania is forecasted to experience the second-highest growth of 2.6% by 2050. Figures 1 and 2 illustrate the estimated future global and percentage shares of global trade, respectively, up to 2050.

Approximately 22 billion in trade volume was recorded in 2021, including both intra- and intercountry trade movements. Excluding intracountry movements reduces this figure to 15 billion tons, whereas excluding intraregional trade further decreases it to 11 billion tons. However, as this study aims to assess the impact of such trade on global shipping energy demand, both intracountry and intraregional movements are considered.

Global trade is expected to rise to 44 billion tons, with 2.4% average annual growth by 2050. By 2030, it is expected to reach 28 billion tons with a

[3] Refer to IMO (2020) for details.

Figure 6. Historical trends of trade/exports by region including domestic trade.



Source: Authors' analysis using the MINT (2023) dataset.

3% average annual growth rate, and by 2040, it is forecasted to reach 36 billion tons with an average annual growth rate of 2.6% (see Figure 7).

According to Figure 8, OECD Asia Oceania emerges as the top contributor to global exports, a trend projected to continue until 2050. Other Asia initially ranks third, with the Middle East and Africa in second place. However, during the forecast period, Other Asia surpasses the Middle East and Africa to claim the second-highest position in contributing to global exports. Similarly, OECD America's contribution surpasses that of Latin America during the forecast period.

The trend of regional shares to global exports has been decreasing for five regions over the years, except for OECD Asia Oceania and Other Asia. The share of OECD Europe has declined by approximately 0.87%, followed by OECD America by 0.67%, Eurasia by 0.41%, the Middle East and Africa by 0.39%, and Latin America by 0.38%. Conversely, the contribution from Other Asia has increased by 1.02%, whereas that from OECD Asia Oceania has slightly increased by 0.21% (see Figure 8).

5.3 Impact on Future Energy Demand: 2022-2050

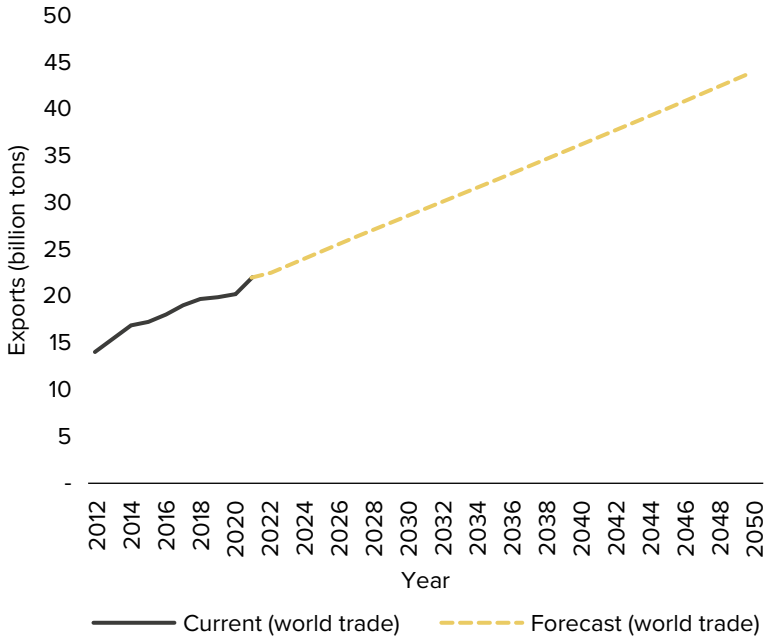
The objective of curbing the increase in GHG emissions to targeted levels has spurred the international community to collaborate in reducing GHG emissions globally. While significant efforts have been directed toward national commitments for local emission reductions, an increasing portion of GHG emissions originates from international shipping. According to estimates by the IMO, CO_2

Table 3. Historical and estimated export numbers up to 2050 (in billion tons).

Year	Global trade
2012	14.20
2013	15.60
2014	16.90
2015	17.27
2016	18.03
2017	19.02
2018	19.69
2019	19.88
2020	20.20
2021	22.03
2022	22.52
2023	23.31
2024	24.09
2025	24.87
2026	25.63
2027	26.39
2028	27.13
2029	27.88
2030	28.63
2031	29.38
2032	30.13
2033	30.89
2034	31.64
2035	32.39
2036	33.14
2037	33.89
2038	34.65
2039	35.41
2040	36.18
2041	36.95
2042	37.74
2043	38.53
2044	39.32
2045	40.12
2046	40.91
2047	41.70
2048	42.50
2049	43.28
2050	44.07

Source: Authors' analysis using the MINT dataset (2023).

Figure 7. Estimated world's future exports up to 2050.



Source: Authors' analysis using MINT (2023) dataset.

emissions from international shipping escalated to 1,056 million tons in 2018, marking a 9.3% growth from 2012 levels, and are projected to surge to between 90% and 130% of 2008 emission levels by 2050 (IMO 2020).

Following the Kyoto Protocol, the IMO has assumed responsibility for reducing emissions from shipping (Perera and Mo 2016). The IMO has been actively engaged in efforts to mitigate GHG emissions from the shipping industry. The Marine Environment Protection Committee (MEPC) oversees the regulatory framework for environmentally friendly shipping and reviews emission regulations such as the EEDI, EEOI, EEXI, and SEEMP (Zhang et al. 2019). These measures aimed at eco-efficiency in the shipping sector ultimately strive to increase the EE of ships. As the EEDI standards become progressively stringent, newly constructed vessels are required to be more energy efficient than are existing vessels (Ahn et al. 2019).

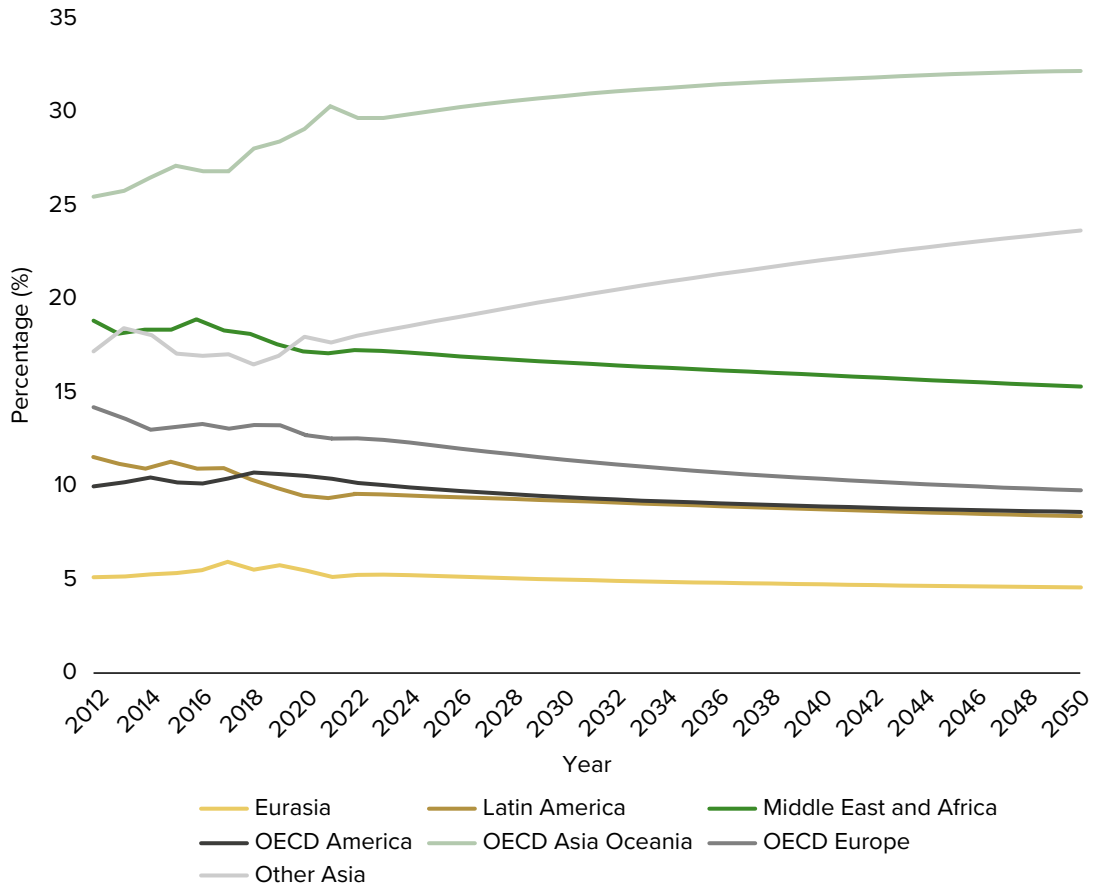
5.3.1 Scenario Descriptions to Forecast Energy Demand

As per published data from the IEA (2021), we develop the following three scenarios to comprehend the influence on future energy demand:

1. **Business-as-usual (BAU) scenario:** In the BAU scenario, there is no consideration of EE or SD assumptions, which implies that development growth relies primarily on fossil fuel utilization and that future energy demand is projected to follow historical trends without implementing substantial mitigation measures.

2. **Energy efficiency (EE) scenario:** As previously discussed, implementing measures to increase EE is crucial for reducing emissions. Hence, it is assumed that a certain level of EE can

Figure 8. Percentage contribution to global exports by region.



Source: Authors' analysis using MINT (2023) dataset.

be attained by adhering to the IMO's EE regulations, including the EEDI, SEEMP, EEXI, and EEOI. Consequently, in this scenario, it is assumed that an approximately 1.5% improvement in EE can be realized.

3. **Sustainable development (SD) scenario:** This scenario depicts a comprehensive pathway toward deep decarbonization, incorporating both EE measures and alternative fuel options concurrently. By utilizing clean energy and implementing EE measures, significant improvements in energy intensity levels can be achieved. The SD scenario reflects the necessary contribution from clean energy technology innovation for a transition to clean energy, aiming for net-zero CO_2 emissions by 2050. This scenario outlines the broad evolution of the energy sector required to achieve the key energy-related goals of the United Nations, including the climate goal of the Paris Agreement (SDG 13) and universal access to modern energy by 2030 (SDG 7). In this scenario, a 2% improvement in EE is assumed.

5.3.2 Energy Intensity Scenarios

We utilize the IEA EEOI data for international shipping, which describes the EE and SD scenarios, covering the period from 2005 to 2030 (IEA 2020). On the basis of this understanding, we assume and develop the three scenarios described earlier.

Taking this understandings into account, Figure 9 depicts the energy intensity numbers from 2022 to 2050, highlighting the improvements in EE.

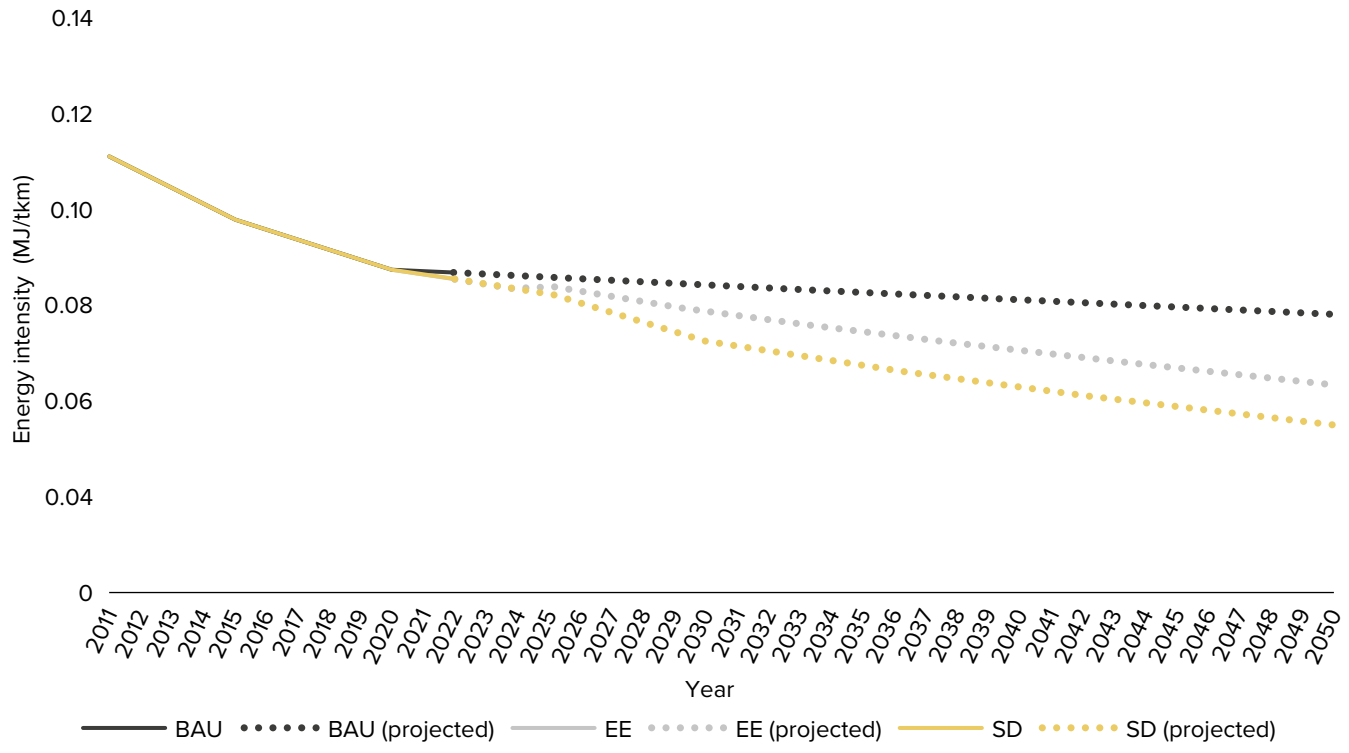
In essence, our estimation of future energy consumption for the shipping sector incorporates anticipated EE enhancements and export volumes by region up to 2050. Energy intensity is measured in MJ/t-km and converted to its oil equivalent.

5.3.3 Global Future Energy Demand

An increase in GDP increases the volume of international trade, consequently leading to an increase in final energy demand. Embracing clean energy and efficiency measures can serve as vital mechanisms in mitigating this final energy demand. The transition toward clean energy and the commitments outlined in the Paris Agreement propel the adoption of renewable energy and EE measures. These endeavors suggest that under the SD scenario, energy demand in the shipping sector is expected to decrease significantly compared with that under the other two scenarios. To estimate the impact on energy demand, the following two key considerations are taken into account:

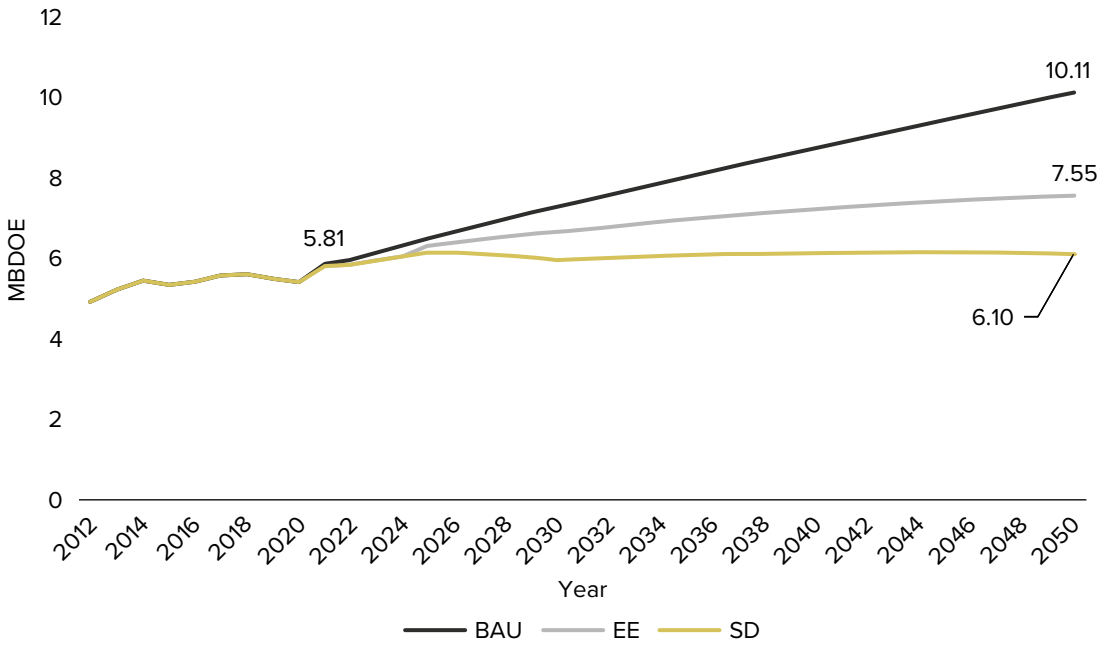
1. We utilize the average global shipping energy intensity numbers (Figure 9).

Figure 9. Energy intensity from 2011 to 2050.



Source: Authors' analysis using IEA (2021) data.

Figure 10. Global energy demand in the shipping sector.



Source: Authors' analysis using the MINT (2023) dataset.

2. A global average (weighted) export distance of 4,100 nautical miles (NM) is employed (Rodrigue 2020; WWF 2011).

Figure 10 presents a projection of the final energy demand up to 2050 for the various scenarios outlined in this study.

In the absence of mitigation measures to improve EE in international shipping, the BAU scenario anticipates a 72% overall increase in energy demand by 2050 compared with 2021 levels, translating to an average annual growth rate of 1.89%. Similarly, under the EE scenario, the final energy demand is projected to increase by a total of 30%, with an average annual growth rate of 0.91%. Conversely, the SD scenario indicates only a 5% increase in energy demand, equating to an average annual growth rate of 0.17%. Notably, a substantial reduction in energy demand is expected under the EE and SD scenarios compared with under the BAU scenario. For example, by 2050, the EE and SD scenarios foresee energy demands of 7.55 mboe/d and 6.10 mboe/d, respectively, compared with 5.81 mboe/d in 2021. Conversely, the BAU scenario would lead to an increase in energy demand to 10.11 mboe/d by 2050, which suggests that SD efforts could reduce energy demand by approximately 40%, whereas EE measures might result in a reduction of approximately 25% compared with BAU measures.

6.0 Conclusions

This study aims to provide insights into future energy demand in the global shipping sector and outlines the methodology and data used for analysis. This study encompasses an analysis of 159 countries worldwide, categorized into the following seven regions: Eurasia, Latin America, the Middle East and Africa, OECD America, OECD Asia Oceania, OECD Europe, and Other Asia. We categorize these regions to comprehend regional energy demand trends up to 2050. Notably, China, the U.S., and India significantly influence the global economy in terms of GDP, population size, and consequently energy demand.

The SD scenario may achieve reduced energy consumption through a combination of improved energy intensity with low-carbon energy sources and technological advancements in ship design. Compared with those under other scenarios, these innovations facilitate a smoother transition to a lower-emission system, resulting in less pronounced effects on energy demand. Thus, the energy demand in the SD scenario remains below the levels projected under the BAU scenario. Under the SD scenario, the global energy demand in the shipping sector rises to 6.10 mboe/d by 2050, up from 5.81 mboe/d in 2021. This still represents a reduction of more than 4 mboe/d compared with the BAU scenario in 2050. Similarly, the EE scenario forecasts a lower energy demand than does the BAU scenario. Under the EE scenario, the global energy demand in the shipping sector increases to 7.55 mboe/d by 2050, increasing from 5.81 mboe/d in 2021. Despite this increase, it still represents a reduction of more than 2.5 mboe/d relative to the BAU scenario in 2050.

The EE and SD scenarios outlined in this paper underscore the potential impact of feasible EE measures, highlighting the significant potential to reduce future energy demand, thereby positively contributing to emission reduction efforts. Consequently, it is imperative to integrate all viable mitigation options, including technological innovations, enhanced EE measures, and alternative fuels, into future strategies. Establishing a coherent, holistic, and integrated approach is challenging yet essential in steering the world toward a sustainable, energy-efficient, and net-zero trajectory. Hence, collaboration among relevant stakeholders is paramount to identify and promote partnerships and cooperative initiatives aimed at investing in technology and innovation to foster inclusive solutions.

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Appendix

Table A. List of countries by region.

Eurasia (12)	Latin America (36)	Middle East and Africa (51)	OECD America (7)	OECD Asia Oceania (5)	OECD Europe (19)	Other Asia (29)
Albania	Antigua and Barbuda	Algeria	Canada	Australia	Belgium	Azerbaijan
Bulgaria	Argentina	Angola	Chile	China	Denmark	Bangladesh
Croatia	Aruba	Bahrain	Greenland	Japan	Estonia	Brunei
Cyprus	Bahamas	Benin	Mexico	Korea, South	Finland	Cambodia
Latvia	Barbados	Cameroon	Puerto Rico	New Zealand	France	Chinese Taipei
Lithuania	Belize	Cape Verde	U.S.		Germany	Fiji
Malta	Bermuda	Comoros	Virgin Islands, U.S.		Greece	Georgia
Moldova	Brazil	Congo (Democratic Republic)			Iceland	Hong Kong, China
Montenegro	Cayman Islands	Cote D'ivoire			Irish Republic	India
Romania	Colombia	Djibouti			Italy	Indonesia
Russia	Costa Rica	Egypt			Netherlands	Kazakhstan
Ukraine	Cuba	Equatorial Guinea			Norway	Kiribati
	Dominica	Eritrea			Poland	Korea, North
	Dominican Republic	Gabon			Portugal	Macao, China
	Ecuador	Gambia			Slovenia	Malaysia
	El Salvador	Ghana			Spain	Maldives
	Grenada	Guinea			Sweden	Myanmar
	Guadeloupe	Guinea-Bissau			Turkey	Pakistan
	Guatemala	Iran			United Kingdom	Papua New Guinea
	Guyana	Iraq				Philippines
	Haiti	Israel				Samoa
	Honduras	Jordan (Gulf)				Singapore
	Jamaica	Kenya				Solomon Islands
	Martinique	Kuwait				Sri Lanka
	Nicaragua	Lebanon				Thailand
	Panama	Liberia				Tonga
	Paraguay	Libya				Turkmenistan
	Peru	Madagascar				Vanuatu
	St Kitts and Nevis	Mauritania				Vietnam
	St Lucia	Mauritius				
	St Vincent and The Grenadines	Morocco				
	Suriname	Mozambique				
	Trinidad and Tobago	Namibia				
	Uruguay	Nigeria				
	Venezuela	Oman				
	Virgin Islands, British	Qatar				
		Reunion				

(Continued)

Appendix

Eurasia (12)	Latin America (36)	Middle East and Africa (51)	OECD America (7)	OECD Asia Oceania (5)	OECD Europe (19)	Other Asia (29)
		Sao Tome and Principe				
		Saudi Arabia				
		Senegal				
		Seychelles				
		Sierra Leone				
		Somalia				
		South Africa				
		Sudan				
		Syria				
		Tanzania				
		Togo				
		Tunisia				
		United Arab Emirates				
		Yemen				

Note: The numbers in parentheses reflect the total numbers of countries within the regions.

Table B. Estimated fixed effects of each O-D pair.

SL_OD	OD_Label *	Origin (O)		Destination (D)	Estimated fixed effects of each O-D pair
1	11	OECD America	To	OECD America	4.813
2	12	OECD America	To	Middle East and Africa	3.658
3	13	OECD America	To	OECD Europe	3.863
4	14	OECD America	To	OECD Asia Oceania	4.201
5	15	OECD America	To	Latin America	4.655
6	16	OECD America	To	Other Asia	3.814
7	17	OECD America	To	Eurasia	3.042
8	21	Middle East and Africa	To	OECD America	3.872
9	22	Middle East and Africa	To	Middle East and Africa	5.859
10	23	Middle East and Africa	To	OECD Europe	4.823
11	24	Middle East and Africa	To	OECD Asia Oceania	5.388
12	25	Middle East and Africa	To	Latin America	4.087
13	26	Middle East and Africa	To	Other Asia	5.698
14	27	Middle East and Africa	To	Eurasia	4.043
15	31	OECD Europe	To	OECD America	3.590
16	32	OECD Europe	To	Middle East and Africa	4.780
17	33	OECD Europe	To	OECD Europe	5.298
18	34	OECD Europe	To	OECD Asia Oceania	2.913
19	35	OECD Europe	To	Latin America	3.770
20	36	OECD Europe	To	Other Asia	3.983
21	37	OECD Europe	To	Eurasia	4.375
22	41	OECD Asia Oceania	To	OECD America	4.104

(Continued)

SL_OD	OD_Label *	Origin (O)		Destination (D)	Estimated fixed effects of each O-D pair
23	42	OECD Asia Oceania	To	Middle East and Africa	4.073
24	43	OECD Asia Oceania	To	OECD Europe	3.210
25	44	OECD Asia Oceania	To	OECD Asia Oceania	6.409
26	45	OECD Asia Oceania	To	Latin America	3.950
27	46	OECD Asia Oceania	To	Other Asia	5.695
28	47	OECD Asia Oceania	To	Eurasia	3.418
29	51	Latin America	To	OECD America	4.257
30	52	Latin America	To	Middle East and Africa	4.620
31	53	Latin America	To	OECD Europe	4.239
32	54	Latin America	To	OECD Asia Oceania	4.787
33	55	Latin America	To	Latin America	5.645
34	56	Latin America	To	Other Asia	4.437
35	57	Latin America	To	Eurasia	3.239
36	61	Other Asia	To	OECD America	3.439
37	62	Other Asia	To	Middle East and Africa	5.421
38	63	Other Asia	To	OECD Europe	4.409
39	64	Other Asia	To	OECD Asia Oceania	5.569
40	65	Other Asia	To	Latin America	3.723
41	66	Other Asia	To	Other Asia	6.572
42	67	Other Asia	To	Eurasia	3.819
43	71	Eurasia	To	OECD America	2.542
44	72	Eurasia	To	Middle East and Africa	4.425
45	73	Eurasia	To	OECD Europe	4.794
46	74	Eurasia	To	OECD Asia Oceania	4.011
47	75	Eurasia	To	Latin America	3.084
48	76	Eurasia	To	Other Asia	3.829
49	77	Eurasia	To	Eurasia	5.025

* Label of regions: 1 – OECD America; 2 – Middle East and Africa; 3 – OECD Europe; 4 – OECD Asia Oceania; 5 – Latin America; 6 – Other Asia; 7 – Eurasia. 11 stands for from OECD America to OECD America; 21 stands for from Middle East and Africa to OECD America, and so on.

Source: Authors' analysis using the MINT dataset (2023).

Notes

Notes

About the Authors



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About the Project

The increasing global seaborne trade volume is the major driver of the marine fuel market. According to the International Chamber of Shipping, over 90% of the world's shipped goods travel by marine cargo vessels. Seaborne trade is continuously expanding, adding benefits for consumers through competitive freight costs. Trade expansion in the marine sector has significant implications for marine fuel demand. Additionally, a few interventions introduced by the IMO will have an impact on future oil demand and on fuel shifts across the global marine industry. Therefore, the maritime sector will continue to experience unique energy demand and consumption trends. This project is designed to draw insights from the characteristics and energy decisions of the maritime sector in different regions of the world.



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