Does Fuel Choice Matter? Investigating Fuel Choice Impact on Vessel Value and Freight Rates

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Abstract

With a rising awareness of climate change and Greenhouse Gas (GHG) emissions, there has been a push towards alternative fuels in the maritime industry. In this paper, we use linear regression, adaptive lasso regression, and XGBoost on a novel dataset of transactions in the freight market and second-hand vessel market for gas carriers to investigate the effect of fuel choice on vessel value. We find evidence that choosing alternative fuels does not affect the vessel's value either positively or negatively, or the freight rate the vessel obtain in freight markets.

1 Introduction

Climate change constitutes an existential threat to humanity. The rise in global temperatures is problematic, but it will also disrupt livelihoods and intensify extreme weather, including prolonged droughts and increased occurrences of heavy rainfall. This will pose significant risks to critical ecological and socio-economic systems humanity relies on. One of the prime drivers of climate change is emissions of Greenhouse gases (GHGs) from human activity (Calvin et al., 2023). The maritime sector is a notable contributor to global GHG emissions. According to estimates from the International Maritime Organization (IMO), this sector contributed about 2.8% of global GHG emissions in 2018 (IMO, n.d.). Given its substantial environmental footprint, decarbonizing shipping has emerged as an important challenge facing the industry. In response, the IMO has developed a GHG reduction strategy that sets ambitious emission reduction targets of 20% in 2030, 70% by 2040, and net zero in the 2050s ("Revised GHG reduction strategy for global shipping adopted", n.d.).

Substantial investments are needed if the industry is to reach such ambitious goals. One key strategy for reducing emissions is to transition to alternative fuels. Replacing traditional marine diesel and heavy fuel oil with less polluting alternatives like LNG or zero-emission fuels, like ammonia and hydrogen, has the potential to significantly reduce the sector's carbon footprint (Al-Enazi et al., 2021).

For the transition to succeed, multiple independent factors must be in place. The regulatory frameworks require adaption, infrastructure must be developed, and existing vessels must either be retrofitted or replaced. Ultimately, the transition is shaped by individual decision-makers. Therefore, to better understand the green transition, we need to understand why people make the choices that they do. This paper addresses this gap by examining the relationship between fuel choice, vessel value, and earning potential within the freight market.

Consider a shipper who integrates climate considerations into their business decisions. Several factors may drive this approach. First, the shipper may have a genuine interest in reducing emissions. Alternatively, their financial structure may involve green financing mechanisms, which necessitate compliance with climate-related key performance indicators (KPIs). Failure to meet the KPIs results in a higher cost of financing. Another potential driver is regulatory compliance, as the shipper may operate within a jurisdiction where emissions are regulated somehow, e.g., with a carbon tax, emission quotas, or similar policies. Additionally, if the shipper is part of a supply chain, others in the same supply chain could be willing to pay for lower transportation emissions (Schwartz et al., 2022). In such a scenario, there could be a plausible case for shippers paying a premium for lower emissions in the freight market.

On the other hand, alternative fuels are generally more expensive (Solakivi et al., 2022). If the vessel is fixed under contractual terms where the charterer is responsible for fuel costs, like a time charter, it is expected time charter rates wil adjust to reflect the higher cost.

Moreover, consider a scenario in which vessels powered by alternative fuels are more expensive to operate than vessels powered by traditional marine fuels. Additionally, assume that certain shipping routes command higher freight rates, potentially due to factors such as physical risks or infrastructure constraints. In such a market, all vessels would accept the high-rate fixtures, but only traditional-fueled vessels would accept the lower-rate fixtures. This selection effect could lead to a higher average rate for alternative-fueled vessels. However, disentangling selection effects from genuine price premiums for lower-emission vessels presents a methodological challenge.

Competing forces influence pricing dynamics in the second-hand vessel market. On the one hand, a vessel's market value is fundamentally determined by its discounted expected cash flow. If transitioning to a more expensive fuel leads to increased operating costs, the resulting decline in net cash flow will decrease, reducing the vessel's overall valuation.

On the other hand, there is evidence that consumers exhibit a willingness to pay for products with lower carbon footprint (Solakivi et al., 2022). Given that transportation emissions are part of the scope 3 emissions for many companies (Team, n.d.), it is reasonable to expect a corresponding willingness to pay for freight services with lower GHG emissions. Moreover, regulatory developments may impose a direct cost on GHG emissions from vessels. A notable example is the inclusion of shipping into the European Union (EU) Emissions Trading System (ETS) ("FAQ – Maritime transport in EU Emissions Trading System (ETS)", n.d.), which introduces additional compliance costs for ships operating within European markets. However, beyond its immediate financial implications, this policy change also underscores the broader regulatory risks that shipping companies may face in other jurisdictions if similar measures are adopted globally.

Thus, two opposing forces influence vessel valuation in the second-hand market: the higher operating cost associated with alternative fuels, which negatively affects value, and the potential premium or regulatory risk driving up the value. In this paper, we investigate how the choice of fuel affects freight rates and second-hand value.

2 Literature Review

2.1 Freight Market

Freight markets facilitate the exchange of transportation services, which have been integral to human economic activity for millennia. Consequently, the study of freight markets has garnered considerable academic interest over time. The modern field of maritime economics is often tracked back to the foundational contributions of Jan Tinbergen (Tinbergen, 1934) and Tjalling Koopmans (Koopmans, 1939), whose pioneering works laid the groundwork for subsequent research. (Tinbergen, 1934) developed indices for supply and demand based on historical data. (Koopmans, 1939) introduced a partial equilibrium framework specifically tailored to the tanker freight market, advancing the theoretical understanding of shipping economics. Zannetos expanded the research on tanker freight markets in (Zannetos, 1964) by analyzing the competitive dynamics of tanker freight markets, demonstrating that despite the oligopolistic structure of the petroleum markets, the tanker freight market exhibited near-perfect competition.

Major advancements in the literature on freight markets emerged during the 1980s, exemplified by works such as (Norman & Wergeland, 1981) and (Strandenes, 1986). These studies modeled the freight market as an integral component within a broader system of interconnected maritime markets, including the sale and purchase (S&P) market, the newbuild market, and the scrapping market. By adopting a more systemic approach, these papers provided a more comprehensive understanding of the interdependencies shaping maritime economic dynamics.

The literature on freight markets has gradually shifted from structural models to univariate models. (Birkeland, 1998) argues that this is partly due to the complexity and difficulties in estimating model parameters. The univariate literature can be broadly categorized into two streams of reasearch: continuous and discrete models. Research within the continuous stream typically models freight market rates as stochastic processes governed by stochastic differential equations (SDEs). An early contribution in this stream of literature is (Bjerksund & Ekern, 1995), which employs the Ornstein-Uhlenbeck process to represent spot freight rates as mean-reverting. This approach was further extended by (Tvedt, 1997). More sophisticated models based on SDEs have later been proposed. For instance, (Adland & Cullinane, 2006) proposed a non-parametric Markov model. (Adland et al., 2008) applied a linear SDE to analyze LPG markets. (Benth et al., 2015) applied an exponential Lévy process to capture complex market features like heavy tails, stochastic volatility, and memory. Additionally, (Poblacion, 2015) uses a three-factor model to capture seasonality, while (Población & Serna, 2018) uses a two-factor model to capture long-term equilibrium behavior in tanker markets.

The second stream of literature on freight markets uses time series models to analyze market dynamics. Several papers have utilized Vector Autoregression (VAR) to investigate long-term relationships in freight markets (A. W. Veenstra & Franses, 1997) and (Yin et al., 2017). In a comparative analysis of predictive models (Alizadeh et al., 2007) compared the Vector Error Correction Model (VECM) and Autoregressive Moving Average (ARIMA) models against Forwards Freight Agreements (FFAs), concluding that FFAs have superior predictive performance. This finding is corroborated by (Kavussanos & Nomikos, 2001). Similarly, (Batchelor et al., 2007) compare the predictive performance of VECM, ARIMA, and VAR models. To incorporate heteroskedasticity, (Goulas & Skiadopoulos, 2012) used VECM and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to analyze the International Maritime Exchange index. Further expanding upon these, (Munim & Schramm, 2017) compared ARIMA, ARCH, and ARIMARCH, finding that ARIMARCH outperforms the alternative models. (Chen et al., 2012) adopted a broader framework and applied ARIMA, ARIMAX, VEX, and VAR models. The adaptability of GARCH models has made them particularly popular for capturing volatility dynamics in freight markets. (Kavussanos, 1996b) (Gavriilidis et al., 2018) (Drobetz et al., 2012) and (Alizadeh & Nomikos, 2011) have applied various GARCH specifications to model price dynamics and volatility in freight markets.

The stationarity of spot freight rates has been a long-standing debate in the freight market literature. Theoretically, freight rats are expected to be mean reverting and stationary, as suggested by (Tvedt, 2003). Empirical works supporting this view include (Koekebakker et al., 2006) and (Adland & Cullinane, 2006), who argue that stationarity is non-linear and primarily found at the extremes of the price distribution and therefore hard to detect. Moreover, (Kou & Luo, 2015) contends that structural breaks exist in shipping data but that rates are stationary between the breaks. Conversely, numerous works like (Kavussanos, 1996a), (Berg-Andreassen, 1997), (Glen & Rogers, 1997), (A. W. Veenstra & Franses, 1997) and (Yin et al., 2017) all find shipping freight rates to be non-stationary. The Augmented Dicky-Fuller test is the primary statistical tool used to investigate stationarity in these papers. (Kou et al., 2018) attributed the discrepancies in findings to variations in sample window and sample length, highlighting the sensitivity of results to methodological differences.

Another debate in the freight market literature concerns the nature of seasonality in shipping markets. Given the well-documented seasonal patterns in international trade, seasonal patterns are expected to manifest within freight markets. Empirical studies such as (Alizadeh & Kavussanos, 2002) and (Yin & Shi, 2018) provide evidence supporting deterministic seasonality, suggesting that seasonality is consistent and predictable over time. In contrast, (Poblacion, 2015) and (Población & Serna, 2018) advocate for a stochastic seasonality. Arguing that seasonality is prone to random shocks and fluctuations and, therefore, less predictable. This distinction between deterministic and stochastic seasonality remains an area of discussion in the analysis of freight market dynamics.

The introduction of the Baltic Freight Index (BFI) in 1985 ("History", n.d.) marked a significant milestone in the development of new financial derivatives linked to the freight market. By providing a standardized benchmark for settling financial contracts, such as Forward Freight Agreements (FFAs), the BFI facilitated the expansion of freight derivatives trading and stimulated new research in this area. Early work, such as (Chang & Chang, 1996) and (Kavussanos & Nomikos, 1999), studied the predictive capacity of futures contracts (FFAs) in forecasting spot rates. Building on these foundations, (Kavussanos & Nomikos, 2001) investigated the mechanisms of information transmission between spot and forward markets, offering insights into the price discovery process. Further advancements were made by (Kavussanos & Visvikis, 2004), who analyzed the lead-lag relationship between spot and forward markets, focusing on mean and volatility interactions. More recently, (Yin et al., 2017) identified a long-term causal relationship between spot and forward markets, enhancing the understanding of their interdependencies. This body of work highlights the BFI's critical role in shaping freight market derivatives' development and analysis.

Much of the literature on freight markets has relied on shipping indexes. This reliance stems from the inherent heterogeneity of transactions, as freight rates negotiated between vessel owners and charterers often reflect specific vessel and voyage characteristics in addition to the broader market conditions. Shipping indexes are often constructed to represent a "typical" market price. They are often based on a standard vessel and are usually based on reports from shipbrokers (Ltd, 2023). Their simplicity and accessibility have contributed to their widespread adoption as a convenient proxy for market freight rates. However, as highlighted by (A. Veenstra & van Dalen, 2008), this reliance presents several methodological challenges and limitations. Despite the prevalence of shipping indexes, several works have also employed fixture-level data to provide a more granular analysis of freight rate formation. (Bates, 1969) pioneered this approach by studying the transportation of sugar. Later, (Tamvakis & Thanopoulou, 1995) used tanker fixtures to investigate the potential existence of a two-tier market for crude oil tankers, a framework that was subsequently extended to the dry bulk market by (Tamvakis & Thanopoulou, 2000). Further advancements were made by (Alizadeh & Nomikos, 2011) and (Alizadeh & Talley, 2011), who investigated how vessel and fixture characteristics influenced freight rates in the tanker and dry bulk market. More recently, (Adland et al., 2016) identified charterer and owner fixed effects on the freight rates in tanker markets, while (Adland, Alger, et al., 2017) constructed a hedonic price index using fixture data from the Anchor Handling vessels (AHV) and Offshore Supply Vessels (OSV) markets. These studies underscore the value of fixture-level data in capturing the complexities of freight rate determination, providing a more detailed and nuanced understanding than aggregate shipping indices. This paper is closely related to these works.

2.2 S&P Market

The literature on vessel Sale and Purchase (S&P) markets can be broudly divided into three main streams of literature: structural models, time series models based on price indices, and models utilizing individual transaction data.

The earliest stream of literature focuses on structural models, which seek to explain market dynamics through theoretical frameworks and econometric models. These models often take a holistic approach and model the interaction between different maritime markets. An early contribution is (Charemza & Gronicki, 1981), who proposed a model for the second-hand vessel market based on supply and demand functions. In contrast, (Beenstock, 1985) proposed that vessels should be valued as a capital asset, establishing a framework that has since been expanded in subsequent works (Beenstock & Vergottis, 1989a)(Beenstock & Vergottis, 1989b)(Beenstock & Vergottis, 1993). A notable advancement in structural modeling is the previously mentioned work (Norman & Wergeland, 1981), who constructed a model for the S&P market of very large crude oil tankers (VLCC) while incorporating freight markets. Building on the foundations, (Strandenes, 1986) proposed a comprehensive model connecting S&P markets, newbuild, freight and scrapping markets. Although intricate structural models have become less prevalent in recent decades. Modern structural models increasingly incorporate advanced econometric techniques. For example, (Tsolakis, 2005) employed sophisticated econometric methods to enhance model accuracy. (Adland & Koekebakker, 2007) demonstrates the methodological evolution of this stream of literature by proposing a structural model for handysize dry-bulk using Multivariate Density Estimation (MDE) models.

The second stream of literature on S&P markets focuses on time series models of price indices, which aim at modeling the market for a standardized vessels rather than individual transactions. These models adopt a longitudinal perspective, analyzing price fluctuations over time and abstracting from the heterogeneity of individual vessels. Modeling the S&P markets was of secondary concern in many of the early works within the time series stream of literature. (Hale & Vanags, 1992) applied an autoregressive model but centered their analysis on co-integration dynamics rather than explicit modeling of S&P market. (Glen†, 1997) employed a VAR model to investigate long-term co-integration. A significant advancement in the area came with (Kavussanos, 1996b), who introduced ARCH Models to analyze the difference in volatility across S&P tanker markets of varying sizes. This was followed by (Kavussanos, 1997), who conducted a similar study on dry-bulk S&P markets. Both papers found that larger vessels exhibited greater price volatility than their smaller counterparts. Building on these contributions, (Syriopoulos & Roumpis, 2006) employed an Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model to analyze the relationship between volume, price, and size in tanker and dry-bulk S&P markets. These advancements highlight the increasing sophistication of time series approaches in capturing the dynamic nature of SP price movements.

The Efficient Market Hypothesis (EMH) states that market prices reflect all available information, thereby preventing systematic excess returns (Fama, 1970). The extent to which S&P vessel markets adhere to this principle has been a central question in the academic literature. Given that time series models often have been used to investigate EMH there is some overlap between the time series and market efficiency literature. (Hale & Vanags, 1992) investigated Granger causality and co-integration relationships and concluded that S&P markets were not efficient. Based on their findings, they argue that the structural models based on the assumption that S&P markets are efficient, like (Beenstock, 1985), were not valid and therefore obsolete. Similarly, (Glen & Rogers, 1997) found evidence of co-integration between multiple pairs of S&P markets but did not reject the EMH outright. Subsequent research provided more nuanced indsigts. (Kavussanos & Alizadeh, 2002) found that while certain S&P markets exhibited efficiency, other failed to do so due to time-varying risk premiums. (Adland & Koekebakker, 2004) evaluated the profitability of different trading rules in S&P markets and discovered that out-of-sample profits were generally not achievable for most tanker and dry bulk markets, except for Panamax. (Sødal et al., 2009) tested market efficiency by analyzing vessel switching decisions between the dry-bulk and the tanker markets, concluding that S&P markets markets were largely efficient throughout most of the analysis period, with the exception of inefficiencies observed in the early 2000s. A recurring argument within the literature attributes inefficiencies in S&P markets to the prolonged time required for transaction execution, which impedes shipowners from responding swiftly to trading signals. These temporal delays may contribute to the divergence between theoretical assumptions of market efficiency and empirical observations.

The third stream of literature on S&P markets is based on individual transaction-level data, as opposed to price indices based on a standard vessel characteristic. Given the heterogeneity of vessel and transaction characteristics, this approach enables a more granular analysis of how specific vessel and transaction characteristics influence price formation. (Köhn, 2008) pioneered this stream by employing Generalized Additive Models (GAM) to analyze pricing dynamics in chemical tanker data. Building on this, (Adland et al., 2019) utilized transaction-level data to study the chemical tanker markets. In a related work, (Chou & Chen, 2019) leveraged micro data to investigate the application of different technical trading rules in S&P markets. Recent advancements in this stream include the application of machine learning techniques to enhance predictive accuracy and analytical depth. (Adland et al., 2023) utilized extreme gradient boosting on micro-level data, demonstrating the potential of advanced computational methods in modeling vessel prices. This paper fits into this stream of literature and is related to (Adland et al., 2018), which use transaction-level data to investigate the impact of energy efficiency on vessel value. The focus on granular data in this literature stream underscores its significance in capturing the nuances of vessel-specific and market-specific dynamics, providing a complementary perspective to index-based modeling approaches.

2.3 Green transition

The decarbonization of shipping is an important area of research and policy discussion, driven by the urgent need to mitigate GHG emissions while ensuring safety, economic viability and equity in the transition process. Multiple actions have been proposed to achieve emission reduction, including in energy efficiency, adoption of low-carbon alternative fuels, and operational measures such as speed optimization.

Fuel consumption constitutes a major portion of operational costs for vessel operators, and traditional maritime fuels are a significant source of GHG emissions. Consequently, improving energy efficiency is not only in the interest of the environment but also in the economic interest of the operator. (Adland et al., 2018) examined the impact of energy efficiency on vessel value in S&P markets. They find a negative relationship between energy efficiency and vessel value. (Agnolucci et al., 2014) and (Adland, Alger, et al., 2017) found that due to the split incentives between charterers and shipowners in time charter markets, only some of the savings due to energy efficiency accrue to the shipowner. As a result, energy efficiency improvements do not necessarily in higher vessel value, reducing the incentive for shipowners to invest in efficiency-enhancing technology. (Köhn & Thanopoulou, 2011) find that only dry-bulk vessels with exceptionally high fuel consumption receive a discount in time charter markets, suggesting that efficiency considerations play a role primarily at the extremes of the market. (Prakash et al., 2016) finds little evidence for freight rate premium for fuel efficiency.

An alternative approach to reducing emissions in the shipping industry involves adopting alternative fuels. However, ongoing debate persist within the industry on which alternative fuel presents the most viable long-term solution. Alternative fuels are fuels who wither produce no emissions or less emissions compared to traditional maritime fuels, e.g., LNG, ammonia, mydrogen, and methanol. Dispite their potential environmental benefits, the large scale adoption of alternative fuels faces several challenges . (Balcombe et al., 2019) identifies key challenges like high cost, safety concerns, and lack of infrastructure. The economic feasibility of alternative fuels remains contested issue. (Solakivi et al., 2022) predicts that the costs of alternative fuels will remain high in the long-term and that the changing regulatory framework, particularly in the EU, will lead to higher fuel prices overall. LNG, for example, has been identified as a potential transitional fuel that can improve air quality, lower fuel costs, and reduce greenhouse gas (GHG) emissions by up to 28% (Balcombe et al., 2021). However, the environmental benefits of LNG is counterbalance by methane leakage within the LNG supply chain, which significantly undermine its overall climate impact. Biofuels present another viable alternative. However, biofuels depend on feedstocks as a production factor, raising food security concerns and possibly competition for arible land (Tan et al., 2022). The optimal pathway for decarbonization also remains a matter of debate. (Solakivi et al., 2022) advocate for a phased transition from fossil fuels to e-fuels via biofuels. In contrast, (Lindstad et al., 2021) suggest that dual-fuel engines represent a more robust and pragmatic approach to achieving emission reductions. This ongoing discourse underscores the complexity of selecting an optimal fuel transition strategy, as technological, economic, and regulatory factors continue to evolve.

3 Methodology

3.1 Elastic net, Ridge, Lasso, and linear regression

Linear Multiple Regression is a well-known statistical technique used in many fields of science. It is commonly estimated using the Ordinary Least Square (OLS) method, which determines the coefficients *beta* by minimizing the sum of square residuals,

$$\min_{\beta}\{||Y - X^t\beta||^2\}. \tag{1}$$

Where β is an $N \times 1$ vector of coefficients, X is an $N \times M$ matrix containing N observations of M explanatory variables, and Y is an $N \times 1$ vector of dependent variables. The sign and magnitudes of the coefficients β provide insights into the relationship between independent variable X, and the dependent variable Y. The coefficients are calculated using OLS. OLS is the best linear unbiased estimator (BLUE) under the Gauss-Markov assumptions (Stock, 2015). An estimator that is both unbiased and characterized by minimal variance is generally considered advantageous for ensuring the reliability and interpretability of regression results.

Hedonic price indexes, first introduced in (Rosen, 1974), is an econometric approach to estimate price changes over time while accounting for variation in product characteristics. A well known challenge in national accounting is that products undergo subtle modifications over time making it insufficient to observe simply the raw price change when measuring inflation or market trends over time. Hedonic price indexes addresses this issue by adjusting for the individual characteristics of the products, ensuring a more accurate assessment of price dynamics. One common way to construct a hedonic price index involves estimating a multiple linear regression on transaction-level data, where product-specific characteristics are included as explanatory variables and dummy variables representing distinct time periods introduced in the regression, allowing the estimated coefficient to form a price index that reflects the adjusted price trend over time. This study employs similar hedonic adjustments to evaluate overall market conditions in the shipping industry. There are examples in the academic shipping literature of hedonic price indexes being used. (Adland, Cariou, & Wolff, 2017) demonstrating its relevance for assessing market trends while accounting for vessel-specific heterogeneity.

Elastic Net regression is a generalization of linear regression that incorporates both $L1$ (Lasso) and $L2$ (Ridge) regularization penalties on the magnitude of coefficients. This method is designed to exploit the relationship between model complexity and model prediction accuracy. A key challenge in statistical modelling is the balance between bias and variance. A more complex model tend to exhibit low bias as they capture intricate relationships within the training data. However, they often suffer from high variance, meaning that their predictive performance declines when applied to new unseen data. Conversely, simpler models tend to have low variance, leading to more stable predictions on new data, but they may fail to capture systematic relationship, hence having higher bias. This is called the bias-variance trade-off (Hastie et al., 2009).

The elastic net regression model finds the coefficients β by solving the following optimization problem,

$$\min_{\beta}\{||Y - X^t\beta||^2 + \lambda_1||\beta|| + \lambda_2||\beta||^2\}, \tag{2}$$

where $\lambda_1, \lambda_2 \in \mathcal{R}$ and $||\cdot||^p$ is the Lp norm, i.e., the magnitude of the vector β raised to the power p (Hastie et al., 2009). The tuning parameters λ_1 and λ_2 control the relative importance of these penalties, determining the the regularization applied to the model. Linear regression is a special case of elastic net where $\lambda_1 = \lambda_2 = 0$.

Ridge regression is a special case of elastic net regression where $\lambda_2 = \lambda$ and $\lambda_1 = 0$. The Ridge estimator is obtained by solving the minimization problem,

$$\min_{\beta}\{||Y - X^t\beta||^2 + \lambda||\beta||^2\}, \tag{3}$$

Ridge regression alleviates some of the problems associated with multicolinearity. In OLS regression highly correlated independent variables tend to produce coefficients estimates with large variance, leading to instability in the model. By imposing a penalty on the magnitude of coefficients, Ridge regression reduce variance, thereby improving predictive performance and generalizability.

Lasso regression is another special case of elastic net regression where $\lambda_1 = \lambda$ and $\lambda_2 = 0$. Lasso coefficients are found by solving the following minimization problem,

$$\min_{\beta}\{||Y - X^t\beta||^2 + \lambda||\beta||\}, \tag{4}$$

The $L1$ penalty introduces non-linearity in the optimizations problem (2), and there is no close form estimator for the coefficients. This contrasts ridge regression, where the $L2$ maintains linearity in Y in the optimization problem (2). The $L1$ penalty also has the property to drive some variables coefficients to 0. This characteristic makes Lasso regression particularly useful in high-dimensional settings where feature selection is essential for model interpretability and reducing overfitting (Hastie et al., 2009).

Lasso regression is vidly recognized as an effective variable selection method due to its ability to shrink some regression coefficients to exactly zero, thereby eliminating irrelevant predictions from the model. Consider a linear regression model with the independent variables X, and suppose that the true model is given by variables constituting a subset of X. A variable selection scheme that selects the true model and has an optimal estimation rate is said to possess the Oracle property (Zou, 2006). This means that if we have m observations of n variables and the true model of the phenomenon we study is constituted by $r < n$ variables, then a variable selection process with the Oracle property will find the correct variables and estimate them with as little data as possible. Under certain conditions, Lasso regression has this property (**donoho_for_2006**) and is consistent (**meinshausen_high_dimensional_2006**). However, (Zou, 2006) finds that modifying the lasso minimum optimization problem makes it possible to derive a regression method that retains the Oracle property under more general conditions. This modified approach, called the Adaptive Lasso, allows for more robust variable selection while preserving consistency and efficiency.

Adaptive Lasso regression is a generalization of the regular Lasso regression by allowing for individual penalization of each explanatory variables. Unlike regular lasso, which applies a uniform penalty across all coefficients. The Adapted Lasso regression coefficients are found by solving the following minimization problem,

$$\min_{\beta}\{||Y - X^T\beta||^2 + \lambda\omega|\beta|\} \tag{5}$$

Note that this is similar to (4), but the penalty parameter λ is a vector $\lambda\omega$, where λ is a constant and $\omega = (\omega_1, \omega_2, \ldots, \omega_m)$ is a vector. Each element in ω adjusts the penalty to each coefficient. The individual entries in ω are given by,

$$\omega_j = \frac{1}{|\beta_j^{\text{ridge}}|^\gamma}. \tag{6}$$

Any initial estimate of β can be used as a penalty in the denominator of ω. However, many practitioners prefer using the corresponding estimated ridge regression coefficient to stabilize the penalty term. γ is a tuning parameter, and some preliminary testing suggests that 1 is a reasonable estimate with negligible improvements in results with further tuning. Other methods also exhibit the Oracle property. One such alternative is the the Garrote estimator (Zou, 2006).

3.2 XGBoost

Boosting is a wide class of machine learning algorithms based on the idea that aggregating prediction made by a large group of simple models can yield highly accurate results. A classic historical example of this idea dates back from (**galton_vox_1907**), who observed a weight-guessing contest at a fair in 1906. Although individual guesses varied widely, the average of all estimates turned out to be accurate within 1%. Most boosting methods operates by training a large ensemble of simple models on a subsample of the data and combining their output into an aggregate predicition.

Extreme Gradient Boosting (XGBoost) is a widely adopted tree-based boosting algorithm implemented in an open-source library in many common programming languages. XGBoost is based on a gradient boosting framework, which works by iteratively refines the model by fitting subsequent sub-models to the residual of the previous iteration (**noauthor_xgboost_nodate**). This process allows the algorithm to incrementally minimize errors and improve predictive accuracy.

Although XGBoost is often categorized as a complex machine learning model, it is not entirely a black box.One of its interpretability features is the ability to identify the most influential variables in the model by counting the frequency with which each variable is selected in the submodels. This feature enables researchers and practitioners to assess variable importance and gain insights into the underlying patterns captured by the model.

3.3 Goodness-of-fit and Model Evaluation

The Akaike information criterion (AIC) is a widely used metric for model evaluation, balancing model fit with complex to prevent overfitting (Devore et al., 2021). The AIC is defined,

$$AIC = 2k - 2\log(L). \tag{7}$$

Where k is the number of parameters in the model, and L denotes the likelihood of the model given the observed data. The number of parameters (k) serves as a measure model complexity. As the number of parameters increases, the risk of overfitting also rises. Overfitting occurs when a model fits the training data exceptionally well but fails to generalize to unseen data, leading to poor performance on out-of-sample data (Devore et al., 2021). The Likelihood function, L, represents the probability of observing the data given that the proposed model is the true model. Therefore, a model with a high likelihood indicates that the model explains the data better than a model with a lower likelihood. However, likelihood tends to increase with model complexity and number of parameters (Stock, 2015). The AIC addresses this trade-off by introducing a penalty term ($2K$) for model complexity, ensuring that additional parameters are only incorporated if they lead to a significant improvement in model fit. This approach makes AIC particularly useful for model selection, favoring models that achieve a balance between explanatory power and parsimony.

In addition to AIC, some models in this paper are evaluated using the Mean Square Error (MSE), a widely adopted performance matrix in the machine learning literature. The mean square error is given by,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2, \tag{8}$$

where y_i is observation i, and $\hat{y}_i$ is the model prediction of observation i.

In this paper, Cross-validation is used to train and evaluate XGBoost and adaptive lasso. Cross-validation is a training process where data is partitioned into K equal subsetes, called folds. The model is iteratively trained on K-1 folds and evaluated on the remaining fold. Ten folds are used in this paper for the aforementioned models. Cross-validation is particularly valuable for assessing a model's ability to generalize to unseen data by testing it on observations that were not part of the training set. This is especially important for situations where the amount of data is limited, as it allows for efficient re-use of data while mitigating issues relating to overfitting. For models like XGBoost, the K-1 training folds are used to train sub-models, and the last fold is used to evaluate. As additional models are trained, the risk of overfitting increases, which can lead to a reduction in training error. However, for regularization based models like adapted lasso, cross-validation is primarily used to find the optimal value of a tuning parameter λ that minimizes the training error. This ensures that the model achieves an appropriate balance between complexity and predictive accuracy.

4 Data

This paper studies four distinct markets: the freight market for LNG tankers, the freight market for LPG tankers, the S&P market for LNG tankers and the S&P market for LPG tankers. Give the diversity of these markets multiple datasets and sources are utilized. However, all markets are analyzed using transaction-level data to ensure granular and robust examination of market dynamics.

4.1 S&P Market Data

The data for the S&P markets are obtained from Clarkson's World Fleet Register (WFR). Transactions involving vessels characterized as gas carriers at the time of sale are included in the analysis. The dataset comprises a total of 400 recorded transactions spanning the period from January 2005 to December 2023. Summary statistics of transaction data are presented in Table 1

Table **??** presents summary statistics for 400 S&P transactions involving gas carriers and includes 14 variables. Dwt is the deadweight tonnage of a vessel. Price (sale) denotes the transaction price at sale in USD. Speed is the vessel's design in knots. 10Y US treasury yield is included as a proxy for the cost of debt, reflecting brauder financial conditions. Alternative Fuel is an binary indicator variable signifying whether a vessel is equipped with alternative fuel technology. Age and Age2 captures vessel age at the time of sale and its its square to account for any nonlinearity. South Korea, China, P.R., Japan, and Other Countries are indicator variables for builder countries and serve as possible perceived quality indicators. Man Energy Solutions, Mitsubishi, and Other Designers are indicator variables for the main engine design groups. Lastly, diesel 2-stroke, diesel 4-stroke, steam turbine, diesel-electric, and hybrid mechanic/electric are indicator variables for the type of engine in each vessel.

The dataset exhibits considerable variation in DWT and transaction price.

Table 1: Summary statistics for S&P transaction data. Source: Clarksons World Fleet Register. Alternative Fuel, South Korea, China P.R., MAN Energy Solutions, Mitsubishi,Diesel 2-Stroke, Diesel 2-Stroke, Steam Turbine, Diesel Electric and Hybrid Mech./Elec. are categorical variables. Age is the age of the vessel at the transaction point and age2 is the square of the age.

Statistic	N	Mean	St. Dev.	Min	Max
DWT	400	29,597.850	26,770.120	1,003	96,811
Price (Sale)	400	47.910	105.806	0.900	1,400.000
Speed (knots)	400	15.465	2.106	10.500	20.400
10Y US treasury yields	400	2.700	1.094	0.000	5.190
Alternative Fuel	400	0.075	0.264	0	1
Age	400	13.590	7.914	0	38
Age2	400	247.160	229.680	0	1,444
South Korea	400	0.280	0.450	0	1
China P.R.	400	0.095	0.294	0	1
Japan	400	0.552	0.498	0	1
Other Countries	400	0.072	0.260	0	1
MAN Energy Solutions	400	0.545	0.499	0	1
Mitsubishi	400	0.238	0.426	0	1
Other Designer	400	0.218	0.413	0	1
Diesel 2-Stroke	400	0.787	0.410	0	1
Diesel 4-Stroke	400	0.108	0.310	0	1
Steam Turbine	400	0.060	0.238	0	1
Diesel Electric	400	0.043	0.202	0	1
Hybrid Mech./Elec.	400	0.002	0.050	0	1

The smallest vessel in the sample is 1 003 DWT, and the largest is 96 811 DWT. Similarly, the lowest price in our sample is 900 000 USD and the greatest price is 1.4 billion USD. The substantial disparity between the smallest and greatest values suggests the presence of outliers in the sample. To mitigate the potential influence of extreme values and improve model robustness, key variables are log-transformed. Exploratory data analysis suggests that model performance is improved by also log transforming speed.

Both Age and Age^2 are included as suggested by (Adland et al., 2023). The Depreciation of vessel value by age is well-documented, primarily due to increased maintenance, technology obsolescence on board, and so on. (Stopford, 2008) suggests that depreciation follows a linear pattern. However, as vessels age, the probability of scraping increases. The residual value of a scrapped vessel is largely determined by the salvageable metal content. Therefore, vessel value should asymptotically converge to the scrapping value over time. (Adland et al., 2023) suggest that this convergence is non-linear and best described using a squared age term.

A majority of gas carriers are built in Japan, with South Korea and China ranking as the second and third largest builders.Although other countries also produce gas carriers, these three countries account for 92.7% of all gas carriers that are built. Therefore, indicator variables for other countries are collected in a single variable. A similar pattern emerges for main engine design group. MAN Energy Solutions and Mitsubishi designing the vast majority of engines. MAN or Mitsubishi account for 78.3% of engines designed. Other producers, like Wartsila, hold relatively small market share and they are combined into a single variable. Lastly, indicator variables are included for vessel engine types: diesel 2-stroke, diesel 4-stroke, steam turbine, diesel-electric, and hybrid mechanic/electric. 2-stroke engines or 4-stroke engines are the most prevalent with 78.8% of vessels in the dataset. Exploratory data analysis suggests that controlling for engine type is important, likely due to differences in fuel efficiency, operational costs, and maintenance requirements, which influence vessel valuation and market performance.

4.2 Freight Market Data

Freight market dynamics for LPG and LNG vessels are analyzed using fixture data. The data is sourced from Clarkson's Shipping Intelligence Network (SIN) and Refinitiv Eikon. Due to differences in data availability across segments, Time Charter (TC) fixtures are utilized for the LNG freight market, and Voyage Charter (VC) fixtures are employed for studying the LPG market. This ensures that the most comprehensive and representative data is used for each market segment.

The fixture dataset summarized in Table 6 comprises 50 LNG Time Charter contracts. The sample is constrained due to data availability. Period days represents the duration of the time charter contract measured in days. Rate is the agreed TC rate in thousands of USD per day. DWT is the total carrying capacity of the vessel. Capacity is the cargo capacity measured in cubic meters.

Table 2: Summary statistics for LNG Fixtures

Statistic	N	Mean	St. Dev.	Min	Max
Period Days	50	245.960	744.307	6	3,870
Rate	50	60.100	85.246	16	487
DWT	50	84,105.360	5,372.181	67,552	97,169
Capacity (m3)	50	158,819.100	11,018.740	125,631	180,145
Alternative Fuel	50	0.860	0.351	0	1
Age	50	4.580	5.489	0	30

Table 3: Summary statistics for LPG Fixtures.

Statistic	N	Mean	St. Dev.	Min	Max
Capacity (m3)	800	82,733.540	7,734.477	1,155	100,947
Rate	800	102.861	53.421	1.350	318.000
Alternative Fuel	800	0.184	0.388	0	1
DWT	800	54,173.500	5,100.750	715	59,479
Age	800	8.224	5.451	0	47

Alternative Fuel is a categorical variable include wether the vessel operates on an alternative fuel.

The fixture dataset presented in Table 3 consists of 800 LPG voyage charter contracts. Capacity is the transportation capacity measured in cubic meters. Rate is the agreed voyage rate in USD per tonn. Alternative fuel is a categoric variable indicating whether the vessel operates on an alternative fuel. DWT is the deadweight tonnage of a vessel. The age is the vessel age at the time of the fixture. Voyage charter were selected due to the availability of data. The same set of explanatory variables are used for the LPG fixtures and LNG fixtures. However, one important distinction exists between TCs and VCs. VCs are contracts for transportation from one port to another, whereas TCs are contracts where a vessel is hired for a predetermined time period. The duration is included in the LNG fixture data, because the it is reasonable to expect that duration should influence rates. In contrast, the duration is hard to determine for VCs, as external effects like weather and route affect voyage length. While, the exact route is not available from any of the data sources the area of loading and discharging is provided. However, some provided locations are very generalized, such as ”US East” and ”India.” Given that the US East Coast is over 2 500 nautical miles long and the coastline of India is over 2 000 nautical miles accurately estimating voyage duration based on theses designation is impractical. As an alternative, this paper used indicator functions as proxies for route length. An indicator variable is used for each combination of load and discharge area. There are fewer than 100 unique combinations, and therefore,

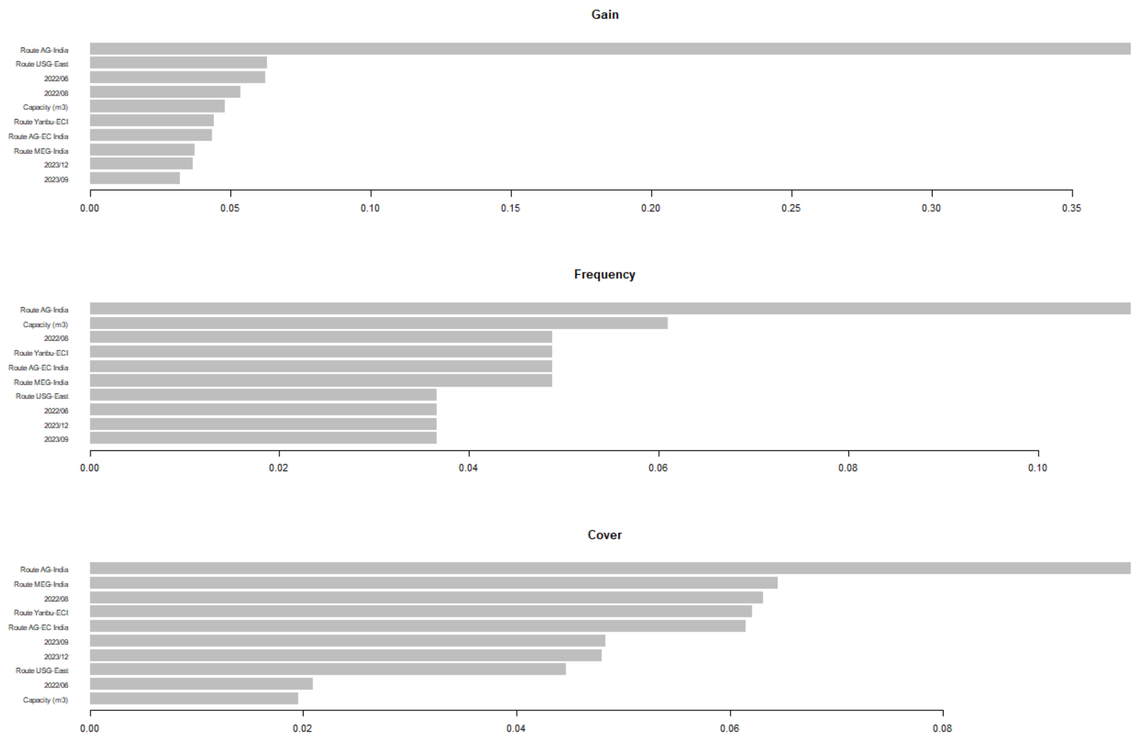

Figure 1: XGBoost: different measures of variable importance.

the number of additional variables to be estimated is not problematic when we have 800 fixtures.

In addition to fixtures and transactions data this study constructs a hedonic price index for all examined markets markets, following the methodology in (Adland, Cariou, & Wolff, 2017). The estimation frequency of the index varies depending on data availability across market segments. For S&P and LPG freight markets the high volume and frequency of data allow us to estimate the hedonic price index on a monthly basis. However, due to the low number of LNG fixtures observed in the sample, a yearly resolution is adopted.

5 Results

5.1 LPG Fixtures

Table 4 presents the results of the linear regression model applied to the LPG fixture data. Models (1), (2) and (3) incorporates vessel characteristics like power type, tonnage, vessel age, and cargo capacity. These specifications aim to

Table 4: LPG Fixtures linear regression

	Dependent variable:		
	Rate		
	(1)	(2)	(3)
Constant	10.342	18.406	42.984
	(44.498)	(64.882)	(34.856)
Alternative Fuel	6.356	8.161**	−1.612
	(4.875)	(4.138)	(2.961)
Power Type (D 4-S)	70.780	56.746	−2.009
	(45.420)	(60.439)	(33.875)
DWT	0.001	0.0003	−0.0004
	(0.001)	(0.001)	(0.001)
Age	−2.405***	−2.050***	−0.070
	(0.648)	(0.505)	(0.336)
Age2	0.049**	0.049***	0.011
	(0.021)	(0.014)	(0.012)
Capasity (m3)	0.001**	0.001**	0.001
	(0.0002)	(0.0003)	(0.0003)
Year FE	Yes	No	No
Year & Month FE	No	Yes	Yes
Route FE	No	No	Yes
Observations	800	800	800
R^2	0.220	0.496	0.808
Adjusted R^2	0.212	0.468	0.778
AIC	8456.169	8172.779	7535.291
Residual Std. Error	47.433 (df = 791)	38.949 (df = 758)	25.174 (df = 690)
F Statistic	27.808*** (df = 8; 791)	18.172*** (df = 41; 758)	26.679*** (df = 109; 690)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: LPG Fixtures Adapted Lasso

	Dependent variable:
	Rate
	(1)
(Intercept)	0.000
Capacity (m3)	0.066
Alternative Fuel	.
DWT	.
Age	.
Age2	0.012
Year FE	No
Year & Month FE	Yes
Route FE	Yes

capture the relationship between vessel attributes and freight rates in the LPG market.

Model (1) incorporates time-fixed effect on a yearly basis, effectively estimating a hedonic price index with yearly resolution. The results suggest that there is an age-related pricing pattern. Where younger vessels command a premium and vessels older than approximately 5 years experience a discount. Moreover, the findings indicate that larger cargo capacity is associated with a price premium.

Model (2) extends the time-fixed effects to a monthly frequency, leading to a substantial model improvement, as measured by AIC. Results from model (2) suggests the presence of a rate premium for vessels utilizing alternative fuel. However, the coefficient is only significant at a 5% level, indicating a potential risk of a spurious result.

Model (3) is the best-performing model, and incorporates both route-fixed effects in addition to time-fixed effects with a monthly resolution. None of the vessel characteristics are statistically significant when route-fixed effects are accounted for. One possible interpretation of these results is that the effects in Models (1) and (2) may be driven by a systematic difference in vessels deployment across routes rather than intrinsic vessel characteristics. Specifically, more profitable routes may be served by newer and larger vessel while older and smaller vessels may be allocated to less profitable routes. From a model selection perspective, model (3) is the preferred model, as indicated by superior AIC value. Moreover, Model (3) explains approximately 80% of the variation as measured by the R^2 statistic.

Table 4 does not show any strong evidence of a significant premium on the freight rate associated with the choice of fuel. Model (2) suggests a potential premium for vessels using alternative fuel, the coefficient is only y significant at a 5%-level, indicating a risk that the effect may not be robust. In light of Model (3), a possible explanation for the results in Model (2) is that the result is either spurious, or driven by a underlying route-specific factor. One potential explanation is that smaller ports may lack the necessary infrastructure to refuel gas carriers operating on alternative fuels. Since the ports are smaller and tend to handle smaller trade volumes they may also be associated with a lower rate. Consequently, vessels operating on alternative fuels may be restricted to more profitable routes where adequate refuling infrastructure exists. This would explain why the apparent premium on alternative fuel disappears when routes fixed effects are introduced in Model (3).

To asses heteroscedasticitiy in the regression models a Breusch-Pagan test conducted on all three models. The test results indicate a statistically significant rejection of the null hypotheses ($p < 0.001$), suggesting the presence of heteroscedastic residuals. Consequently, heteroscedasticity-robust standard errors are employed to ensure the validity of statistical inference.

Table 5 presents the adapted lasso results, revealing that alternative fuel is not one of the variables selected by the variable selection procedure. This further supports the findings that the LPG freight market does not exhibit a systematic fuel choice premium. The only vessel characteristics that are selected are the Age^2 and capacity, suggesting that these factors play a more influential role in determining freight rates. At first glance, may appear inconsistent with the results in Model (3) from Table 4. However, the lack of statistical significance in the linear regression model does not necessarily imply that the variables are irrelevant to the true underlying relationship. The lack of significance can also stem from factors such as small sample size.

Figure 1 presents the ten most importan variables in the XGBoost model with respect to gain, frequency, and cover. The gain measures the contribution to variable based n the improvements in model performance when thevariable is used for a split. The frequency is the percentage of time the variables have been used in a sub-model. Lastly, the cover is related to how many observations are related to the variable (**chen_xgboost_2014**).

The results indicate that the most important variables predominantly time-based or route-based, with capacity being the sole vessel specific characteristic among the ten most important variables. While the ranking of variables differs across the three measures, routes to India seems to be important, suggesting that specific routes exert a notable influence on freight rates.

5.2 LNG Fixtures

The Breusch-Pagan indicate that residuals are heteroscedastic, and, therefore, robust standard errors are used.

Table 6 presents the results of the linear regression analysis of the LNG fixtures. Note the low number of observations, only 50 observations, as a result the standard error of coefficients is high. This could limit the models ability to detect significant relationships. Furthermore, the Breusch-Pagan test indicates

Table 6: LNG fixtures linear regression

	Dependent variable:			
	log(Rate)			
	(1)	(2)	(3)	(4)
Constant	−2.082	7.002***	7.086***	7.871***
	(2.126)	(1.828)	(1.725)	(1.957)
Alternative Fuel	1.051***	0.060	0.265	0.233
	(0.322)	(0.247)	(0.292)	(0.371)
Age	0.159	0.003	−0.006	0.009
	(0.097)	(0.044)	(0.046)	(0.046)
Age2	−0.003	−0.001	−0.001	−0.002
	(0.009)	(0.004)	(0.004)	(0.004)
DWT	0.0001*	−0.00004**	−0.00004**	−0.00005**
	(0.00003)	(0.00002)	(0.00002)	(0.00002)
Period Days				0.0003
				(0.0004)
Year FE	No	Yes	Yes	Yes
Power type FE	No	No	Yes	Yes
Observations	50	50	50	50
R^2	0.323	0.838	0.849	0.881
Adjusted R^2	0.263	0.806	0.811	0.846
AIC	109.292	45.914	46.218	36.487
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: LNG Fixtures Adapted Lasso

	Dependent variable:
	Rate
	(1)
(Intercept)	0.000
Period Days	0.016
DWT	.
Capacity	.
Alternative Fuel	.
Age	.
Age2	.
Year 2015	-0.122
Year 2016	.
Year 2021	.
Year 2022	0.674

the present of heteroscedasticity in the residuals and therefore hetereroscedastic robust standard errors are used.

Model (1) exhibits the highest AIC value, indicating that it is the model that fit the data the worst. Despite this, the results suggests that tonnage and fuel choice are statistically significant factors. This model does not take time varying effects into account. It is therefore possible that the observed effects for alternative fuels reflects broader market sentiment and changes in fleet composition over time rather than a true premium associated with fuel choice.

Model (2) introduce time-fixed effects to account for changes market conditions over time. Notably, once time-fixed are controlled for alternative fuel is not longer statistically significant. This supports the hypothesis that the effect in Model (1) was likely due to broader market sentiment or fleet composition. Note that the sign of the coefficient for tonnage reverses in Model (2), suggesting that omitting time-fixed effects may have introduced bias in Model (1). Moreover, Model (2) demonstrates a substantial improvement in model fit. AIC is reduced to less than half the value observed in Model (1). Additionally, the increase in R^2 indicate that Model (2) explains the variation better than Model (1).

Model (3) extends the analysis by including the power type as an additional explanatory variable. However, this does not conclusively improve model performance. While R^2 and Adjusted R^2 show a slight improvement in explanatory power, AIC is higher for Model (3) than for Model (2). Moreover, the statistical significance of the key variables remains largely unchanged between Model (2) and Model (3), indicating that the inclusion of power type does not materially change the conclusions drawn from Model (1).

Model (4) extends the analysis further by including the number of days in a time charter contract. However, similar to previous results alternative fuel does not emerge as a statistically significant variable in Model (4). Among the estimated models, Model (4) is the best performing mode with the lowest AIC and highest R^2. Model (4) explains well over 80% of the variance in the data sample.

The linear models in Table 6 do not provide empirical evidence of either a discount or a premium associated with the use of alternative fuel in the LNG tanker freight market. This can be interpreted in several ways. One possible interpretation is that LNG tankers operating on alternative fuels are cost-competitive with thous that run on conventional fuels, resulting in no observable difference in freigth rates. In this scenario, charterers may not perceive a need to pay a premium for alternative fuel vessels, as their operating costs are comparable to traditionally fueled tankers. Alternatively, consider the counterfactual in which there is a statistically significant positive relationship between alternative fuels and freight rates. Such a finding could be interpreted in two ways. Either charterers are willing to pay a premium based on fuel choice due to regulatory compliance, corporate sustainability goals, or a willingness further down in the supply chain. Alternatively, vessels operating on alternative fuel may require higher rates to offset higher operating costs leading them to only accept higher-rate fixtures.

The Adapted Lasso results are presented in Table 7 and show that alternative fuel is not one of the variables selected. This further supports conclusion that alternative fuel does not have a significant impact on the rates in the freight market. Adapted Lasso select three variables: length of the contract, and indicator variables for the years 2015 and 2022. The contract length was not statistically significant in Table 6, but this could be due to the low number of observations. The selection of the years 2015 and 2022 are consistent with historical market conditions. 2015 was a year characterized by relatively low freight rates, whereas 2022 experience significantly higher rates. The selection of these two indicator variables therefore emphasize the importance of market conditions for freight rates.

Due to the low number of observations in the LNG dataset XGBoost only selects two variables: the years 2021 and 2022. Therefore, we are not able to report the results in a similar fashion as for LPG freight and S&P markets.

5.3 S&P Markets

Table 8 presents the results of four linear regression models for analyzing the determinants of vessel value f gas carriers in the sale and purchase (S&P) market. Given the presence of some overlap between LNG and LPG carrying vessels in the data sample, the analysis considers the whole market for gas carriers instead of two segments.

Model (1) indicates that fuel choice is a significant variable that influences the value of a vessel in the second hand market, however, Model (1) does not adjust for any time effect, suggesting that the significance of fuel choice may be

Table 8: Vessel value linear regression

	Dependent variable:			
	log(Price (Sale))			
	(1)	(2)	(3)	(4)
Constant	-5.901^{***}	-3.801^{***}	-4.297^{***}	-3.675^{***}
	(0.776)	(0.917)	(1.148)	(1.103)
Alternative Fuel	0.360^{***}	-0.061	-0.258	-0.476
	(0.125)	(0.212)	(0.259)	(0.367)
log(Dwt)	0.637^{***}	0.611^{***}	0.594^{***}	0.598^{***}
	(0.036)	(0.034)	(0.038)	(0.038)
log(Speed (knots))	1.258^{***}	0.767^{**}	0.747^{*}	0.625
	(0.360)	(0.380)	(0.411)	(0.385)
10Y US treasury yields	0.054^{**}	-0.017	0.022	0.030
	(0.022)	(0.033)	(0.082)	(0.087)
Age	-0.039^{***}	-0.049^{***}	-0.048^{***}	-0.054^{***}
	(0.014)	(0.014)	(0.016)	(0.017)
Age2	-0.001^{***}	-0.001^{**}	-0.001^{**}	-0.001^{*}
	(0.001)	(0.0004)	(0.001)	(0.001)
Power Type FE	No	Yes	Yes	Yes
Build Country FE	No	Yes	Yes	Yes
Year FE	No	Yes	No	No
Month Year FE	No	No	Yes	Yes
Type FE	No	No	No	Yes
Observations	400	400	400	400
R^2	0.858	0.892	0.951	0.953
Adjusted R^2	0.856	0.882	0.913	0.914
AIC	547.191	495.152	460.710	456.922
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 9: Vessel value Adapted Lasso

	Dependent variable:
	Rate
	(1)
(Intercept)	0.000
Dwt	0.584
Speed (knots)	0.084
10Y US treasury yields	0.029
Alternative Fuel	.
age	-0.215
age2	-0.278
South Korea	0.031
China P.R.	.
Japan	.
MAN Energy Solutions	.
Mitsubishi	-0.013
FSRU	0.028
Fully Cellular Container	.
LNG Carrier	0.053
LNG/Ethylene/LPG	.
LNG/FSU	.
LNG/Regasification	0.038
LPG Carrier	-0.062

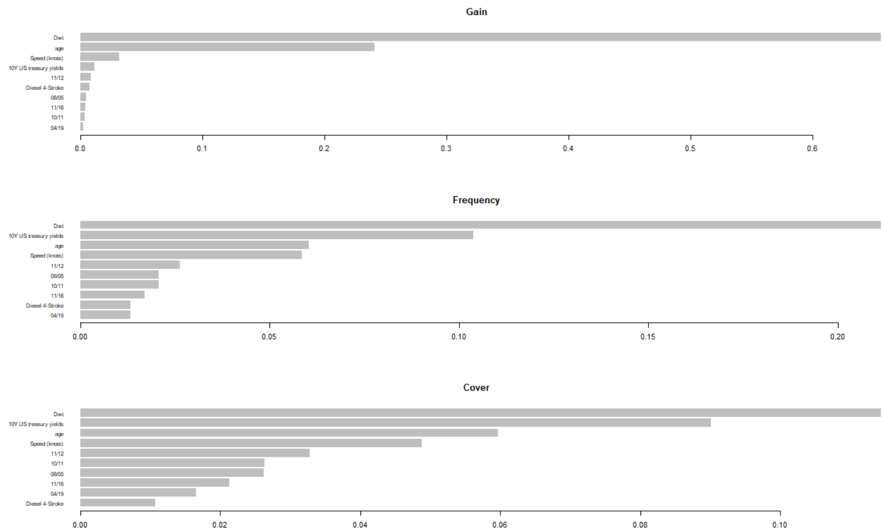

Figure 2: Variable importance S&P Markets

influenced by broader market conditions. For instance , if a disproportionally number of vessels with alternative fuels were traded during periods with elevated market prices. This is reinforced by by the fact that alternative fuel is not significant for any other model where time is accounted for. This may also be the case for the 10 year US treasury yield, which serves as a proxy for financing costs. Moreover, vessel size, speed, and age are all significant variables at the 1% level. Interestingly, note that the square term for age is also significant. This supports the hypothesis that vessel depreciation is non-linear in contrast to the linear depreciation argued for in (Stopford, 2008).

In Model (2) builder country, power type, and a time-fixed effect are controlled for, and alternative fuel and treasure yield are no longer statistically significant. This finding supports the hypotheses that the significance of the coefficient for alternative fuel and treasure yields was attributed to broader market conditions at the time of the transactions, rather than an inherent valuation premium associated with fuel choice or financing cost. Furthermore, age2 and the log of speed is only significant at the 5% level. This suggests that while these factors still influence vessel valuation, their effects may be weaker than initially estimated or subject to variation across different market conditions.

Model (3) refines the time-fixed effect by using a monthly resolution instead of a yearly resolution. Using monthly fixed effects allows the model to capture intra-year changes in market conditions. Increasing the granularity of the time-fixed effects improves model performance according to both AIC value and R^2, indicating a better overall fit. Furthermore, the statistical significance of speed is further weakened in Model (3) and is now only significant at a 10% level.

Alternative fuel is not significant at any level, reinforcing the conclusion that fuel choice does not exert a meaningful impact on vessel valuation in second-hand markets.

Model (4) introduce controls for vessel type, distinguishing between LNG, LPG and other gas carriers. This improves the model marginally with respect to AIC. However, the inclusion of types does not alter variables are significant, suggesting that hte previously observed relationship remain robust.

Furthermore, the Breusch-Pagan test indicates the presence of heteroscedasticity in the residuals. To account for this, all models are estimated using heteroscedasticity robust standard errors.

The results presented in Table 9 indicate that alternative fuel is not among the variables selected. This is consistent with the findings above that fuel choice does not significantly affect the value of a gas carrier. On the other hand, several vessel characteristics are selected, like size, speed, financing cost, age, build country, and whether the vessel is an LNG or LPG carrier. Not surprisingly, a larger, faster, and younger vessel is more valuable than a smaller, slower, or older vessel. The selection of Age2 further supports the hypothesis that vessels depreciate non-linearly. Among the building country dummies is South Korea. This could suggest a quality premium for gas carriers built in South Korea. Neither China nor Japan is selected, suggesting no systematic discounts are associated with vessels built in these countries. Unlike the freight market analysis, which examined LNG and LPG fixtures separately, the S&P markets for LNG and LPG vessels are analyzed within a single model. The results in Table 9 reveal a premium for LNG carriers and a corresponding discount for LPG carriers, suggesting distinct market dynamics between these two vessel types in the second-hand market

The results of the XGBoost model indicate that size, age, cost of financing, and speed are all important variables with respect to all three metrics: gain, frequency, and cover. Conversely, alternative fuel does not appear to be significant under any of the measures, further reinforcing ht conclusion that fuel choice does not play a crucial role in determining vessel value. Interestingly, the importance of financing conflicts with the results in 8 where the treasury yields were not significant after adjusting for time-fixed effects. This discrepancy suggests that financing costs may exhibit non-linear or interaction effects that tree-based models better capture than linear regression. Tonnage in the form of DWT is the single most important variable according to the three metrics for variable importance. Lastly, note that the dummy variable for 4-stroke diesel engine is among the top ten most important variables, suggesting that engine type may have a measurable impact on vessel valuation, possibly due to efficiency, operational costs, or market preference considerations.

The market conditions represented by the dummies for year and month constitute about half of the top ten most important variables. These time-fixed effects capture market conditions like the freight rate. Theory (Stopford, 2008) suggests that current and expected freight rates play a fundamental role in the vessels since the rates determine the expected cash flow from operating the vessel. It is, therefore, not surprising that time-fixed effects emerge as significant predictors in the model, reinforcing the idea that vessel prices are tied to broader market conditions and cyclical fluctuations in the shipping market.

6 Discussion

This paper finds no evidence to suggest that the use of alternative fuels influences the freight rates achieved in the freight market for gas carriers. This finding has two implications. First, it suggests no demand premium for lower emissions vessels from charterers, indicating that environmental considerations do not yet play a major role in freight rate determination. Second, the absence of significance means that we do not find any evidence for a systematic selection effect, where alternative fuel vessels select higher or lower rates due to underlying market conditions. Tables 6, 4, and 8 all contain linear models where alternative fuel has a significant positive coefficient. However, the effect seems to disappear when time-fixed effects are included. This suggests that transactions involving alternative fuel vessels, both in the freight and S&P market, tend to happen during times with high rates or high vessel values rather than reflect an inherent premium associated with alternative fuels.

Suppose a counterfactual case where alternative fuel had a positive significant effect on freight rates. This could be interpreted as evidence of a premium for alternative vessels. Such a premium could arise from several mechanisms. One possible mechanism could be that a willingness to pay a premium could be a reflection of the preferences of the charterer. This willingness to pay could be due to regulatory compliance reasons, particularly for charterers subject to regional emission quota schemes like the EU's ETS. Additionally, public relations considerations or green financing mechanisms, where higher emissions lead to a higher financing cost. Alternatively, a positive significant coefficient could arise due to a sampling effect. If gas carriers operating on alternative fuels were associated with higher operational costs, then such vessels might only accept fixtures at higher rates to ensure profitability. In this scenario, the observed premium would not necessarily reflect charterers' preferences but rather the economic necessity for operators to secure higher freight rates to cover increased fuel or operational expenditures.

The findings do not provide conclusive evidence for alternative fuels influencing vessel valuation in the second-hand market either. While Model (1) in Table 8 initially shows a statistically significant effect, the effect disappears when time-fixed effects, and hence market conditions, are controlled for. This suggests that Model (1) does not capture an intrinsic alternative fuel premium but rather reflects underlying market conditions. A plausible explanation is that vessels utilizing alternative fuels tend to be transacted during periods when the market conditions warrant higher prices. Consequently, the observed effect in Model (1) likely stems from variations in market dynamics rather than the fundamental impact of fuel choice on vessel valuation.

While fuel choice and power type are related, they are far from perfectly correlated. Five distinct power types are included in the dataset: Diesel 2-stroke, 4-stroke, diesel-electric, hybrid mechanical/electrical, and steam turbine. The choice of engine naturally constrains what kinds of fuels the vessel is able to run on, leading to an observable correlation between the alternative fuel and certain power type variables. The strongest correlation is between alternative fuel and diesel-electric engines (0.64). Additionally, a strong negative correlation is observed between alternative fuel and 2-stroke (-0.48) and a positive correlation between alternative fuel and steam turbine engines (0.41). High correlation between independent variables is potentially problematic in linear regression models as they may lead to multicollinearity and unstable coefficient estimates. However, re-estimating Model (4) in 8 without controlling for power type does not alter the conclusion.

The findings provide clear evidence for non-linear depreciation of vessels with aga, contradicting the linear depreciation model in (Stopford, 2008). These findings align with (Adland et al., 2023), who also find evidence supporting a non-linear depreciation. The mechanism causing the non-linearity is likely the scrapping market. Vessels are capital assets with a limited lifetime, typically 20-30 years. Most vessels are sold for scrap when they reach the end of their life. The residual value is determined primarily by the recoverable material content, particularly steel. This scrap value effectively establishes a price floor for second-hand vessel value. If the scrapping value of a vessel exceeds its second-hand, it would be economical to buy the vessel directly in the second-hand market solely for scraping, leading to an increase in prices. Consequently, as a vessel ages and its eventual scrapping becomes more imminent, its market value declines non-linearly, gradually converging toward its scrap value.

7 Conclusion

This paper examines the impact of fuel choice on freight rates in the gas carrier markets and its effects on second-hand vessel valuation. The empirical analysis finds no evidence to suggest that the choice of fuel has significant influence either freight rates or second-hand vessel value. These findings indicate that adopting alternative fuel does not translate into systematic premium or discount in either freight or S&P markets for gas carriers.

Linear regression, adapted lasso, and XGBoost are used to investigate the importance of fuel choice in freight markets for LNG and LPG and the second-hand market for gas carriers. Linear regression is used to find the cross-sectional drivers of rates and vessel value. The methodology is similar to (Adland, Cariou, & Wolff, 2017), where a hedonic price index is constructed to account for time-varying effects like market conditions. By incorporating time-fixed effects, this approach ensures that the remaining explanatory variables are not biased by the timing of transactions. The Adapted Lasso extends lasso regression by adjusting the size penalty of coefficients in a way that retains the oracle property. XGBoost is a gradient-boosting machine learning algorithm that constructs an ensemble of decision trees to improve predictive accuracy. During the training process, the model is iteratively improved and, by keeping track of how explanatory variables are used, variable importance can be assessed.

We find no conclusive evidence that alternative fuel significantly affects freight rates in the LNG freight markets once time-fixed effects are controlled for and not in LPG freight markets when routes are corrected for. While certain specifications of the freight market models seem to suggest that fuel choice is statistically significant, these effects appear to be driven by underlying market dynamics rather than intrinsic premiums for alternative fuel vessels. In the LNG freight market, the observed significance of fuel choice in some models is most likely attributed to the timing of fixture contracts and the low number of observations. In LPG markets, the apparent fuel choice effect could also be due to systematic differences between routes. Vessels operating on alternative fuels may be disproportionally assigned to specific routes that command higher freight rates. Moreover, the choice of fuel is not a variable selected by either the adapted lasso or the XGBoost for any of the markets. Adapted lasso and XGBoost primarily identify time-related variables, which capture effects like fleet size and demand at a certain time. Additionally, the LPG market exhibits a strong dependence on route characteristics, reinforcing the conclusion that the observed rate differential is primarily due to voyage-specific factors rather than fuel type.

This paper finds no evidence that alternative fuel significantly influences the S&P market either. Once time-fixed effects are incorporated into the linear regression models, the significance of fuel choice disappears. This suggests that transactions involving vessels with alternative fuels might have occurred during periods when the price of gas carriers was elevated. Both linear regression and variable selection techniques (Adapted Lasso and XGBoost) suggest that vessel characteristics like size, power type, vessel type (LNG or LPG carrier), and age are more primary drivers of vessel value in second-hand vessel markets. Moreover, the results also suggest that vessel depreciation follows a non-linear pattern, reinforcing the hypothesis that second-hand vessel value converge towards the scrapping price.

One of the weaknesses of this paper is it is inherently backward-looking, as the analysis is based on historical trading data. This is a particular issue with the freight market fixtures, where past fixtures do not consider future regulatory developments or cost structures. However, the transactions in the second-hand vessel market may provide insights into the market participants' forward-looking expectations. Buyers and sellers in the S&P market make investment decisions based on expected future revenues and costs. If the buyers expect alternative fuel to increase operating costs without a corresponding increase in revenue, the discounted cash flow will decline, leading to lower willingness to pay and, subsequently, a discount for alternative fuel vessels. Conversely, if the buyer expects future regulatory policies, such as the EU Emissions Trading System (EU ETS), to increase the future operating cost of traditional fuels, alternative fuel vessels may offer comparative cost advantages over time. In this scenario, buyers would expect lower future operating costs for alternative fuel vessels, leading to higher expected discounted cash flow compared to vessels using conventional fuels. Thus, second-hand vessel transactions reflect not only current market conditions but also market participants' expectations regarding the long-term financial implications of fuel choice.

There are multiple possible avenues for future research on this topic. A natural extension would be to investigate the impact of fuel choice on other types of vessels like container ships and bulk carriers. Data availability was one of the reasons gas carriers were chosen in this paper. However, more alternative fueled vessels are under construction and will enter the freight and s&p market, providing a richer dataset for empirical research in the future. Moreover, the newbuild market presents a compelling area for further research. Shipowners are intimately involved in the design and building process. Therefore, technology preferences may be more clearly reflected in the newbuild market. Moreover, due to the time lag between investment decisions and vessel delivery, the newbuild market may better capture the long-term expectations regarding fuel cost, regulatory developments, and market conditions. There could be interesting opportunities in the methodological direction as well. One potential approach would be to apply quantile regression to examine whether fuel choice has a heterogeneous effect at different price classes of vessels.

References

Tinbergen, J. (1934). Annual Survey of Significant Developments in General Economic Theory. *Econometrica*, *2*(1), 13. https://doi.org/10.2307/1907948

Koopmans, T. C. (1939). Tanker Freight Rates and Tankship Building. *The Netherlands Economic Institute nr. 27*.

Zannetos, Z. S. (1964). *The theory of oil tankship rates: An economic analysis of tankship operations.* [Publisher: [Cambridge, Mass., MIT]]. Retrieved November 2, 2023, from https://dspace.mit.edu/bitstream/handle/1721.1/49200/theoryofoiltanks00zann.pdf?sequence=1

Bates, T. H. (1969). A linear regression analysis of ocean tramp rates. *Transportation Research*, *3*(3), 377–395. https://doi.org/10.1016/S0041-1647(69)80021-3

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383. https://doi.org/10.2307/2325486

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, *82*(1), 34–55. https://doi.org/10.1086/260169

Charemza, W., & Gronicki, M. (1981). An econometric model of world shipping and shipbuilding [Publisher: Routledge _eprint: https://doi.org/10.1080/03088838100000019]. *Maritime Policy & Management*, *8*(1), 21–30. https://doi.org/10.1080/03088838100000019

Norman, V. D., & Wergeland, T. (1981). *Nortank: A simulation model of the freight market for large tankers* [Accession Number: 998420341884702202 ISSN: 0332-8333 Publication Title: Norbok Source: NO-TrBIB Type:

book]. Retrieved June 13, 2024, from https://urn.nb.no/URN:NBN:no-nb_digibok_2016071909120
Beenstock, M. (1985). A theory of ship prices [Publisher: Routledge _eprint: https://doi.org/10.1080/03088838500000028]. *Maritime Policy & Management*, *12*(3), 215–225. https://doi.org/10.1080/03088838500000028
Strandenes, S. P. (1986). *NORSHIP: A simulation model for bulk shipping markets*. Norwegian School of Economics; Business Administration.
Beenstock, M., & Vergottis, A. (1989a). An Econometric Model of the World Tanker Market [Publisher: [London School of Economics, University of Bath, London School of Economics and University of Bath, London School of Economics and Political Science]]. *Journal of Transport Economics and Policy*, *23*(3), 263–280. Retrieved January 17, 2024, from https://www.jstor.org/stable/20052891
Beenstock, M., & Vergottis, A. (1989b). An Econometric Model of the World Tanker Market [Publisher: [London School of Economics, University of Bath, London School of Economics and University of Bath, London School of Economics and Political Science]]. *Journal of Transport Economics and Policy*, *23*(3), 263–280. Retrieved January 11, 2024, from http://www.jstor.org.ezproxy.nhh.no/stable/20052891
Hale, C., & Vanags, A. (1992). The market for second-hand ships: Some results on efficiency using cointegration. *Maritime Policy & Management*, *19*(1), 31–39. https://doi.org/10.1080/03088839200000003
Beenstock, M., & Vergottis, A. (1993). *Econometric modelling of world shipping* (First edition). Chapman & Hall.
Bjerksund, P., & Ekern, S. (1995). Contingent claims evaluation of mean-reverting cash flows in shipping. In *Real options in capital investment: Models, strategies, and applications* (pp. 207–219). Preager Westport, CT.
Tamvakis, M. N., & Thanopoulou, H. A. (1995). An investigation into the existence of a two-tier spot freight market for crude oil carriers. *Maritime Policy & Management*, *22*(1), 81–90. https://doi.org/10.1080/03088839500000034
Chang, Y.-T., & Chang, H. B. (1996). Predictability of the dry bulk shipping market by BIFFEX [Publisher: Routledge _eprint: https://doi.org/10.1080/03088839600000068]. *Maritime Policy & Management*, *23*(2), 103–114. https://doi.org/10.1080/03088839600000068
Kavussanos, M. G. (1996a). Comparisons of Volatility in the Dry-Cargo Ship Sector: Spot versus Time Charters, and Smaller versus Larger Vessels [Publisher: [London School of Economics, University of Bath, London School of Economics and University of Bath, London School of Economics and Political Science]]. *Journal of Transport Economics and Policy*, *30*(1), 67–82. Retrieved January 12, 2024, from https://www.jstor.org/stable/20053097
Kavussanos, M. G. (1996b). Price risk modelling of different size vessels in the tanker industry using Autoregressive Conditional Heterskedastic (ARCH) models [Num Pages: 16 Place: Vancouver, Canada Publisher: University of British Columbia, Faculty of Commerce and Business

Administration]. *Logistics and Transportation Review*, *32*(2), 161. Retrieved January 12, 2024, from https://www.proquest.com/docview/197446331/abstract/CD20F577A73949CFPQ/1

Berg-Andreassen, J. A. (1997). The relationship between period and spot rates in international maritime markets. *Maritime Policy & Management*, *24*(4), 335–350. https://doi.org/10.1080/03088839700000042

Glen†, D. R. (1997). The market for second-hand ships: Further results on efficiency using cointegration analysis. *Maritime Policy & Management*, *24*(3), 245–260. https://doi.org/10.1080/03088839700000029

Glen, D., & Rogers, P. (1997). Does Weight matter? A Statistical analysis of the SSY Capesize index. *Maritime Policy & Management*, *24*(4), 351–364. https://doi.org/10.1080/03088839700000043

Kavussanos, M. G. (1997). The dynamics of time-varying volatilities in different size second-hand ship prices of the dry-cargo sector. *Applied Economics*, *29*(4), 433–443. https://doi.org/10.1080/000368497326930

Tvedt, J. (1997). Valuation of VLCCs under income uncertainty [Publisher: Routledge _eprint: https://doi.org/10.1080/03088839700000067]. *Maritime Policy & Management*, *24*(2), 159–174. https://doi.org/10.1080/03088839700000067

Veenstra, A. W., & Franses, P. H. (1997). A co-integration approach to forecasting freight rates in the dry bulk shipping sector. *Transportation Research Part A: Policy and Practice*, *31*(6), 447–458. https://doi.org/10.1016/S0965-8564(97)00002-5

Birkeland, S. (1998). *Bulk shipping and freight rates* [Doctoral dissertation, Norwegian School of Economics and Business Administration].

Kavussanos, M. G., & Nomikos, N. K. (1999). The forward pricing function of the shipping freight futures market [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/%28SICI
9934%28199905%2919%3A3%3C353%3A%3AAID-FUT6%3E3.0.CO%3B2-6]. *Journal of Futures Markets*, *19*(3), 353–376. https://doi.org/10.1002/(SICI)1096-9934(199905)19:3<353::AID-FUT6>3.0.CO;2-6

Tamvakis, M. N., & Thanopoulou, H. A. (2000). Does quality pay? The case of the dry bulk market. *Transportation Research Part E: Logistics and Transportation Review*, *36*(4), 297–307. https://doi.org/10.1016/S1366-5545(00)00005-3

Kavussanos, M. G., & Nomikos, N. K. (2001). Price Discovery, Causality and Forecasting in the Freight Futures Market. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.271072

Alizadeh, A. H., & Kavussanos, M. G. (2002). Seasonality Patterns in Tanker Shipping Freight Markets. *Economic Modelling*, *19*(5), 747–782. Retrieved January 12, 2024, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1435288

Kavussanos, M. G., & Alizadeh, A. H. (2002). Efficient pricing of ships in the dry bulk sector of the shipping industry [Publisher: Routledge _eprint: https://doi.org/10.1080/03088830210132588]. *Maritime Policy & Management*, *29*(3), 303–330. https://doi.org/10.1080/03088830210132588

Tvedt, J. (2003). A new perspective on price dynamics of the dry bulk market. *Maritime Policy & Management*, *30*(3), 221–230. https://doi.org/10.1080/0308883032000133413

Adland, R., & Koekebakker, S. (2004). Market Efficiency in the Second-hand Market for Bulk Ships. *Maritime Economics & Logistics*, *6*(1), 1–15. https://doi.org/10.1057/palgrave.mel.9100092

Kavussanos, M. G., & Visvikis, I. D. (2004). Market interactions in returns and volatilities between spot and forward shipping freight markets. *Journal of Banking & Finance*, *28*(8), 2015–2049. https://doi.org/10.1016/j.jbankfin.2003.07.004

Tsolakis, S. (2005). Econometric Analysis of Bulk Shipping: Implications for investment strategies and financial decision-making. Retrieved October 8, 2024, from https://repub.eur.nl/pub/6717/

Adland, R., & Cullinane, K. (2006). The non-linear dynamics of spot freight rates in tanker markets. *Transportation Research Part E: Logistics and Transportation Review*, *42*(3), 211–224. https://doi.org/10.1016/j.tre.2004.12.001

Koekebakker, S., Adland, R., & Sødal, S. (2006). Are Spot Freight Rates Stationary? *Journal of Transport Economics and Policy (JTEP)*, *40*(3), 449–472.

Syriopoulos, T., & Roumpis, E. (2006). Price and volume dynamics in second-hand dry bulk and tanker shipping markets. *Maritime Policy & Management*, *33*(5), 497–518. https://doi.org/10.1080/03088830601020729

Zou, H. (2006). The Adaptive Lasso and Its Oracle Properties. *Journal of the American Statistical Association*, *101*(476), 1418–1429. https://doi.org/10.1198/016214506000000735

Adland, R., & Koekebakker, S. (2007). Ship Valuation Using Cross-Sectional Sales Data: A Multivariate Non-Parametric Approach. *Maritime Economics & Logistics*, *9*(2), 105–118. https://doi.org/10.1057/palgrave.mel.9100174

Alizadeh, A. H., Ådland, R. O., & Koekebakker, S. (2007). Predictive power and unbiasedness of implied forward charter rates [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002 *Journal of Forecasting*, *26*(6), 385–403. https://doi.org/10.1002/for.1029

Batchelor, R., Alizadeh, A., & Visvikis, I. (2007). Forecasting spot and forward prices in the international freight market. *International Journal of Forecasting*, *23*(1), 101–114. https://doi.org/10.1016/j.ijforecast.2006.07.004

Adland, R., Jia, H., & Lu, J. (2008). Price dynamics in the market for Liquid Petroleum Gas transport. *Energy Economics*, *30*(3), 818–828. https://doi.org/10.1016/j.eneco.2007.02.008

Köhn, S. (2008, December). *Generalized additive models in the context of shipping economics.* [thesis]. University of Leicester. Retrieved October 8, 2024, from https://figshare.le.ac.uk/articles/thesis/Generalized_additive_models_in_the_context_of_shipping_economics_/10084175/1

Stopford, M. (2008). *Maritime Economics 3e*. Taylor & Francis Group. Retrieved June 14, 2023, from http://ebookcentral.proquest.com/lib/nhh-ebooks/detail.action?docID=371028

Veenstra, A., & van Dalen, J. (2008). Price Indices for Ocean Charter Contracts.

Hastie, T., Tibshirani, R., & Friedman, J. H. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed). Springer.

Sødal, S., Koekebakker, S., & Adland, R. (2009). Value based trading of real assets in shipping under stochastic freight rates. *Applied Economics*, *41*(22), 2793–2807. https://doi.org/10.1080/00036840701720853

Alizadeh, A. H., & Nomikos, N. K. (2011). Dynamics of the Term Structure and Volatility of Shipping Freight Rates. *Journal of Transport Economics and Policy (JTEP)*, *45*(1), 105–128.

Alizadeh, A. H., & Talley, W. K. (2011). Vessel and voyage determinants of tanker freight rates and contract times. *Transport Policy*, *18*(5), 665–675. https://doi.org/10.1016/j.tranpol.2011.01.001

Köhn, S., & Thanopoulou, H. (2011). A gam assessment of quality premia in the dry bulk time–charter market. *Transportation Research Part E: Logistics and Transportation Review*, *47*(5), 709–721. https://doi.org/10.1016/j.tre.2011.01.003

Chen, S., Meersman, H., & Voorde, E. v. d. (2012). Forecasting spot rates at main routes in the dry bulk market. *Maritime Economics & Logistics*, *14*(4), 498–537. https://doi.org/10.1057/mel.2012.18

Drobetz, W., Richter, T., & Wambach, M. (2012). Dynamics of time-varying volatility in the dry bulk and tanker freight markets [Publisher: Routledge _eprint: https://doi.org/10.1080/09603107.2012.657349]. *Applied Financial Economics*, *22*(16), 1367–1384. https://doi.org/10.1080/09603107.2012.657349

Goulas, L., & Skiadopoulos, G. (2012). Are freight futures markets efficient? Evidence from IMAREX. *International Journal of Forecasting*, *28*(3), 644–659. https://doi.org/10.1016/j.ijforecast.2011.11.004

Agnolucci, P., Smith, T., & Rehmatulla, N. (2014). Energy efficiency and time charter rates: Energy efficiency savings recovered by ship owners in the Panamax market. *Transportation Research Part A: Policy and Practice*, *66*, 173–184. https://doi.org/10.1016/j.tra.2014.05.004

Benth, F. E., Koekebakker, S., & Taib, C. M. I. C. (2015). Stochastic dynamical modelling of spot freight rates. *IMA Journal of Management Mathematics*, *26*(3), 273–297. https://doi.org/10.1093/imaman/dpu001

Kou, Y., & Luo, M. (2015). Modelling the Relationship between Ship Price and Freight Rate with Structural Changes. *Journal of Transport Economics and Policy*, *49*.

Poblacion, J. (2015). The stochastic seasonal behavior of freight rate dynamics. *Maritime Economics & Logistics*, *17*(2), 142–162. https://doi.org/10.1057/mel.2014.37

Stock, J. H. (2015). *Introduction to econometrics* (Updated Third, Global edition.). Pearson.

Adland, R., Cariou, P., & Wolff, F.-C. (2016). The influence of charterers and owners on bulk shipping freight rates. *Transportation Research Part E: Logistics and Transportation Review*, *86*, 69–82. https://doi.org/10.1016/j.tre.2015.11.014

Prakash, V., Smith, T., Mitchell, J., Adland, R., & Nishatabbas Rehmatulla. (2016). Revealed preferences for energy efficiency in the shipping markets [Publisher: Unpublished]. https://doi.org/10.13140/RG.2.2.28444.69766

Adland, R., Alger, H., Banyte, J., & Jia, H. (2017). Does fuel efficiency pay? Empirical evidence from the drybulk timecharter market revisited. *Transportation Research Part A: Policy and Practice*, *95*, 1–12. https://doi.org/10.1016/j.tra.2016.11.007

Adland, R., Cariou, P., & Wolff, F.-C. (2017). What makes a freight market index? An empirical analysis of vessel fixtures in the offshore market. *Transportation Research Part E: Logistics and Transportation Review*, *104*, 150–164. https://doi.org/10.1016/j.tre.2017.06.006

Munim, Z. H., & Schramm, H.-J. (2017). Forecasting container shipping freight rates for the Far East – Northern Europe trade lane. *Maritime Economics & Logistics*, *19*(1), 106–125. https://doi.org/10.1057/s41278-016-0051-7

Yin, J., Luo, M., & Fan, L. (2017). Dynamics and interactions between spot and forward freights in the dry bulk shipping market. *Maritime Policy & Management*, *44*(2), 271–288. https://doi.org/10.1080/03088839.2016.1253884

Adland, R., Cariou, P., & Wolff, F.-C. (2018). Does energy efficiency affect ship values in the second-hand market? *Transportation Research Part A: Policy and Practice*, *111*, 347–359. https://doi.org/10.1016/j.tra.2018.03.031

Gavriilidis, K., Kambouroudis, D. S., Tsakou, K., & Tsouknidis, D. A. (2018). Volatility forecasting across tanker freight rates: The role of oil price shocks. *Transportation Research Part E: Logistics and Transportation Review*, *118*, 376–391. https://doi.org/10.1016/j.tre.2018.08.012

Kou, Y., Luo, M., & Zhao, Y. (2018). Examining the theoretical–empirical inconsistency on stationarity of shipping freight rate [Publisher: Routledge _eprint: https://doi.org/10.1080/03088839.2017.1418091]. *Maritime Policy & Management*, *45*(2), 145–158. https://doi.org/10.1080/03088839.2017.1418091

Población, J., & Serna, G. (2018). A common long-term trend for bulk shipping prices. *Maritime Economics & Logistics*, *20*(3), 421–432. https://doi.org/10.1057/s41278-017-0065-9

Yin, J., & Shi, J. (2018). Seasonality patterns in the container shipping freight rate market [Publisher: Routledge _eprint: https://doi.org/10.1080/03088839.2017.1420260]. *Maritime Policy & Management*, *45*(2), 159–173. https://doi.org/10.1080/03088839.2017.1420260

Adland, R., Cariou, P., & Wolff, F.-C. (2019). Comparing Transaction-based and Expert-generated Price Indices in the Market for Offshore Support

Vessels [Publisher: University of Bath]. *Journal of Transport Economics and Policy*, *53*(1), 99–118. Retrieved October 7, 2024, from https://www.jstor.org/stable/90026262

Balcombe, P., Brierley, J., Lewis, C., Skatvedt, L., Speirs, J., Hawkes, A., & Staffell, I. (2019). How to decarbonise international shipping: Options for fuels, technologies and policies. *Energy Conversion and Management*, *182*, 72–88. https://doi.org/10.1016/j.enconman.2018.12.080

Chou, H.-C., & Chen, D.-H. (2019). The use of technical analysis in sale-and-purchase transactions of secondhand ships. *Maritime Economics & Logistics*, *21*(2), 223–240. https://doi.org/10.1057/s41278-017-0096-2

Al-Enazi, A., Okonkwo, E. C., Bicer, Y., & Al-Ansari, T. (2021). A review of cleaner alternative fuels for maritime transportation. *Energy Reports*, *7*, 1962–1985. https://doi.org/10.1016/j.egyr.2021.03.036

Balcombe, P., Staffell, I., Kerdan, I. G., Speirs, J. F., Brandon, N. P., & Hawkes, A. D. (2021). How can LNG-fuelled ships meet decarbonisation targets? An environmental and economic analysis. *Energy*, *227*, 120462. https://doi.org/10.1016/j.energy.2021.120462

Devore, J. L., Berk, K. N., & Carlton, M. A. (2021). *Modern Mathematical Statistics with Applications*. Springer International Publishing. https://doi.org/10.1007/978-3-030-55156-8

Lindstad, E., Lagemann, B., Rialland, A., Gamlem, G. M., & Valland, A. (2021). Reduction of maritime GHG emissions and the potential role of E-fuels. *Transportation Research Part D: Transport and Environment*, *101*, 103075. https://doi.org/10.1016/j.trd.2021.103075

Schwartz, H., Solakivi, T., & Gustafsson, M. (2022). Is There Business Potential for Sustainable Shipping? Price Premiums Needed to Cover Decarbonized Transportation. *Sustainability*, *14*(10), 5888. https://doi.org/10.3390/su14105888

Solakivi, T., Paimander, A., & Ojala, L. (2022). Cost competitiveness of alternative maritime fuels in the new regulatory framework. *Transportation Research Part D: Transport and Environment*, *113*, 103500. https://doi.org/10.1016/j.trd.2022.103500

Tan, E. C. D., Harris, K., Tifft, S. M., Steward, D., Kinchin, C., & Thompson, T. N. (2022). Adoption of biofuels for marine shipping decarbonization: A long-term price and scalability assessment. *Biofuels, Bioproducts and Biorefining*, *16*(4), 942–961. https://doi.org/10.1002/bbb.2350

Adland, R., Jia, H., Harvei, H. C. O., & Jørgensen, J. (2023). Second-hand vessel valuation: An extreme gradient boosting approach [Publisher: Routledge _eprint: https://doi.org/10.1080/03088839.2021.1969601]. *Maritime Policy & Management*, *50*(1), 1–18. https://doi.org/10.1080/03088839.2021.1969601

Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P. W., Trisos, C., Romero, J., Aldunce, P., Barrett, K., Blanco, G., Cheung, W. W., Connors, S., Denton, F., Diongue-Niang, A., Dodman, D., Garschagen, M., Geden, O., Hayward, B., Jones, C., … Péan, C. (2023, July).

IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland. (tech. rep.) (Edition: First). Intergovernmental Panel on Climate Change (IPCC). https://doi.org/10.59327/IPCC/AR6-9789291691647

Ltd, B. E. I. S. (2023, October). Guide to Market BenchmarkBPGs. Retrieved October 31, 2023, from https://www.balticexchange.com/content/dam/balticexchange/consumer/documents/data-services/documentation/ocean-bulk-guides-policies/GMB.pdf

FAQ – Maritime transport in EU Emissions Trading System (ETS). (n.d.). Retrieved September 27, 2023, from https://climate.ec.europa.eu/eu-action/transport/reducing-emissions-shipping-sector/faq-maritime-transport-eu-emissions-trading-system-ets_en

History. (n.d.). Retrieved October 7, 2024, from https://www.balticexchange.com/en/who-we-are/history.html

IMO. (n.d.). Fourth Greenhouse Gas Study 2020. Retrieved May 15, 2024, from https://www.imo.org/en/OurWork/Environment/Pages/Fourth-IMO-Greenhouse-Gas-Study-2020.aspx

Revised GHG reduction strategy for global shipping adopted. (n.d.). Retrieved May 8, 2024, from https://www.imo.org/en/MediaCentre/PressBriefings/Pages/Revised-GHG-reduction-strategy-for-global-shipping-adopted-.aspx

Team, G. P. I. (n.d.). The Greenhouse Gas Protocol: A Corporate Accounting and Reporting Standard revised edition.