Choose Clean Energy or Green Technology? Empirical Evidence from Global Ships

Abstract

On January 1st, 2020, the International Maritime Organization (IMO) implemented a new regulation for a 0.50% global sulphur cap for marine fuels, which was a dramatic decrease from the previous emissions cap of 3.5%. The new regulation will have an enormous impact on the shipping market. At present, there are different feasible schemes for reducing sulphur emissions from ships. Shipowners need to consider the economic cost, energy feasibility, and other relevant factors of different schemes before making decisions. This paper empirically explores the factors that affect shipowners' energy choices. Based on the new emerging individual ship dynamic data, Automatic Identification System (AIS), and other relevant databases, we apply various data mining methods and a threshold discrete choice model combined with an oversampling technique to conduct quantitative measurements and statistical analyses of factors for each ship type that affect the shipowners' choices. Three groups of indicators, including ship characteristics, shipowner characteristics, and market conditions, are considered in our analysis. In the model, we also address the heterogeneity of the carriers towards environmental awareness. This study provides important practical implications for responding to the new emissions regulations among maritime and maritime-related industries and policymakers.

Keywords: *IMO emissions regulation, energy choice, AIS data, policy formulation, ship behaviour.*

1. Introduction

While water transport is considered to be the most energy-efficient transport mode compared with rail, road, and air (IMO, 2009), the cumulative NOx and SOx emissions from international shipping are considerable. It is estimated that NOx and SOx produced by international shipping represent 13% and 12% of the global NOx and SOx from anthropogenic sources, respectively (IMO, 2015). In recent years, there has been increasing concern about ship emissions. In response to the rising pollution from ships, the International Maritime Organization (IMO) has implemented a regulation with a 0.5% global sulphur cap for marine fuels since 2020, which is a dramatic decrease from the previous emissions cap of 3.5%.

Shipowners must make a choice on different energy schemes to satisfy the sulphur cap regulation. At present, there are mainly three feasible schemes, and the shipowners need to consider various factors before making their decisions because each scheme has its advantages and disadvantages. The first scheme is to use low-sulphur residual fuel oil (LSFO) or marine gas oil (MGO), whose overall sulphur content is reduced to less than 0.5%. The second scheme is to use alternative types of fuel, such as liquefied natural gas (LNG). LNG can significantly reduce the emission of sulphur oxides, nitrogen oxides and particulate matter. The third scheme is to install a scrubber and continue using high-sulphur residual fuel oil (HSFO). A scrubber removes sulphur from the exhaust gas, thus reducing the sulphur emissions. The benefits, cost, and limitations of each scheme are summarized in Table 1.

Table 1 – The benefits, cost and limitations of each scheme

Scheme	Benefits	Cost	Limitations
Use low-sulphur residual fuel oil (LSFO) or marine gas oil (MGO)	· Save the cost of capital investments in modifying ships · Save the cost of learning the operation of new equipment	The high price of low-sulphur oil will vastly increase the operating cost.	There would be an increase in safety-related incidents onboard due to the use of blended fuel (Einemo, 2018).
Use alternative types of fuel, such as liquefied natural gas (LNG)	LNG is usually cheaper in Europe and the US.	· High cost of conversion · Operators and crew must learn how to operate new facilities	· LNG fuels require approximately twice as much space as conventional fuels, which reduces the load capacity (Grimmer and Myers, 2017) · Lack of LNG supply facilities and maintenance facilities
Install a scrubber and continue to use high-sulphur residual fuel oil (HSFO)	· Low fuel cost · Easy to learn how to operate the new equipment · Fuel reliability and safety can be guaranteed	High installation cost	· Certain power requirements and space requirements · Lack of maintenance facilities

The new IMO 2020 regulation will profoundly impact the shipping market and related industries. AlixParners (2019) estimated that the container-shipping industry must offset up to $10 billion in costs to accompany the new regulations. For shipowners, the cost of different schemes varies significantly, and the decision will have an enormous impact on their revenues. The choice of shipowners will also, in turn, greatly influence the fuel supply chain and other related industries.

A considerable number of studies have been conducted on how shipowners choose among the alternative options to adapt to the related regulations. Most studies adopt cost-benefit analysis (Lindstad et al., 2015; Zis et al., 2016; Zhu et al., 2020). These studies compare different options from the perspective of shipowners' benefits and cost. Some other studies apply optimization models to model shippers' decision processes (Balland et al., 2015; Patricksson and Erikstad, 2017; Zhen et al., 2020). Multi-criteria decision-making (MCDM) methods are also common approaches to solve the energy choice problem (Yang et al., 2012; Schinas and Stefanakos, 2014; Ren and Lutzen, 2015).

It is noted that these existing studies have limitations, which could lead to a gap between academic research and the actual shipowners' choices in the shipping industry. These limitations include the following: 1) Cost-benefit analysis ignores the role of non-economic factors, such as the technical maturity of different schemes, which plays an essential role in decision-making (Balland et al., 2015). 2) Considering the uncertainties of parameters, assumptions and estimates of the parameters' values or distributions made in the optimization models or cost-benefit analysis might not accurately reflect the actual situation, which could mislead the results (Zhu et al., 2020). 3) Although MCDM can solve problems in the cost-benefit analysis by considering the non-economic criteria, as the weights of the criteria and the relative performances of the alternatives are usually determined in the light of the experts' experiences, sometimes the MCDM does not perform very well due to the vagueness, ambiguity and subjectivity of human judgements (Ren and Lutzen, 2015). 4) We also note that previous studies are mainly focused on a paricular scope of ships or specific areas, such as existing Emission Control Areas (ECA), failing to reflect the overall situation, while the IMO 2020 regulation is a global concern.

This study aims to contribute to the current literature by conducting an empirical study on shipowners' energy choices at the shipping carrier level. Various factors can determine shipowners' energy choices. Some can be directly retrieved from existing databases, while some are difficult to obtain directly, such as a ship's operational pattern. The difficulty in accurately measuring these factors limits the empirical research on this issue. Automatic Identification System (AIS) data, a type of emerging satellite data that reports on individual ship dynamic information, makes it possible to derive determinants that are difficult to obtain by traditional means. With increasing accuracy and broad geographic coverage, AIS enables us to perform detailed analysis at the individual ship level. However, it is also noted that the super large scale of the global AIS data makes it difficult to conduct empirical studies. This study adopts large-scale data processing techniques and develops data mining algorithms to solve this problem. Subsequently, we derive factors for different ship types that could influence shipowners' choices from the AIS data. Based on a broad scope of factors that we have retrieved, a discrete choice model is used to empirically reveal the carriers' concerns and preferences of different ship types in their energy scheme choices. Nevertheless, due to the extreme sample imbalance in our dataset and the heterogeneity of the shipowners' preferences for different energy schemes, a standard discrete model could lead to biased and inaccurate estimation. An oversampling technique is adopted to balance the dataset and ensure the estimation reliability to remedy this concern. In addition, we note that heterogeneity can exist among the carriers towards their environmental awareness, which is also tested through a threshold discrete choice model that incorporates the interaction terms.

This study enriches the literature concerning AIS applications in discovering ship behaviours. Although AIS has served as an important data source for studies in various fields (Hansen et al., 2013; Winther et al., 2014; Adland et al., 2017), limited attention has been paid to its application in discovering ship's operational behaviour. In this study, we adopt data mining techniques and develop a clustering-based algorithm to analyse a ship's operational patterns on an individual voyage level with AIS data. These algorithms provide fundamental methods for future research. For example, a clustering-based algorithm that measures a ship's trading route diversity is proposed, significantly improving the accuracy and efficiency compared with traditional methods. It enriches the toolbox for trading pattern analysis, an important issue that is receiving rising attention in maritime studies (Prochazka et al., 2019).

In practice, this study provides important managerial implications for relevant stakeholders in maritime and related industries. For example, this study reveals the aggregate choice of global shipowners towards energy scheme choices, which helps to benchmark their choices against alternatives. This study can also enable the related industries to know how the key determinants influence the shipowners' choices and develop strategies that optimize their resource utilization. More importantly, findings can help policymakers to formulate efficient policies to maximize the overall social welfare, for example, reduce the emissions with the least cost.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 outlines the methodology for model building. Section 4 presents data extraction and descriptive statistics. Section 5 presents our empirical results. Section 6 discusses the implications. Finally, some conclusions are drawn in Section 7.

2. Literature Review

This paper can be related to two strands of literature: first, the choice among various energy alternatives; second, AIS applications in solving practical problems in shipping. This section briefly reviews the decision-making process in marine energy choices and AIS data applications in shipping.

2.1. Marine energy choices

With increasing attention being paid to sulphur emission regulation issues, exploring the best solution for sulphur emission regulation compliance has become a research hotspot in recent years. To solve this problem, various methods have been proposed in previous studies. A large number of existing studies adopt cost-benefit analysis. For example, Zis et al. (2016) used a cost-benefit analysis method to perform a case study and highlighted the importance of operating patterns (e.g., speed, engine load, and time at berth) to the payback time of different options. Lindstad et al. (2015) assessed each scheme's total cost as a function of the engine size, the annual fuel consumption in the ECA, and the foreseen future fuel prices. They confirmed that the fuel price significantly influences the shipowners' decisions. However, Jiang et al. (2014) noted that most of these studies consider only the private costs of the shipowners and do not account for other criteria, such as social benefits. Balland et al. (2015) pointed out that non-economic factors (such as the technical maturity of different schemes, safety risk, and complexity of operation) play an important role in selecting air emission controls in shipping. Furthermore, the parameters' uncertainty is not considered in the cost-benefit analysis, which could lead to misleading results.

Some studies apply optimization models to the decision problem. Balland et al. (2015) developed an optimization model that considers both economic and non-economic factors. Patricksson and Erikstad (2017) accounted for the uncertainty of future fuel prices and proposed a stochastic optimization model for the equipment selection problem. They found that the fuel price and the associated uncertainty have a significant impact on the shipowners' choices. Nevertheless, certain assumptions and estimates of the parameters' values or distributions are made in optimization models, which largely decides their findings' reliability.

MCDM is also one broadly adopted approach in this regard. In addition to overcoming the barrier of single-dimensional thinking, MCDM overcomes the barrier in current cost-benefit analysis techniques and enables shipowners to make decisions based on multiple criteria, including cost savings and environmental protection. Yang et al. (2012) constructed a model for selecting emissions controls that combines the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) and Analytic Hierarchy Process (AHP) techniques. Schinas and Stefanakos (2014) proposed a decision-making framework based on the Analytic Network Process (ANP) to help shipowners comply with MARPOL Annex VI. However, there are no objective standards by which people assess each criterion's weights and the performances of the alternatives in AHP/ANP. In practice, alternatively, they are usually evaluated by experts. This approach could lead to vagueness and subjectivity (Ren and Lutzen, 2015).

In terms of the research scope, previous studies have mainly focused on particular areas or scope, e.g., existing Emission Control Areas (ECAs) (Lindstad et al., 2015), and Europe (Patricksson and Erikstad, 2017) or China's offshore areas (Fan and Gu, 2019). Besides, case studies are often conducted for a particular vessel type (Zhu et al., 2020). Comparing different compliance options globally, including broad shipping segments, has remained untapped.

With the formal implementation of sulphur limit regulations by IMO in 2020, it is urgent and of great importance to propose a method to fill the existing research gap. In this study, an integrated decision-making framework incorporating data mining technologies and a discrete choice model with a broad scope of explanatory variables is proposed to reveal shipowners' concerns in energy scheme choices. This work is conducted at a micro level considering all ship types worldwide.

2.2. Applications of AIS data in shipping

Recently, increasing number of studies focused on the application of AIS in solving shipping problems (Zhang et al., 2019; Regli and Nomikos, 2019). Current studies on shipowners' energy choices mainly focus on economic factors or ship physical characteristics, such as fuel cost or engine size (Lindstad et al., 2015), because they are easy to collect or can be retrieved directly from existing databases. We note that insufficient attention has been paid to a ship's operational characteristics (such as trading routes), which is difficult to quantify but could play a critical role in decision-making (Zis et al., 2016). In this study, we fill this gap by deriving ship characteristics and behaviours from the AIS data. AIS provides detailed information on ship characteristics, such as the ship's type, length and width, latitude and longitude, timestamp, etc. (Yang et al., 2019). From the position and time stamp in the AIS, a ship's historical trajectory can be constructed. Li et al. (2016) processed ship trajectories to estimate time-in-modes in the Pearl River Delta region, evaluating the trip time spent in the Emission Control Area (ECA). Zhou et al. (2019) classified the travel patterns using the static ship characteristics, paths, and speed derived from the AIS. These attributes and others can be the determinants of carriers' energy choices (Fevre, 2018). In this study, multiple data mining techniques are adopted to derive a range of attributes that capture a ship's operational pattern and behaviour, such as a ship's trading route diversity and the trip distance from a ship's historical trajectories and other information provided by AIS as well as other databases. These algorithms provide references for ship behaviour analysis and enrich the toolbox for future relevant studies.

Based on the above literature review, the gap between academic research and energy choice practice in the shipping industry has been identified. First, our work is one of the first studies to empirically analyze shipowners' response using revealed preference (RF) data. Empirical model using RF data has some advantages over traditional methods and helps to fill the gaps in the previous works. Second, a broader coverage of determinants and the consideration of shipowners' heterogeneity distinct our work from the few existing empirical research. Different from previous works (Solakivi et al., 2019; Li et al., 2020; and Kokosalakis et al., 2021), we devote attention to dynamic determinants including market conditions and operational characteristics obtained by AIS data mining. Moreover, we consider the heterogeneity among different vessel types and shipowners with different environmental awareness, which deepens and enriches the understandings on this issue. Finally, cross-disciplinary technologies are adopted in achieving the research objective.

3. Methodology

This study proposes an analytical framework that consists of three modules to reveal the rationale of shipowners' decisions on which energy scheme to adopt to comply with the IMO's new rule. The framework is illustrated in Figure 1.

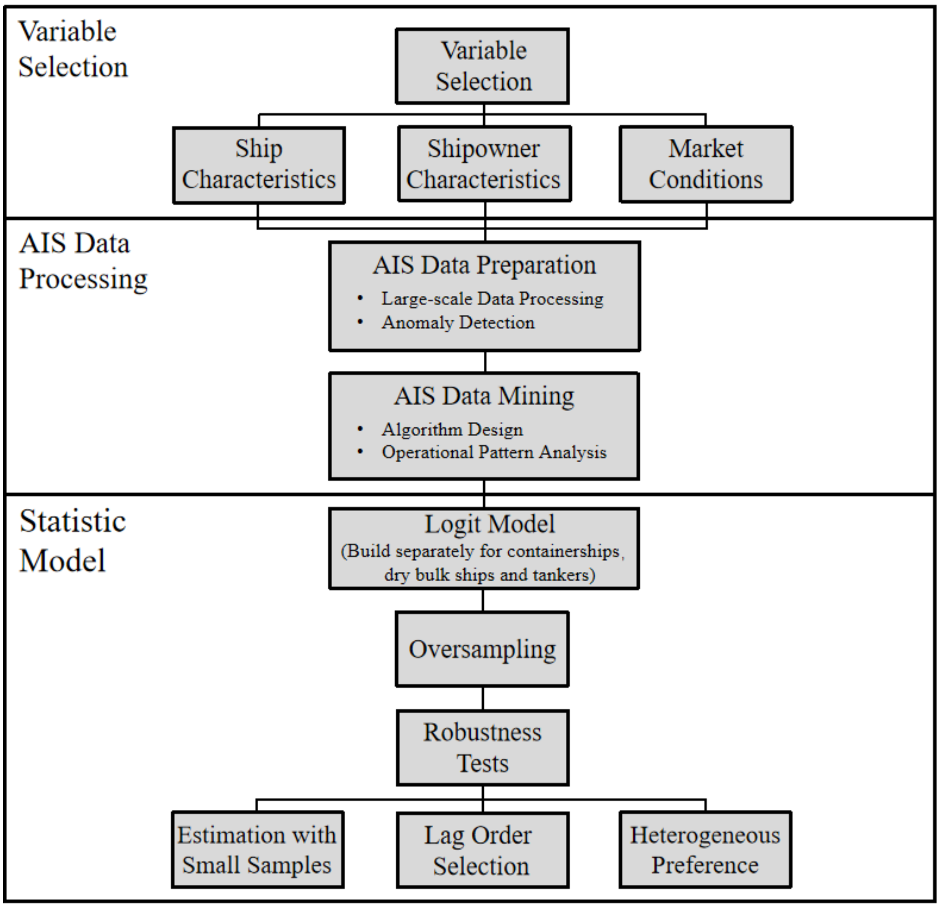


Figure 1 – Analysis framework

Source: drawn by authors

Module 1 is variable selection. Based on previous studies and information collected from the industry, a broad scope of explanatory variables is considered, and the variables are classified into three categories: ship characteristics, shipowner characteristics, and market conditions. Module 2 is the AIS data processing. This module proposes several algorithms using multiple technologies, such as large-scale AIS data processing and data mining to derive shipowners' operational characteristics from AIS data, which are fed into Module 3. Module 3 develops a logit model to assess the influence of certain determinants on a shipowner' s choices, in which the shipowners' decision is modelled as a function of the explanatory variables discussed in Module 1. In particular, the logit model is built for different types of ships separately, as the business models of container ship, bulk ship and tanker are different. Since extreme sample imbalance exists, it is not reliable to directly perform statistical analysis using the raw dataset.

Therefore, we adopt Random Over-Sampling Examples (ROSE) to balance our dataset. Furthermore, we perform several robustness checks to test our empirical results' robustness.

3.1. Variable selection

Based on previous relevant literature and our investigations of the shipping industry, we select the main determinants of the shipowners' choices and classify them into three categories: ship characteristics (e.g., ship age and deadweight), shipowner characteristics (e.g., operational pattern and environmental awareness) and market conditions (e.g., fuel price differential and freight rates). The following hypothesized relationships are proposed.

3.1.1. Ship characteristics

The ship age and **deadweight** can affect the shipowners' choices. The investment would be financially more attractive for a younger vessel with a longer remaining lifespan (Jiang et al., 2014). Furthermore, larger ships are more likely to install a scrubber as these ships are often equipped with powerful engines and consume more fuel. Thus, it is easier to recoup the investment for larger vessels (Lindstad et al., 2015). The theoretical relationship between these two determinants and ship energy choice has also been empirically validated by several existing studies (Solakivi et al., 2019; Li et al., 2020; Kokosalakis et al., 2021), and we adopt them as control variables in our research.

3.1.2. Shipowner characteristics

We propose two aspects of determinants for shipowner characteristics: operational pattern and environmental awareness.

The ship's operational pattern, such as **speed** and **trading routes,** could be critical factors determining the owner's choice. Because the fuel consumption can be approximated as a cubic function of the speed (Norstad et al., 2011), an increase in the speed would result in more trips per year at higher fuel costs per trip, which in turn would incentivize owners to install a scrubber (Zis et al., 2016). Similarly, a longer **trip distance** leads to more sailing time per year and higher annual fuel consumption, making the option of installing a scrubber more economically viable. Furthermore, Lindstad et al. (2015) noted a need for more focus on cost assessments as a function of annual fuel consumption in ECA. Due to the stricter emission control in ECA, ships often **sailing within ECA** need to use more costly ultra-low sulphur fuel oil (ULSFO) with even lower sulphur content compared to LSFO, which increases the fuel cost. Thus, the owners of such ships might prefer to install a scrubber. Last but not least, Grimmer and Myers (2017) found that as the number of maintenance facilities for scrubbers is limited and their distribution is concentrated, ships that follow regular routes on fixed schedules will be more motivated to install scrubbers compared with vessels that have **diverse trading routes,** because they have advanced knowledge of the routes and can reasonably plan for equipment maintenance. The shipowners' **environmental awareness** can also affect the shipowners' choices (Fevre, 2018). Shipowners with higher environmental awareness might take proactive measures in response to the upcoming sulphur cap. Hence, Hypothesis A is proposed as follows:

Hypothesis A The energy choice of a vessel depends on shipowner characteristics. The shipowner is intended to install a scrubber when the ship is operated with a higher speed, longer trip distance, higher frequency sailing within the ECA, less diverse trading routes or when the shipowner has a stronger environmental awareness.

3.1.3. Market conditions

The **price differentials between the HSFO and LSFO/MGO** play a critical role in shipowners' choices (Jiang et al., 2014; Zis et al., 2016; Patricksson and Erikstad, 2017). When faced with a low-price differential, shipowners favour the option with the lowest investments, i.e., to use LSFO/MGO, while a high price differential makes the solutions that require higher initial investments but with potentially higher fuel cost savings more attractive (Lindstad et al., 2015). Moreover, the impact of the **freight earnings** of ships also matters. It usually takes nearly one month or even a much longer time to install a scrubber, during which the ship docks at the yard and is unable to ship goods. Hence, high market earnings lead to a significant revenue loss during installation. In this case, shipowners tend to delay their plan for installing a scrubber. Notably, this indicator is only applicable to containerships. The installation generally occurs during interim and regular ship inspection time, so that bulk and tanker shipowners would not incur any freight revenue loss if the ship is under time charter and any long-term contracts, even the market earnings is low. We use average containership earnings to represent the market conditions. In addition, as **the implementation date of the IMO 2020 rule** approaches, shipowners are under increasing pressure and can be more motivated to take actions, such as installing a scrubber, to comply with the new regulation. Therefore, Hypothesis B is set as:

Hypothesis B The energy choice of a vessel depends on market conditions. The shipowner is intended to install a scrubber when he faces high fuel price differentials between HSFO and LSFO/MGO or low average earnings per day or when the implementation date of the IMO 2020 rule approaches.

3.2. AIS data mining

The operation pattern-related determinants (e.g., the speed and trading routes) cannot be obtained directly from any database. In this section, we propose various methods to derive them from AIS data.

3.2.1. AIS data preparation

Pre-processing should be made on raw AIS data before variable extraction. Because a ship's operational characteristics usually depend more on the shipowner's strategy and stay relatively stable over time, the operational determinants are derived from one-year AIS data to serve as a proxy for a ship's long-run operational characteristics. Due to the super large scale of raw AIS data with over 100 GB and the presence of massive noise (Li et al., 2017), using raw AIS data to estimate determinants will lead to low computational efficiency and unreliable results. To reduce the data scale without losing generality, we lower the data reading frequency and read AIS data every half an hour. In addition, an outlier detection procedure is developed to remove observations whose speed or position is abnormal to avoid estimation bias caused by outliers. Since most ships sail at a speed of less than 20 knots, we set the threshold of identifying abnormal speed to 20 knots. If an observation's speed is higher than 20 knots, it will be recognized as an outlier and will be removed from the dataset. For position anomalies, we develop the following recognition procedure. When position anomalies exist, the position reported by this observation will be distinctly different from that of the previous observation. Therefore, we compute the distance between the reported positions of the two observations and the time interval between them. Then, the average speed between the two observations can be derived by dividing the distance by the time interval. If the speed is too high, this observation will be detected from the dataset as an observation with an abnormal position report.

3.2.2. Operational characteristics recognition

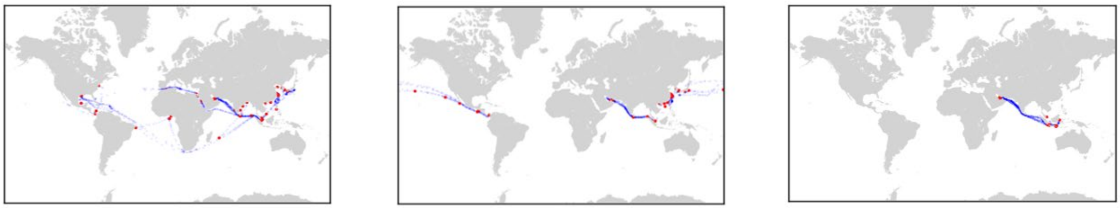
The data pre-processing procedure produces high-quality AIS data sets and enables us to recognize ships' operational characteristics base on AIS data. The following sections describe the procedures for ship operational characteristics recognition.

The average trip distance is calculated as the total sailing distance covered between two port calls. A port call is identified when a vessel's speed is maintained below 1 knot for over 18 hours.

The average speed is computed as the average reported speed of a given ship whose speed is higher than 1 knot (Jia et al., 2017).

The trading route diversity is measured by the spatial concentration of port calls. The Clustering with Dynamic Time Warping (DTW) distance (Li et al., 2017) was initially proposed to assess the similarity of a ship's different trajectories and thus evaluate the trading route diversity. However, this method is not applicable for large-scale data processing due to high algorithm complexity, up to $O\ (n^2 logn)$. DTW can be invalid and not reliable when considering a ship's speed changes. For example, when a ship sails at changing speeds in a fixed route between two ports, because the AIS data are reported at a constant frequency, the positions of the observations on different trip trajectories as reported by AIS markedly differ from each other. In this case, DWT can conclude that these trajectories do not share similarities, which contradicts reality. To overcome the drawbacks in the existing approaches, we propose a *k*-means clustering algorithm to discover the ships' trading patterns. Instead of addressing all of the observations reported by the AIS system, this method focuses only on a ship's port calls, which are much fewer in size than the observations, and it assesses a ship's route diversity by clustering the longitude and latitude coordinates of the port calls. The Silhouette Coefficient (Rousseeuw, 1987), a metric for evaluating clustering performance whose value is between 0 and 1, is used as a proxy for the route diversity in this algorithm. A smaller Silhouette Coefficient indicates more diverse trading routes for a vessel.

By this means, the DTW estimation bias caused by a ship's changing speed is avoided. Figure 2 shows the trajectories of the three ships. It can be seen that from left to right, the diversity of the ship's trading route decreases. Then, the DTW-based algorithm and *k*-means clustering algorithm are used to estimate the route diversity. The results are shown in Table 2. We can see that the estimates by *k*-means clustering are consistent with the intuition that we have from Figure 2. The score increases from left to right, which indicates that the route diversity decreases. However, the estimates by the DTW method are not consistent with our observation. These results suggest that our proposed new algorithm performs better in estimation accuracy. Additionally, the new algorithm reduces the time complexity from $O(n^2 logn)$ to $O(n^2)$. The detailed comparison of the two algorithms' complexity is illustrated in the Appendix.



Ship A　　　　Ship B　　　　Ship C

Figure 2 – Trajectories and port calls of three ships

Source: drawn by authors

Table 2 – Two algorithms' estimation results on the trading route diversity

Algorithm	Silhouette Coefficient		
	Ship A	Ship B	Ship C
DTW-based Algorithm	-0.057	-0.007	-0.107
K-means Clustering Algorithm	0.729	0.863	0.923

Effect of ECA. The share of observations within the ECA in the total observations is conducted to measure how often a ship sails in ECAs. ECAs are located along the coasts with a distance of up to 200 nautical miles or are in specifically defined areas. As shown in Figure 3, the ECAs specified in regulation 14 of MARPOL Annex VI (IMO, 2011) are identified in this study (shown in light grey colour), which are located in Northern Europe, along with the American coasts.

Figure 3 – ECAs specified in regulation 14 of MARPOL Annex VI

Source: drawn by authors based on MARPOL Annex VI (IMO, 2011)

3.3. Statistical model

3.3.1. Logit model

Since there is a very limited number of ships fuelled by LNG by 2017, we are not able to test empirically with a statistics model. Thus, the scheme that use LNG as an alternative fuel is not accounted for in this study. Assume that a shipowner i, in month t, faces a choice between scheme 1 : using LSFO/MGO, and scheme 2: installing a scrubber and continuing to use HSFO. The shipowners would obtain a certain level of utility from each scheme. In the logit model, the utility for shipowner i to use scheme j in month t can be specified as follows:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, j \in \{1, 2\} \tag{1}$$

where V_{ijt} is the deterministic utility, and ε_{ijt} represents the random error term, which captures the uncertainty and is independent and identically (i.i.d.) distributed. The probability that a shipowner in month t chooses scheme j is

$$P_{ijt} = \frac{e^{V_{ijt}}}{\sum_{j=1}^{2} e^{V_{ijt}}} \tag{2}$$

The deterministic utility is usually assumed to be a linear function of the observable variables: $V_{ijt} = \beta' X_{ijt}$. Under this assumption, the logit probabilities are specified as

$$P_{ijt} = \frac{e^{\beta' X_{ijt}}}{\sum_{j=1}^{2} e^{\beta' X_{ijt}}} \tag{3}$$

We build our models for different ship types separately, e.g., container, dry bulk and tanker respectively, because the determinants for them vary. For containerships, Eq. (3) is rewritten as

$$ln\left(\frac{P_{i2t}}{1-P_{i2t}}\right) = \beta_0 + \beta_1 Age_{it} + \beta_2 DWT_i + \beta_3 Speed_i + \beta_4 TD_i + \beta_5 ECA_i + \beta_6 TRD_i$$
$$+\beta_7 EA_i + \beta_8 PD_{t-1} + \beta_9 AE_{t-1} + \beta_{10} IMO\ 2020_t \tag{4}$$

where Age_{it} is ship i's age in month t; DWT_i represents ship i's deadweight; $Speed_i$ is ship i's average speed; TD_i is ship i's average trip distance; ECA_i measures ship i's share of sailing in ECA; TRD_i measures ship i's trading route diversity; EA_i represents the environmental awareness of shipowner i; PD_{t-1} is the price differential between HSFO and LSFO/MGO in month $t-1$; AE_{t-1} is the average containership earnings in month $t-1$; $IMO\ 2020_t$ represents the time remaining until the IMO 2020 regulation implementation. For dry bulk ships and tankers, variable AE_{t-1} is not included in the regression model, and Eq. (3) can be written as

$$ln\left(\frac{P_{i2t}}{1-P_{i2t}}\right) = \beta_0 + \beta_1 Age_{it} + \beta_2 DWT_i + \beta_3 Speed_i + \beta_4 TD_i + \beta_5 ECA_i + \beta_6 TRD_i$$
$$\beta_7 EA_i + \beta_8 PD_{t-1} + \beta_9 IMO\ 2020_t \tag{5}$$

3.3.2. Random over sampling examples (ROSE)

Since only 934 ships among a total of 295,275 observations included in this study chose to install a scrubber, the data set was extremely unbalanced. Sample imbalance could lead to biased and inaccurate results from the statistics model (Wasikowski and Chen, 2010). To solve this problem, ROSE (Menardi and Torelli, 2012) was adopted.

ROSE generates new artificial examples from the rare class according to a smoothed bootstrap approach. In a classification task, a training set $T_n = (\boldsymbol{x}_1, \gamma_1), (\boldsymbol{x}_2, \gamma_2), \ldots, (\boldsymbol{x}_n, \gamma_n)$ is observed on n individuals, where the binary response γ belongs to the set $\{\gamma_0, \gamma_1\}$, and a vector of numeric predictors is denoted by $\boldsymbol{x}$. Let the number of individuals in class γ_j, $j = 0, 1$ be denoted by $n_j < n$. The ROSE procedure consists of the following steps:

i. select $\gamma^* = \gamma_j \in \{\gamma_0, \gamma_1\}$ with probability $\frac{1}{2}$

ii. select $(\boldsymbol{x}_i, \gamma_i)$ in T_n such that $\gamma_i = \gamma^*$ with probability $\frac{1}{n_j}$

iii. sample $\boldsymbol{x}^*$ from $K_{H_j}(\cdot,\ \boldsymbol{x}_i)$, with K_{H_j} a normal distribution centered at $\boldsymbol{x}_i$, and H_j a specified covariance matrix.

Essentially, ROSE selects an observation $(\boldsymbol{x}_i, \gamma_i)$ from one of the two classes and generates a new example $(\boldsymbol{x}^*, \gamma^*)$ in its neighbourhood, where the width of the neighbourhood is determined by H_j. Repeating steps i to iii m times generates a new balanced training set T_m^*, of size m, where a 50:50 share between the two classes is achieved. The size m can be set freely. Compared with simple oversampling that duplicates examples of the minority class, ROSE overcomes the drawbacks of overfitting by means of generating new artificial examples. In addition, in contrast with traditional techniques of adopting the strategy of generating synthetic samples, such as the synthetic minority oversampling technique (SMOTE), ROSE is founded on a sound theoretical basis that is supported by the good properties of the kernel methods. ROSE generates examples from an estimate of the density that underlies the data. This approach ensures that the sample distribution of each variable will not change after the sample is balanced, thus avoiding biased and inaccurate estimation results in a statistical model (Menardi and Torelli, 2012). This property can be illustrated by practical examples. Figure 4 presents the sample distribution of the trip distance in the raw dataset, the dataset oversampled by SMOTE and the dataset oversampled by ROSE, respectively. It can be seen that the sample distribution obtained by ROSE is similar to that in the raw dataset. However, the sample distribution in the dataset oversampled by SMOTE is remarkably different from the raw dataset, in which distinct changes in the kurtosis and skewness of the distribution are observed. This finding confirms that compared with SMOTE, ROSE has better performance on fitting the original distribution and generating accurate empirical results.

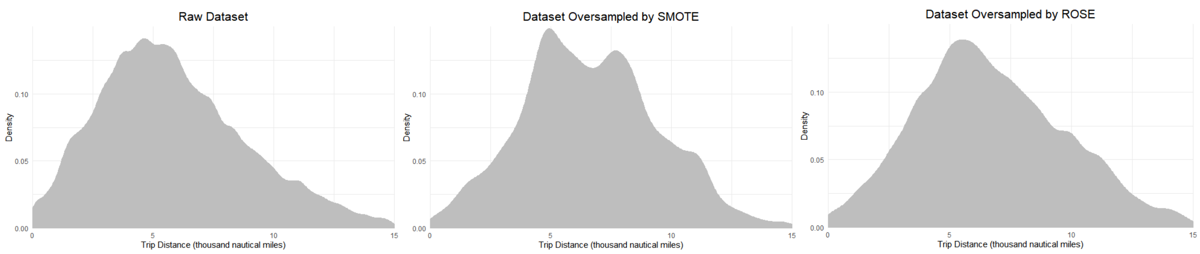


Figure 4 – Comparison of the sample distribution before and after oversampling

Source: drawn by authors

4. Data Extraction and Descriptive Statistics

This section details the sources of our data and specifies our variables. We also perform preliminary analysis on the basic features of variables by means of descriptive statistics.

4.1. Data

In this study, data is collected from various sources. Ship information is gathered from Lloyd's List Intelligence database (2019). Operational pattern-related determinants are calculated based on one-year AIS data. Among the AIS datasets over recent years that we can access, AIS data of the entire 2017 has the best quality and thus is adopted as the data source in our study. Scrubber installation information is obtained from Clarkson Research Services (2019). It is common to have a lead time of approximately six months between a shipping company's decision to retrofit to the point at which a scrubber is installed (Jallal, 2019). In this way, the date that the shipowner makes the decision is inferred based on the installation date. Environmental Performance Index (EPI) is a method of assessing the environmental performance of a country's policies (Wendling et al., 2018). In this study, the EPI of the ships' flag states is used as a proxy for the shipowners' environmental awareness. The price differential between HSFO and MGO is retrieved from Ship and Bunker (2020). The lagged price differential, i.e., last month's price differential, is incorporated in the regression model. Average containership earnings per day is obtained from Clarkson Research Services (2021).

The panel dataset consists of 295,275 observations with a global coverage that are collected over the time period from Jan 2018 to October 2019. A total of 13,685 ships (including 3,819 containerships, 8,256 dry bulk ships, and 1,610 tankers) are included. We exclude ships that are less than 8, 000 dwt (dead weight ton). The threshold is set using the smallest ship in the database that installed a scrubber.

4.2. Descriptive statistics

A description of the variables and their descriptive statistics is presented in Table 3. As seen, observations choosing scheme 1 (using LSFO/MGO) and those choosing scheme 2 (installing a scrubber and continuing to use HSFO) show apparent differences in various variables, and the actual data basically agree with the hypotheses proposed in Section 3.1. Compared with observations choosing to use LSFO/MGO, those choosing to install a scrubber tend to have a higher speed, longer trip distance and more fixed trading routes. Furthermore, ships that often sail within ECA or those whose flag state has a better environmental performance tend to install a scrubber. As the implementation date of the IMO 2020 rule approaches, shipowners tend to install a scrubber.

Table 3 – Variable descriptions and descriptive statistics

Variable	Definition	Mean (SD)					
		Container Ship		Dry Bulk Ship		Tanker	
		Scheme 1	Scheme 2	Scheme 1	Scheme 2	Scheme 1	Scheme 2
Age	Current time minus build time	12.957 (6.432)	8.734 (4.611)	10.593 (7.208)	7.991 (3.731)	12.621 (5.221)	9.682 (3.375)
DWT	The deadweight tonnage of a ship in units of million tons	0.051 (0.040)	0.101 (0.052)	0.071 (0.047)	0.121 (0.057)	0.182 (0.089)	0.219 (0.087)
Speed	The average speed of a ship's observations when the speed is higher than 1 knot	12.632 (1.871)	13.542 (1.360)	10.738 (1.189)	10.715 (1.063)	9.983 (1.962)	10.583 (1.553)
TD (Trip Distance)	A ship's average trip distance covered between two port calls in units of thousand nautical miles	6.506 (3.256)	7.728 (2.583)	5.538 (2.73)	7.166 (2.504)	5.658 (3.504)	7.986 (3.400)
ECA	The share of observations within ECA over the total observations	0.105 (0.238)	0.120 (0.218)	0.081 (0.159)	0.078 (0.146)	0.126 (0.241)	0.158 (0.262)
TRD (Trading Route Diversity)	The Silhouette Coefficient of clustering a ship's port calls	0.800 (0.104)	0.822 (0.097)	0.737 (0.111)	0.751 (0.101)	0.745 (0.113)	0.717 (0.099)
EA (Environmental Awareness)	The 2018 EPI of a ship's flag state	60.239 (13.269)	62.669 (12.522)	60.790 (11.934)	66.039 (13.496)	60.460 (13.779)	65.882 (13.715)
PD (Price Differential)	Last month's price differential between Singapore's 380-centistoke grade bunker fuel and MGO	211.171 (32.823)	209.262 (27.294)	211.080 (32.895)	206.751 (25.843)	211.558 (32.682)	203.198 (24.417)
AE (Average Earnings)	Average earnings in thousand dollars per day	12.483 (1.360)	12.894 (0.981)	- (-)	- (-)	- (-)	- (-)
IMO 2020	Time remaining to IMO 2020 regulation implementation	12.648 (6.314)	7.637 (3.786)	12.623 (6.326)	8.729 (3.879)	12.756 (6.29)	7.774 (3.703)

Notes: Standard deviation in parenthesis.

5. Results

In this section, the model's estimation results are discussed first, followed by a number of robustness tests to validate the model.

5.1. Model estimation results

The regression results from the logit model are presented in Table 4. Model 1, 3, and 5 report the estimation result of the full sample of containerships, dry bulk ships, and tankers, respectively. According to Area Under Curve (AUC) reported in column 1, 3 and 5, the full sample regression underperforms in the classification, which could be due to the imbalance of the full sample. Model 2, 4, and 6 have corresponding sample sizes that are based on samples obtained by oversampling in scheme 2 and random sampling in scheme 1. In these samples, the share between the observation of installing a scrubber and the observation of using LSFO/MGO is 50:50, and the number of samples is 20,000. It can be seen that the model with balanced samples fits the data better than the full-sample model, as the McFadden R^2 increases by approximately 0.2. In addition, the total gain, percentage gain, and AUC indicators all prove that the classification accuracy is significantly improved. For example, the AUC increases from 0.5 to around 0.8 compared with the full-sample model.

Table 4 – Results of energy scheme choice model

Variable	Container Ship		Dry Bulk Ship		Tanker	
	Model 1 (Full Sample)	Model 2 (Balanced Sample)	Model 3 (Full Sample)	Model 4 (Balanced Sample)	Model 5 (Full Sample)	Model 6 (Balanced Sample)
Age	-0.075***(0.016)	-0.089***(0.004)	-0.084***(0.012)	-0.085***(0.004)	-0.122***(0.018)	-0.137***(0.005)
DWT	15.897***(1.393)	17.859***(0.483)	14.140***(0.885)	16.412***(0.397)	2.540**(1.072)	2.466***(0.250)
Speed	0.145***(0.050)	0.207***(0.015)	-0.110***(0.041)	-0.110***(0.017)	-0.001(0.055)	-0.018(0.012)
TD	0.049**(0.024)	0.074***(0.007)	0.045**(0.019)	0.102***(0.008)	0.129***(0.029)	0.172***(0.007)
ECA	0.439(0.312)	1.117***(0.083)	0.464(0.317)	0.489***(0.114)	1.128***(0.323)	0.919***(0.076)
TRD	0.163(0.702)	1.478***(0.203)	-0.281(0.460)	0.145(0.175)	-1.617**(0.732)	-0.780***(0.175)
EA	-0.003(0.004)	0.006***(0.002)	0.036***(0.004)	0.032***(0.001)	0.034***(0.006)	0.028***(0.001)
PD	0.029***(0.003)	0.027***(0.001)	0.017***(0.002)	0.013***(0.001)	0.017***(0.003)	0.011***(0.001)
AE	-0.466***(0.095)	-0.477***(0.023)	-(-)	-(-)	-(-)	-(-)
IMO 2020	-0.350***(0.025)	-0.349***(0.006)	-0.186***(0.011)	-0.200***(0.004)	-0.235***(0.019)	-0.240***(0.004)
Constant	-4.968***(1.696)	-1.511***(0.405)	-9.347***(0.747)	-3.116***(0.286)	-7.548***(0.999)	-1.301***(0.239)
Observations	82,451	20,000	178,530	20,000	34,294	20,000
McFadden R^2	0.1967	0.4135	0.1278	0.3021	0.1508	0.3060
% Correct	99.66	81.66	99.74	76.22	99.43	76.62
% Incorrect	0.34	18.34	0.26	23.78	0.57	23.38
Total Gain	0	31.45	0	26.02	0	26.42
Percentage Gain	0	83.44	0	76.59	0	78.46
AUC	0.500	0.817	0.500	0.762	0.500	0.766

Notes: ***, ** and * indicate the significance at the 1%, 5% and 10%, respectively. The standard errors are in parentheses.
The McFadden R^2 indicates the improvement in the log-likelihood of the estimated model compared with the intercept-only model.
The total gain indicates the improvement ‘‘% Correct” from a constant probability (no model) specification.
The percentage gain is measured as the percent of incorrect (default) prediction corrected by the estimated model compared to using a constant probability (no model) specification.
The AUC is a measure of the performance of the supervised classification rules, and the value is between 0.5 and 1.

As seen in Table 4, the estimation results are generally in line with the hypotheses proposed in Section 3.2. The following analysis is conducted based on the results of Model 2, 4, and 6 as reported in Table 4. Correspondingly, the effect sizes and modified effect sizes for these models, i.e., the sensitivity of the dependent variable to changes in the independent variables, are presented in Table 5. It can be seen that the determinants' relative importance on shipowners' energy choice varies among different types of vessels. Detailed analysis of the determinants is illustrated as follows.

Table 5 – Effect sizes for Model 4

Variable	Container Ship (Model 2)		Dry Bulk Ship (Model 4)		Tanker (Model 6)	
	Effect Size	Modified Effect Size	Effect Size	Modified Effect Size	Effect Size	Modified Effect Size
Age	0.590	1.696	0.607	1.648	0.532	1.881
DWT	2.566	2.566	2.589	2.589	1.247	1.247
Speed	1.418	1.418	0.883	1.133	0.969	1.033
TD	1.251	1.251	1.323	1.323	1.865	1.865
ECA	1.291	1.291	1.078	1.078	1.267	1.267
TRD	1.162	1.162	1.016	1.016	0.920	1.087
EA	1.087	1.087	1.521	1.521	1.479	1.479
PD	2.218	2.218	1.487	1.487	1.392	1.392
FR	0.565	1.769	-	-	-	-
IMO 2020	0.134	7.471	0.324	3.090	0.255	3.923

Notes: The effect size is measured as a factor change in the odds ratio of the dependent variable for a one-SD increase in the independent variable.
We take the opposite of the variables whose effect size is smaller than 1 and re-estimate the model, and we will obtain the modified effect size.
A larger modified effect size indicates a stronger effect that the independent variable has on the dependent variable.

Ship characteristics: It can be seen that as the deadweight increases, so do the odds ratio of installing a scrubber, as evidenced by the positive coefficient for the deadweight. Larger ships are more inclined to install a scrubber since they consume more fuel and will save more fuel cost if this scheme is chosen. Moreover, the effect sizes of containerships and dry bulk ships are much larger than that of tankers. This result means that the deadweight plays a critical role in a shipowner's decision for containerships and dry bulk ships, while tanker owners place less weight on it. In addition, older ships tend not to install a scrubber because it is difficult to recoup the investment in their remaining lives. For every extra SD of the ship's age, the odds ratio decreases by a factor of 0.590, 0.607 and 0.532, for containerships, dry bulk ships, and tankers, respectively. These observations are consistent with the existing studies on ship energy choice (Solakivi et al., 2019; Li et al., 2020; Kokosalakis et al., 2021).

Shipowner characteristics: There is considerable support for the hypothesis that a ship's operational pattern has a significant effect on the shipowner's decision, which supports Hypothesis A. For containerships, when a ship's average speed increases by an SD, the odds ratio increases by a factor of 1.243. However, for dry bulk ships and tankers, the effect sizes of speed are both close to 1, which implies speed is not a key factor in their decision process. We also find evidence that a short trip distance and diverse trading routes are deterrents to installing a scrubber. For all three types of vessels, the effect size of trip distance is larger than 1, while tankers have a larger effect size. It indicates that trip distance is a more important consideration for tankers. It can also be observed that the effect size of trading route diversity is larger than 1 for containerships and is around 1 for dry bulk ships or tankers, which reveals dry bulk shipowners and tanker owners seem to be indifferent to route diversity. Hence, in general, the two hypothesized relationships in Hypothesis A are supported, while the two determinants' importance on shipowners' decision varies among vessel types. In addition, the coefficient for ECA is positive and significant. Since ships that often sail within ECA have to suffer higher fuel costs if they choose to use LSFO/MGO, they tend to install a scrubber. The results also confirm that shipowners whose flag state performs well in environmental protection can have stronger environmental awareness and are active in adopting measures such as installing a scrubber to reduce emissions. However, the impact of environmental awareness on containership owners seems weaker than that on the other two types of vessels, validated by its smaller effect size.

Market conditions: Market factors are also important in the shipowner's decision-making process, supporting Hypothesis B. When fuel price differentials between HSFO and LSFO/MGO are higher, the scheme of using LSFO/MGO is less attractive due to the higher fuel cost, as evidenced by the positive coefficient for the price differential. The effect size of containerships is greater than that of dry bulk ships or tankers, which shows containership owners are more concerned about fuel price differentials when choosing energy scheme. Furthermore, a higher average earning per day exacerbates the loss of revenue during the scrubber installation and decreases the probability of installing a scrubber for containerships. Additionally, as the implementation date of IMO 2020 approaches, the pressure on shipowners' to comply with the new rule increases, and they are more motivated to install a scrubber.

5.2. Robustness tests

In this study, the full sample size is up to 178,530. As Lin et al. (2013) pointed out, in large samples that contain over 10,000 observations, *p*-values go quickly to 0, and statistical tests can be meaningless or even misleading. Therefore, we need to check whether the coefficients are still significant in small samples. By the oversampling of scheme 2 and random sampling of scheme 1, we generate 50 small samples whose sample size increases from 200 to 10,000 and estimate the coefficients with these samples. Here, we use dry bulk ship type as an illustrative case to perform the robustness test. Similar results are obtained when using containerships or tankers to estimate the model, which is not reported here for simplicity. Results are available upon requests from authors. Confidence Interval Charts for increasing the sample sizes coupled with *p*-value charts are presented in Figure 5 and 6 to show how the sample size affects the estimation of the parameters. It can be seen that as the sample size increases from 0 to 10,000, the *p*-values of speed, trip distance, and ECA fall rapidly to 0, and their confidence intervals tend to stabilize, while trading route diversity's *p*-values fluctuate between 0 and 1. It reveals that the first three determinants significantly impact energy choice while the trading route seems not to play a critical role, which is in line with the results reported in Table 5. These findings indicate that the estimation results with small samples are basically consistent with the results with large samples, and therefore, the regression results are robust.

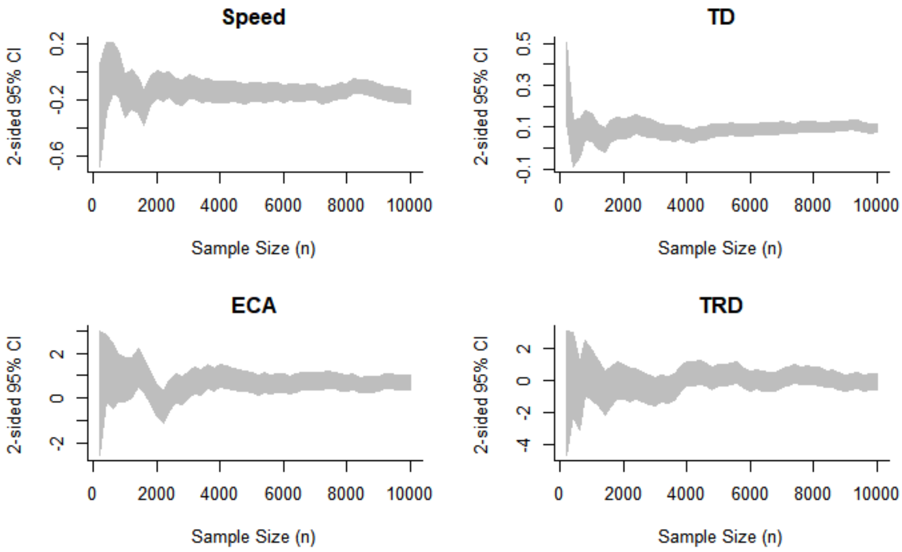


Figure 5 – Two-sided 95% confidence interval for coefficients vs. sample size

Source: drawn by authors

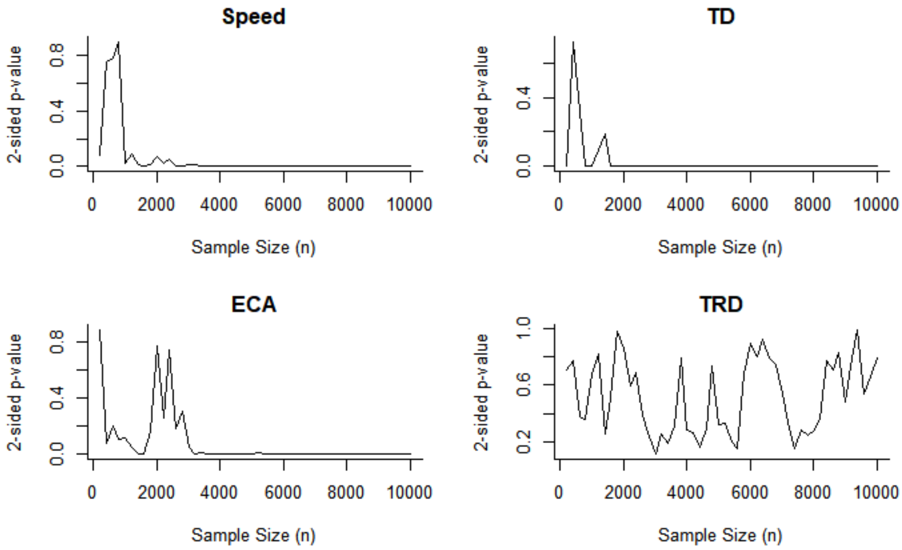


Figure 6 – Two-sided p-value for coefficients vs. sample size

Source: drawn by authors

Furthermore, the standard logit model assumes that the preference of the decision-maker is homogeneous. Under this assumption, only one fixed vector of parameter estimates is estimated for the deterministic utility function specified in Eq. (4) or (5). However, this approach can be divergent from reality. For example, shipowners from countries with sound environmental performance could value environmental protection over economic factors. To check whether heterogeneity exists, we incorporate interaction terms between a binary variable that indicates the environmental performance of the ship's flag state and all of the determinants into the regression. Using the dry bulk ship as the illustrative case again, when the heterogeneity is taken into consideration, Eq. (4) can be rewritten as

$$\begin{aligned} ln\left(\frac{P_{i2t}}{1-P_{i2t}}\right) = {} & \beta_0 + \beta_1 Age_{it} + \beta_2 DWT_i + \beta_3 Speed_i + \beta_4 TD_i + \beta_5 ECA_i + \beta_6 TRD_i + \beta_7 EA_i \\ & + \beta_8 PD_{t-1} + \beta_9 IMO\ 2020_t + \beta_{10} Age_{it} \times High\ EPI_i + \beta_{11} DWT_i \times High\ EPI_i \\ & + \beta_{12} Speed_i \times High\ EPI_i + \beta_{13} TD_i \times High\ EPI_i + \beta_{14} ECA_i \times High\ EPI_i \\ & + \beta_{15} TRD_i \times High\ EPI_i + +\beta_{16} EA_i \times High\ EPI_i + \beta_{17} PD_{t-1} \times High\ EPI_i \\ & + \beta_{18} IMO\ 2020_t \times High\ EPI_i \end{aligned} \tag{6}$$

We classify the countries into two groups regarding their environmental performance, i.e., EPI, by setting a threshold on the EPI. Countries whose EPI is higher than the threshold are regarded as high-environmental-performance countries, while other countries are classified as low-environmental-performance countries. To determine an appropriate threshold, we propose a two-step estimation method. The threshold regression model specified in Eq. (5) is simplified as

$$ln\left(\frac{P_{i2t}}{1-P_{i2t}}\right) = X_{it}'\beta + X_{it}'\delta 1\{EPI_i > \gamma\} \tag{7}$$

where P_{i2t} is the probability of installing a scrubber, X_{it} is a vector of explanatory variables, and $\theta = (\beta', \delta')'$ is the set of regression parameters excluding the threshold parameter γ. Then, given that there are n observations, the likelihood function is

$$L(\theta, \gamma) = \prod_{i=1}^{n} P_i^{y_i} (1 - P_i)^{1-y_i} \tag{8}$$

In the first step of the estimation, for a fixed γ, the maximum likelihood estimator of θ can be obtained with

$$\hat{\theta}(\gamma) = \mathrm{argmax}_{\theta} L(\theta, \gamma) \tag{9}$$

In the second step, McFadden R^2 is adopted as the criterion for selecting the optimal threshold $\hat{\gamma}$, because a larger McFadden R^2 indicates that the threshold has a better explanatory power on the heterogeneity of the shipowners' preferences. The estimator of γ can be specified as

$$\hat{\gamma} = \mathrm{argmax}_{\gamma} McFadden\ R^2\left(\hat{\theta}(\gamma), \gamma\right) \tag{10}$$

Then, the set of parameters θ is estimated as $\hat{\theta}(\hat{\gamma})$.

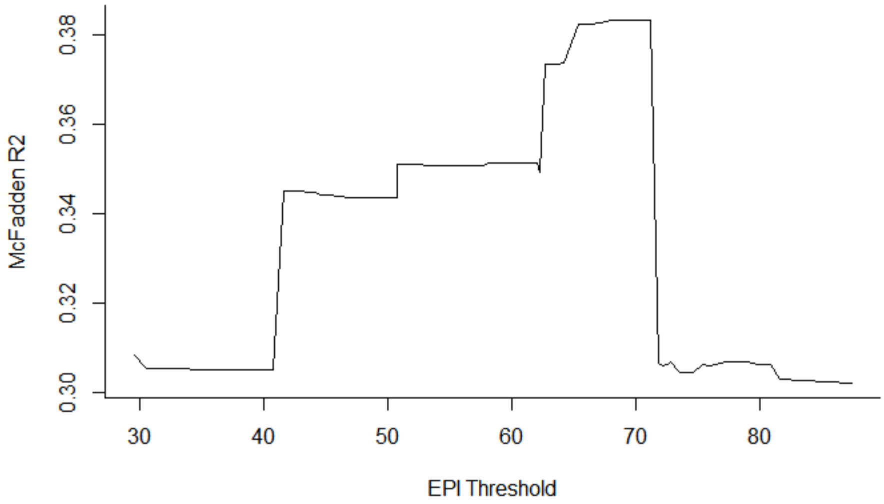


Figure 7 – Relationship curve between McFadden R^2 and EPI threshold

Source: drawn by authors

Figure 7 shows the relationship curve between the model's McFadden R^2 and EPI threshold γ. When γ is equal to 67.85, the McFadden R^2 reaches its maximum. Thus, we set the EPI threshold to 67.85, and we estimate the model with maximum likelihood estimation. Table 6 presents the estimation results of this model. It can be found that most of the coefficients of the interaction terms are significant at the 1% significance level. This finding indicates that preference heterogeneity among shipowners exists. We can also see that the signs of the interaction terms' coefficients are usually different from their main effects. This finding suggests that in the utility function of the shipowners from countries with high environmental performance, the absolute values of the economic factors' coefficients are smaller. Therefore, we can conclude that shipowners from countries with low environmental performance could place more weight on economic factors.

Table 6 – Results of the robustness tests on the preference heterogeneity

Variable	Model 7
Age	-0.093***(0.006)
DWT	17.435***(0.566)
Speed	0.102***(0.027)
TD	0.077***(0.012)
ECA	1.683***(0.170)
TRD	1.307***(0.271)
EA	-0.083***(0.003)
PD	0.010***(0.001)
IMO 2020	-0.180***(0.007)
Age×High EPI	0.019**(0.009)
DWT×High EPI	-0.811(0.868)
Speed×High EPI	-0.191***(0.033)
TD×High EPI	0.032*(0.017)
ECA×High EPI	-1.846***(0.241)
TRD×High EPI	-0.740**(0.357)
EA×High EPI	0.074***(0.006)
PD×High EPI	0.005***(0.001)
IMO 2020×High EPI	-0.049***(0.009)
Constant	-0.278(0.367)
Observations	20,000
McFadden R^2	0.3835
% Correct	80.40
% Incorrect	19.60
Total Gain	30.20
Percentage Gain	81.41
AUC	0.804

Notes: ***, ** and * indicate the significance at the 1%, 5% and 10% level, respectively. Standard errors are in parentheses. McFadden R^2 indicates the improvement in the log-likelihood of the estimated model compared with the intercept-only model.
The total gain indicates the improvement ''% Correct" from a constant probability (no model) specification.
The percentage gain is measured as the percent of incorrect (default) prediction corrected by the estimated model compared to using a constant probability (no model) specification.
The AUC is a measure of the performance of supervised classification rules, and it has a value between 0.5 and 1.

6. Discussion and Policy Implication

The findings of this study provide important implications to the industry in understanding the unrevealed rationale of shipowners when choosing energy schemes to adapt to the IMO 2020 regulation. First, this study discloses the shipowners' aggregate preference toward energy scheme choices, which can help shipowners benchmark their choice with others. Faced with different energy schemes, economic factors, including the deadweight, which is strongly linked to the fuel consumption and ship age that the payback period is sensitive to, are the top concerns for shipowners. Moreover, the relative importance of the determinants on shipowners' decision varies across vessel types. Compared to dry bulk vessels and tankers, the overall model fitness is better for containerships (McFadden R-squared for containerships, dry bulk and tankers being 0.41, 0.30, and 0.31 respectively using balanced sample). This indicates the higher economic rationality and consistence in container shipowners' decision-making process.

Additionally, the shipowners' environmental awareness has a significant effect on the decision, but this aspect can be different between shipowners from different countries as well as between shipowners operating different types of vessels. Those coming from countries with high environmental performance and those operating dry bulk vessels or tankers are more affected by the environmental determinant.

On the other hand, this study enables diverse stakeholders in the maritime industry to understand the shipowner's perception of key determinants in energy option choices, develop strategies accordingly and optimize the resource utilization. For example, scrubber suppliers could adapt their strategies to the changes in market factors such as price differentials and freight rates. When future price differentials tend to be high, shipowners are more likely to install a scrubber. This finding means that scrubber suppliers can make use of fuel price trends to predict shipowners' demands, thus adjusting their supply to meet the demand. In addition, the results show that the loss of revenue during the scrubber installation is also a significant factor for shipowners. When the loss is high, shipowners could choose to use LSFO/MGO rather than installing a scrubber. Therefore, scrubber suppliers must optimize their installation process to shorten the lead time and reduce the shipowners' losses, thus making the option of installing a scrubber more attractive. Moreover, the empirical results in this study also help scrubber suppliers to precisely discover their potential customers. For example, marketing to large companies and companies from high-environmental-performance countries can be effective, because they usually have a higher probability of installing a scrubber.

Last but more importantly, the findings provide a reference for policymakers to formulate efficient policies. With regard to the externality of shipping, the emissions from ships lead to a loss in social welfare. To maximize social welfare, policymakers need to understand the shipowners' behaviours and make proper policies to reduce the emissions with the least cost. As an example, to popularize the use of clean energy, China rolled out a policy that offered subsidies to owners of LNG-powered ships in 2014. However, the policy did not achieve the expected effect due to inadequate LNG refuelling facilities and low-price differentials between LNG and bunker oil (Li, 2018). This failure could be partially attributed to the inadequate understanding of shipowners' perceptions of energy choices. This study suggests more targeted policy formulations based on the model results. As presented in Table 5, the large effect sizes of the fuel consumption-related factors, including speed, and trip distance, suggest that the fuel cost is one of the shipowners' main concerns when faced with energy scheme choices. It can be an effective measure to provide subsidies for low sulphur fuels, such as LSFO or MGO. In this way, the shipowners will be well motivated to use cleaner fuels. Furthermore, ships with diverse trading routes are less likely to install a scrubber. This finding suggests that a limited number of and concentrated distribution of maintenance facilities for scrubbers could have been deterrents to installing a scrubber. To motivate shipowners to install a scrubber to reduce emissions, governments should provide policy support for the development of maintenance infrastructure for scrubbers. It can also be seen from the results that ships that often sail within ECA are more motivated to take actions to mitigate emissions, such as installing a scrubber. This finding provides a helpful reference, i.e., to establish ECA, for emissions control in high-emission areas. In addition, ships whose flag state performs well in environmental policies and environmental protection are active in adopting environmentally friendly measures. This finding suggests that the government could help shipowners form environmental awareness by increasing their policy support and promoting environmental protection campaigns, to control emissions more effectively.

7. Conclusions

This study is a preliminary attempt to empirically reveal the reasons behind shipowners' energy choices under regulatory changes from a global coverage at a micro-level. To solve this problem, cross-disciplinary methods, including large-scale AIS data processing, data mining, and statistical analysis, are adopted to develop a practical decision-making framework. Attributes from three categories, including ship characteristics, shipowner characteristics, and market conditions, are considered. The results indicate that determinants that belong to all categories are relevant for explaining the shipowners' choices, while their influence varies. The time remaining until the IMO 2020 regulation is implemented, the ship size, and the ship age are considered to be the most critical factors. Furthermore, the influence of factors varies across different ship types, e.g., container, bulk, and tanker. Overall speaking, containership has a better fitness than dry bulk vessels and tankers, implying that container shipowners are more economically and operationally rational in making decisions.

The contribution of this paper is three-fold. First, this study fills the existing research gaps in the shipping energy choice literature by conducting analysis on the global scope and covering individual ships of different types. Second, previous studies have not measured the energy choices of ships empirically. We develop AIS data-based algorithms, such as clustering-based algorithms for assessing the trading route diversity, to make it possible to analyse a ship's behavioural characteristics quantitatively. Additionally, a threshold detection method is proposed to check for preference heterogeneity in a discrete choice model. These methods enrich the toolbox for future relevant research. Finally, this study provides important managerial implications for various stakeholders, including shipowners, related industries, and policymakers.

However, we also note the limitations that exist in this study. LNG as an alternative fuel is also one of the feasible schemes for ships, but it is not accounted for in our model because there are too few ships fuelled by LNG in our database. In our future research, with more data becoming available, we aim to include the scheme of using LNG in our analysis.

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Appendix. Time Complexity of two algorithms for evaluating the trading route diversity

Table A.1 and Table A.2 present the procedures of the two algorithms for evaluating the trading route diversity. For the DTW-based clustering algorithm, the complexity of identifying port calls is $O(n)$, where n represents the total number of observations. Suppose that each trajectory contains k observations on average; then, DTW distance computation consumes approximately $O(k^2)$ time. Given that m trajectories of the ship are identified, the complexity of calculating the similarity matrix based on the DTW distance will be $O(m^2k^2)$, and Affinity Propagation (AP) clustering will require $O(m^2 log\ m)$ time. Finally, it takes $O(m^2)$ to compute the Silhouette Coefficient. Thus, the time complexity of the DTW-based clustering algorithm is $O(n+m^2k^2+m^2 log\ m+m^2)$, where n=mk. Assuming that k is a constant, the complexity will be $O(n+n^2+n^2 log\ n+n^2)$, which can be simplified as $O(n^2 log\ n)$. For the k-means clustering algorithm, the complexity of identifying port calls is also $O(n)$, and the number of port calls will be $O(m)$. Then, k-means clustering requires $O(m)$ time, and the selection of the number of clusters k* by the elbow rule consumes $O(m)$ time. Similarly, the Silhouette Coefficient computation consumes $O(m^2)$ time. Thus, the time complexity of the k-means clustering algorithm is $O(n+m+m+m^2)$ time, which can be simplified as $O(n^2)$. In brief, time complexity analysis of the two algorithms suggests that the algorithm that we propose reduces the complexity of assessing the trading route diversity from $O(n^2 log\ n)$ to $O(n^2)$, and it shows the significant advantage of low computational efficiency compared with the traditional method when addressing a super-large-scale AIS dataset.

Table A.1 – The procedure of the DTW-based clustering algorithm

Input:
D = {d_1, d_2,......,d_n} //set of n observations' longitude and latitude coordinates
S = {s_1, s_2,......,s_n} //set of n observations' speed
T = {t_1, t_2,......,t_n} //set of n observations' timestamp
Output:
Silhouette Coefficient of clustering

Step 1: Identify port calls
Determine whether the ship's speed is maintained below 1 knot for over 18 hours by the reported speed and timestamp;
If true, the observation is identified as a port call.
Step 2: Assess the similarity of different trajectories based on DTW
1) Generate the ship's different trajectories, which consist of observations between two port calls;
2) Compute the DTW distance between two trajectories to assess the similarity of these two trajectories;
3) Conduct a matrix of similarities between pairs of the ship's trajectories based on the DTW distance.
Step 3: Cluster trajectories based on AP clustering
1) Take the similarity matrix as input and the cluster trajectories by AP clustering;
2) Compute the Silhouette Coefficient of the clustering.

Table A.2 – The procedure of the k-means clustering algorithm

Input:

$D = \{d_1, d_2, \ldots\ldots, d_n\}$ //set of n observations' longitude and latitude coordinates

$S = \{s_1, s_2, \ldots\ldots, s_n\}$ //set of n observations' speed

$T = \{t_1, t_2, \ldots\ldots, t_n\}$ //set of n observations' timestamp

Output:

Silhouette Coefficient of the clustering

Step 1: Identify port calls

Determine whether the ship's speed is maintained below 1 knot for over 18 hours by the reported speed and timestamps;

If true, the observation is identified as a port call.

Step 2: Cluster port calls based on k-means clustering

1) Arbitrarily choose the number of clusters k;
2) Cluster port calls by k-means clustering;
3) Select the optimal number of clusters k* by the elbow method;
4) Compute the Silhouette Coefficient of the clustering with k* clusters.