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Empirical Analysis of Charterers' Willingness to Pay for Energy Efficiency

A Study on Time Charter Contract Rates in the Dry Bulk Market and GHG Ratings by RightShip

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Abstract

This thesis investigates whether charterers value energy efficiency in the dry bulk time charter (TC) market using greenhouse gas (GHG) emissions ratings from RightShip and TC fixtures from Western Bulk and Clarksons Shipping Intelligence Network (SIN). An energy efficiency premium in the TC market would incentivize shipowners to invest in energy efficiency technology as they would recoup some or all their investment, strengthening the investment case. Energy efficiency technology on ships allows less fuel consumption for the same speed, effectively reducing harmful emissions (IMO, 2023). Therefore, an increased adaptation of such technology would help the shipping industry to contribute to the worldwide effort to lower carbon emissions.

Applying different multiple linear regression models to the size segments Handysize, Panamax, Capesize, and Supramax, we find no statistically significant energy efficiency premium for any segments. This implies that charterers are unwilling to pay for energy efficiency in the TC market. A TC contract facilitates dynamics that can create principal-agent problems between the shipowner and the charterer. We identify the presence of split incentives and information asymmetry between the contract parties, which can ultimately lead to market failure resulting in a lack of energy efficiency investments by shipowners. It is necessary that the International Maritime Organization (IMO) and the European Union (EU) implement policies that help unite the incentives of the shipowner (principal) and charterer (agent) and equalize the information asymmetries between the two to correct for inefficient market outcomes. Therefore, the EU Monitoring, Reporting, and Verification (MRV) and the IMO 2023 regulations can make a difference.

On the other hand, we find a discount for vessels with below average energy efficiency performance in the Handysize and Supramax segments, showing that a relative lack of energy efficiency technology is penalized. This could incentivize shipowners to invest in energy efficiency as they would otherwise have to accept a discount, lowering their revenue potential. However, no publicly available cut-offs on energy efficiency performance by charterers exist, and there is a low adaptation rate of energy efficiency technology in the shipping industry. Our data sample has weaknesses in terms of size and biased sampling, making the discount representative of one charterer, Western Bulk, rather than the whole market.

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1 Introduction

Even though few people realize it, shipping plays a key role in their everyday life, and everybody in the world benefits from this mode of transportation (Ki-Moon, 2016). Globally, shipping accounts for more than 80% of the volume of world trade, and it is a vital enabler of the benefits associated with trade in terms of economic development and global society (UNCTAD, 2023). Nevertheless, the main reason shipping is a preferred means of transportation is the financial aspect (Stopford, 2009). Shipping offers efficient, low-cost transportation of goods globally.

On the other hand, shipping also significantly contributes to greenhouse gas (GHG) emissions. Since 2012, GHG emissions from shipping have increased by almost 24%, and between 2020 and 2021, emissions increased by 4.7% despite increases in GHG emissions regulations, paradoxically (UNCTAD, 2023). Another concern for the environment is the increase in the average age of the global fleet as older ships pollute more. In 2022 the average age by the number of vessels was 21.9 years. For the shipping industry to contribute to the global emission reduction objectives, investments in new, relatively more environmentally friendly ships or retrofits of older vessels with energy efficiency technology are required (UNCTAD, 2023).

Energy efficiency technology on ships allows less fuel consumption for the same speed (IMO, 2023), reducing the energy cost of operating the vessel. However, the industry appears reluctant to invest in such technology (Johnson & Andersson, 2016). A possible explanation is the occurrence of market failure, one of the multiple barriers to energy efficiency investments (Rehmatulla & Smith, 2015). If market failures occur, policies must be implemented to correct them. An example is the International Maritime Organization's (IMO) metrics Energy Efficiency Existing Ship Index (EEXI) and Carbon Intensity Indicator (CII), covering vessel design and operation features, which initially required owner compliance from 2023 (Simpson Spence Young, 2022). According to Lloyd's List, only about 25% of the global fleet of tankers and bulk carriers would comply with these metrics as of January 2022 (Bockmann, 2022). This percentage implies that several ship-owning companies will have invested heavily in energy-efficient technology and equipment in the last year, although not seemingly the case.

A common market failure in energy efficiency is principal-agent problems, which are the difficulties that might arise in a contractual relationship between two parties with different objectives (Jensen & Meckling, 1976), such as the shipowner and charterer. If principal-agent problems result in shipowners not recouping their investment, energy efficiency investments are not incentivized in the free market. Depending on the contract between charterers and shipowners, this may apply and will be reflected as a lack of an energy efficiency premium in the contract rate.

We will investigate whether an energy efficiency premium exists in time charter (TC) contracts in the dry bulk market 2020-2022 using RightShip's GHG rating system. TC contracts, which involve the charterer hiring a vessel from a shipowner for a fixed period on a per-day rate (Stopford, 2009), facilitate a principal-agent relationship between the shipowner and charterer. This, in turn, might lead to market failure. The contribution of this thesis is twofold. Firstly, we use a recent timeline, including data from 2020 – 2022, allowing us to investigate whether the freight market has valued energy efficiency over the last two years. This timeframe is particularly interesting as the number of regulations, commercial pressure, and voluntary efforts around decarbonizing the shipping industry has increased considerably (RightShip, 2023). Secondly, we use RightShip's GHG emissions rating system as a determinant for the energy efficiency of a ship, which has not previously been done. Using this rating system brings a new aspect as it differs somewhat from the Energy Efficiency Design Index (EEDI) metric used in previous research.

This thesis is structured as follows. Part 2 will include a literature review looking at former relevant research. Part 3 will consist of agency theory and the principal-agent problem. Part 4 will elaborate on the data, and part 5 will focus on the methodology used in the analysis. Part 6 will discuss the findings and results of the analysis, and part 7 will include weaknesses and potential further research. Finally, part 8 will conclude.

2 Literature Review

As this thesis investigates whether there exists a premium for energy-efficient ships in the freight market, the methods and findings in mainly two previous studies are relevant to discuss. Agnolucci et al. (2014) and Ådland et al. (2017) estimated microeconomic models for TC rates in the dry bulk market, with particular focus on energy efficiency. How energy-efficient a ship is, depends on the technical efficiency of the ship – its technical specification, and the operational efficiency of the ship – how it is operated in the surrounding conditions and environment (Agnolucci et al., 2014). Agnolucci et al. (2014) and Ådland et al. (2017) both focused on technical efficiency using the EEDI metric. The EEDI indicates the theoretical design efficiency of a vessel and estimates the CO_2 emissions per capacity mile (Transport & Environment, 2012).

Agnolucci et al. (2014) investigated whether there exists a premium for energy efficiency in TC rates for the dry bulk Panamax segment using data from 2008–2012. They found that, on average, shipowners recover only 40% of the financial savings from energy efficiency investments through higher charter rates (Rehmatulla & Smith, 2015). Moreover, they find a decreasing trend in the share that shipowners recover. When using the 1,000 first fixtures in their dataset, they find that shipowners, on average, recover 50% through higher charter rates, while when using the 1,000 last fixtures in their dataset, they find that only 25% is recovered (Agnolucci et al., 2014).

Ådland et al. (2017) also investigated dry bulk TCs for a freight rate premium reflecting energy efficiency. However, they examined multiple dry bulk size segments, including Capsize, Panamax, and Handymax, and used data from 2001–2016, significantly expanding the data sample as was suggested by Agnolucci et al. (2014) in their limitations section. The expanded data sample used by Ådland et al. (2017) allows for analysis of a complete freight market cycle, which in their work proved useful as they discovered different findings for different underlying market conditions. During normal market conditions, they found a significantly lower effect of fuel savings reflected in higher TC rates than Agnolucci et al. (2014), namely 14% for Panamax, 22% for Handymax, and 27% for Capesize. During the market boom from 2003–2008, they found the opposite: fuel–inefficient vessels gained a rate premium (Ådland et al., 2017).

The technical support to the *European Action Plan to Reduce Greenhouse Gas Emissions from International Maritime Transport* states that fuel efficiency is not a key determinant of freight rates. However, given two otherwise identical ships, the more energy-efficient ship would *a priori* be able to gain a higher daily TC rate in an efficient market (Faber, et al., 2009). Agnolucci et al. (2014) also discuss this perspective in their study, highlighting that this is likely mainly feasible in an oversupplied market. The technical support further states that "the least fuel efficient ship would have to compensate this with other factors in order to get chartered" (Faber, et al., 2009, p. 95). Furthermore, the report adds that at the time of writing, the higher capital costs associated with energy efficiency investments were not recouped by lower voyage costs and that environmental performance is not reflected in the asset price (Faber, et al., 2009), suggesting that neither the freight nor the newbuild market was willing to pay for energy efficiency.

Longarela-Ares et al. (2020) investigated the influence of economic barriers and drivers on energy efficiency investments, emphasizing the principal-agent problem. They looked at the bulk cargo segment and analyzed how different factors affected the probability of a shipowner investing in energy efficiency. Two factors included in the analysis were a TC contract and a voyage charter (VC) contract and the specific dynamics these create in the shipowner-charterer relationship. The impact of the principal-agent relationship will differ under the two types of freight contracts. Longarela-Ares et al. (2020) found that a TC contract harms the probability of investing in energy efficiency, while a VC contract has a positive impact. These results could be understood by agency theory, which will be elaborated on in the theory section.

This thesis will indirectly use the EEDI metric to measure energy efficiency, as this is the primary input into RightShip's methodology for a relative energy efficiency rating. RightShip's GHG emissions rating awards ships for their relative performance within a peer group of vessels, thereby removing the complication for charterers of measuring the relative efficiency of the vessels (RightShip, 2023). The rating system is consequently dynamic, and a vessel's grade changes for energy efficiency developments in the peer group.

RightShip's GHG emissions rating divide vessels into peer groups of similar size and type (RightShip, 2023). A ship is given a grade on a scale from A to G, where A is given to the most efficient ships in their peer group. The rating for an individual ship is based on either the EEDI or the Existing Vessel Design Index (EVDI), both energy efficiency metrics for ships (RightShip, 2023). While the EEDI metric is computed for new ships, the EVDI is a similar metric computed for existing vessels based on available data from shipyards, classification societies, and sometimes the shipowner. Over 60,000 existing ships have been given an EVDI metric. Data for computation of EEDI is sourced from classification societies when a new ship is certified (Transport & Environment, 2012).

In mid-August 2021 RightShip announced in a press release that about 200 independent chartering companies used its expanded vetting criteria (RightShip, 2021). The number of owners voluntarily agreeing to measure their energy efficiency increased with a rising membership base in 2022 (Simpson Spence Young, 2022). Furthermore, 34 charterers and operators have per the end of 2022 signed the Sea Cargo Charter accord (Sea Cargo Charter, 2023), more than four times the companies that initially signed in 2020, showing an increase in voluntary decarbonization efforts against a backdrop of mandatory regulation (Simpson Spence Young, 2022).

3 Theory: Barriers to Energy Efficiency

Even though energy efficiency results in both cost reductions and emissions reductions, aligning profitability and environmental considerations, the adaptation of such technology in the shipping industry is seemingly low (Johnson & Andersson, 2016). More rapid adaptation of energy efficiency technology on vessels may be hindered by different social and institutional barriers (Blumstein et al., 1980), where barriers can be defined as "postulated mechanisms that inhibit investments in technologies that are energy efficient and economically efficient" (Rehmatulla & Smith, 2015, p. 45). Blumstein et al. (1980) identified six classes of barriers to cost-effective energy efficiency measures in their paper, including misplaced incentives, lack of information or misinformation, regulation, market structure, lack of financing, and custom, many of which can be categorized as market failures (Brown, 2001).

According to neoclassical economics, market failure is market barriers that result in inefficient allocation of resources. In the case of the shipping industry, market failure is the most common barrier to energy efficiency investments (Ådland et al., 2017). In some cases, policies implemented by official government bodies can ensure Pareto efficiency when market failures are present (IEA, 2007). Five conditions need to hold for markets to operate efficiently. First, there are sufficiently large numbers of firms in the market, so no one firm influences the price. Second, all firms in the market have perfect information. Third, there are no entry or exit barriers to the market. Fourth, firms act rationally and are profit maximizers. Fifth, there are no transaction costs (IEA, 2007). When one or more of these five conditions does not hold, there is a market failure, and Pareto efficiency is not achieved. Focusing on energy efficiency, "a market failure would imply that more energy is being consumed for the level of service than a rational allocation of resources would justify, in light of consumers and producers' preferences" (IEA, 2007, p. 24). One of the most common market failures preventing energy efficiency is principal-agent problems.

3.1 Agency Theory

Principal-agent problems refer to the difficulties that might arise in a contractual relationship between two utility-maximizing parties with different objectives (Jensen & Meckling, 1976). Typically, one party (the principal) pays and grants decision-making authority to another (the agent) to act on his behalf or provide a service. How well off the principal is after the economic transaction is affected by how the agent makes decisions (Wright et al., 2001). According to agency theory, two conditions are present in the principal-agent relationship. First, agents are autonomous and act opportunistically, meaning they are self-interest seeking at the cost of the principal when their interests conflict (Wright et al., 2001). An agent may act in bad faith, misleading the principal if the transaction is characterized by split incentives. The second condition is the presence of information asymmetry between the principal and the agent. One party has more information than the other and is unable or unwilling to share it (IEA, 2007). These two conditions may lead to suboptimal outcomes in the form of adverse selection and moral hazard (Wright et al., 2001). Principal-agent problems can be challenging to resolve due to the information asymmetry and different risk profiles between the parties (Sharma, 1997).

3.2 Principal-Agent Problems in Energy Efficiency

Slow investment or lack of investments in energy efficiency can be understood through the dynamics present in principal-agent problems. All core elements of agency theory are also present in an energy efficiency transaction, including a contract between a principal and an agent with split incentives and information asymmetry (IEA, 2007). A common example in literature is the relationship between a landlord and a tenant, in which the tenant (agent) pays rent to the landlord (principal) in return for the use of living space. The principal wants to minimize capital costs related to energy-efficient equipment, and the agent wants to minimize the energy cost. Consequently, the owner of the building has no incentive to invest in energy-saving features as the tenant benefits from the reduced energy bill (IEA, 2007). Moreover, research has shown that consumers are often poorly informed about technology characteristics of energy efficiency measures, pointing to a lack of information from the agent's view (Sanstad & Howarth, 1994). Related to the tenant-landlord example, the landlord (principal) typically has much more insight into the characteristics and performance of the energy efficiency equipment than the tenant (agent), creating information asymmetries between the two contract parties (Sanstad & Howarth, 1994).

3.3 The Principal-Agent Relationship in Freight Contracts in Shipping

This thesis will focus on TC contracts in the dry bulk market. In the context of shipping, the type of charter contract will determine whether it arises split incentives between the charterer (agent) and the shipowner (principal). In short, a time charter involves the charterer hiring a vessel from a shipowner for a fixed period on a per-day rate (Stopford, 2009). A key difference from other charter types is how costs are distributed between the shipowner and the charterer. In the case of a TC, capital costs and operating costs, such as wages, maintenance, and insurance, are paid by the shipowner, while voyage costs, such as port and bunker costs, are paid by the charterer (Stopford, 2009). In contrast, the shipowner pays all costs in the case of a VC (Stopford, 2009). This specific distribution of costs in TCs results in a principal-agent problem between shipowners and charterers. More specifically, the shipowner invests in potential energy efficiency technology and thus pays the related capital costs. At the same time, the charterer determines and pays for the operation of the vessel during the charter and benefits from any fuel savings that might result from the technology.

As the principal (shipowner) makes the energy efficiency investment, while the agent (charterer) benefits from the fuel savings, the former has no incentive to invest in such equipment and technology (Longarela-Ares et al., 2020). If, on the other hand, the fuel savings that accrue to charterers was reflected in the TC rate paid in the period, shipowners would recoup some of their investment and have greater incentive to undertake it.

A more energy-efficient vessel is expected to yield both voyage cost reductions and carbon footprint reductions when operated accordingly by the charterer (RightShip, 2023). As the charterer pays voyage costs, the financial benefit of chartering a vessel with a higher GHG rating will accrue to the charterer, suggesting that they should be willing to pay more for a vessel with a high rating. Due to a lack of information on cost savings and economic gains from more energy-efficient vessels, TC rates are unlikely to fully reflect these gains (Longarela-Ares et al., 2020). Typically, the lack of information results from the absence of satisfactory measurement and verification methods for the operation of the energy efficiency equipment and technology and, thus, the environmental performance of the vessel (Longarela-Ares et al., 2020).

3.4 Size Segment Characteristics in the Dry Bulk Market

Vessels within the dry bulk shipping market can be divided into four main categories, ranging from the smallest to the largest: Handysize (10,000–40,000 deadweight tonnage (DWT)), Handymax (40,000-60,000 DWT), Panamax (60,000-100,000 DWT), and Capesize (>100,000 DWT) (Clarksons, 2022), in addition to Supramax (50,000-60,000 DWT) (Menon, 2021), which falls under the Handymax size range. The Handysize is in the smaller range and carries minor bulks or smaller parcels of major bulks. The Handymax is larger than the Handysize but usually carries the same type of bulk cargo (Stopford, 2009). The Handysize and Handymax vessels operate on routes all over the world but visit ports in Europe frequently (Husby, 2023). The Panamax vessel can transit the Panama Canal and typically carry coal, grain, and bauxite (Stopford, 2009). They mainly operate in the Caribbean and South American regions (Husby, 2023). The largest vessel is the Capesize which is too big to transit the Panama Canal. Capesize vessels mainly carry ore and coal (Stopford, 2009) and primarily operate between Brazil and China (Husby, 2023). Smaller vessels can carry small parcels of major bulk, and larger vessels can carry large parcels of minor bulk, making the vessels interchangeable.

Choosing between the different sizes comes down to a trade-off between cost and flexibility. A smaller vessel is more flexible than a larger vessel; however, the unit cost of utilizing it is higher (Stopford, 2009). The larger vessels are more homogenous, while the smaller vessels, particularly Handysize and Supramax vessels, vary more in design and equipment (Husby, 2023). Panamax stands out from the other segments in terms of the competitive landscape. Port congestion and additional market restrictions, combined with parcel distribution, lead to sharp changes in demand (Karaoulanis & Pelagidis, 2021). Moreover, the Panamax segment has many more professional players in the entire value chain compared to the other size segments, which makes the segment more competitive and, in turn, somewhat more “correctly” priced than the other segments (Husby, 2023).

4 Data

The data for this analysis is collected from three sources: 1) Clarksons SIN/World Fleet Register (WFR), 2) Western Bulk, and 3) RightShip. Clarksons SIN allows for downloading TC fixtures within different dry bulk segments and includes a range of contracts specific variables, such as the duration of the TC and where the vessel is delivered. The Clarkson WFR data include observations on dry bulk vessel details, such as the age of the vessel and its DWT. Combining the data from SIN and WFR downloaded on 1 November 2022, results in a dataset of TC fixtures with the belonging contract-specific and vessel-specific variables.

Western Bulk has kindly provided data on TC contracts between August 2013 and October 2022 and vessel specifications. Thus, the Western Bulk data offer additional observations to those constructed from SIN merged with WFR. Moreover, Western Bulk provided port data in October 2022, which we have used to construct a contract-specific variable based on the delivery port. The data provided by RightShip include 96,764 GHG emissions ratings for dry bulk vessels between January 2020 and November 2022, with a few exceptions from previous years. Due to the dynamic nature of the rating system, the over 96,000 observations include multiple ratings given to the same vessel as it is updated over time. These ratings are matched with the relevant contract based on the contract date and the unique IMO number of the vessel.

This thesis focuses on the dry bulk market, and similar to Ådland et al. (2017), it separates between different size segments. TC fixtures from Clarksons SIN and Western Bulk are divided into the size segments Handysize (combining Handysize and Handymax), Supramax (included as a subsegment of Handysize), Panamax, and Capesize. The analysis intends to investigate whether there exists an energy efficiency premium in any of the segments, and potential differences between them.

4.1 Presentation of Variables

A list of the variables used in the regression analyses with their corresponding unit description, expected sign, interpretation, and data source is included in Table 1 below. The sign projections for the variables are based on economic theory and/or shipping industry know-how.

The dependent variable is the daily TC contract rate measured in US dollars. Moving to explanatory variables, Agolucci et al. (2014) include multiple market indicators such as trade volume, fleet size, and commodity price as possible macroeconomic factors affecting freight rates. Ådland et al. (2017) instead include a market rate proxy to account for the full-term structure dynamics, which increases the explanatory power of the regression models (Adjusted R^2). This analysis will include the fuel price and a boom variable to account for macroeconomic factors. We exclude any market rate proxy as it would be based on the TC charter rate (the dependent variable), causing circularity in the estimation (R. O. Ådland, personal communication, February 26, 2023).

The fuel price is the weekly average of prices in Rotterdam and Singapore for high sulfur fuel oil (HSFO) and very low sulfur fuel oil (VLSFO) retrieved from Clarksons SIN. For vessels with missing information regarding fuel type, HFSO was assumed for all scrubber-fitted vessels, and VLSFO for all remaining vessels. This assumption is based on the fact that all observations are from after IMO 2020 came into force, which requires vessels without a scrubber to burn VLSFO (IMO, 2023). The effect of the fuel price on the TC rate is not given one way or the other according to economic theory. However, it is typically expected to negatively impact TC contract rates as it increases the voyage cost for the charterer (Ådland et al., 2017). From the beginning of January 2021 to the beginning of October 2021, the Baltic Exchange Dry Index (BDI) rose from 1,374 to 5,650, indicating a substantial boom in the dry bulk market (Roussanoglou, 2022). The boom dummy is based on this period and is included in the models alone and as an interaction term with energy efficiency. It is expected to positively impact the TC rate as an undersupplied market results in higher rates.

Of ship-specific variables, this regression analysis includes DWT, Age, Age_sq (squared), Flag_D, Japan_D, Electronic_D, Scrubber_D, and a categorical variable for each obtainable GHG emission rating from A-G. Due to increased cargo-carrying capacity and potential economies of scale advantages of a larger vessel, DWT is included to reflect these benefits on the TC contract rate. Age and Age_sq are included to reflect the linear and potential nonlinear effects of older ships. Moreover, specific ports and countries' restrictions on vessel age might negatively affect the obtainable TC rate (Ådland et al., 2017).

Flag_D is a dummy variable created to show the effect of a ship sailing under a flag that is black/grey-listed according to the Paris MoU from 1 July 2022 – 30 June 2023 (Paris MoU, 2022). The black/grey-list status of the flag may have changed over time; however, in this analysis, we have assumed for simplicity that the status is equal to the current status for all contracts, also before the present valid period. The same is assumed for a vessel's flag state, although it might have changed in the period. These assumptions may cause the dummy to equal 1 or fail to equal 1 when the opposite is correct for certain contracts.

Vessels built in Japan are considered to be of higher quality than vessels built in China or South Korea. Better quality means lower consumption and less variation in consumption from one vessel to another. Japanese shipowners often own Japanese newbuilds. They typically describe the ships more conservatively than many other shipowners, which results in less negative variance between actual and expected consumption (Husby, 2023). The Japan_D dummy variable equals 1 if the vessel is built in Japan and is expected to positively impact the contract rate.

A vessel with an electronically controlled main engine, typical for vessels built after 2013, is expected to obtain a higher TC rate as it can operate on lower consumption (Husby, 2023). We have therefore included the dummy variable Electronic_D which will equal 1 if the vessel has an electronic engine. The data sample does not include this information; therefore, we assume all vessels built after 2013 have an electronic engine. This assumption results in some multicollinearity between the variables Electronic_D and Age. However, after conducting a squared scaled Generalized Variance Inflation Factor (GVIF) test with a conservative threshold of 5, we keep Electronic_D for all regression models as the score is below for all models (Appendix A4-A12).

A scrubber-fitted vessel is expected to obtain a higher TC rate as it allows the vessel to run on high-sulfur fuel, cheaper than low-sulfur fuel, resulting in lower voyage costs for the charterer.

Therefore, a dummy variable, Scrubber_D, is included and will equal 1 if the vessel is scrubber-fitted.

RightShip's GHG rating system is used in this analysis to measure energy efficiency. As outlined earlier, the rating for an individual ship is based on either the EEDI or the EVDI. The EEDI formula, as shown below, calculates a newbuild's theoretical design efficiency and approximates CO_2 emissions per capacity mile (Transport & Environment, 2012). It is worth noting that this metric measures the design efficiency of the vessel, not the operational efficiency. Thus, two equal vessels with the same EEDI may have different CO_2 emissions depending on how they are operated and weather conditions (Transport & Environment, 2012).

$$EEDI = \frac{Power\ installed * Specific\ fuel\ consumption * Carbon\ conversion}{Available\ capacity * Speed}$$

The EVDI metric replicates the EEDI formula for existing vessels (Transport & Environment, 2012). Unless a vessel undergoes a major conversion or incorporates mechanical/electrical measures that improve the efficiency of the vessel under EEDI/EVDI conditions, documented by a class or other qualified third party, this metric is fixed (RightShip, 2023). However, the GHG rating may change as it is given relative to peer vessels of similar size and type. The ratings given to vessels within a peer group are normally distributed over RightShip's grading scale (Figure A1 in the appendix). Common measures include vessel energy-saving equipment such as propellor duct or nozzle, propellor boss cap fin, rudder optimization, waste heat recovery, and engine power limitation, amongst others (RightShip, 2023).

Due to the increased commercial pressure in the shipping industry (RightShip, 2023) and the increased voluntary efforts from charterers in terms of environmental performance (Sea Cargo Charter, 2023), we expect that the majority of charterers have a higher willingness to pay for vessels with above average energy efficiency performance. This implies that a vessel that is given a GHG emissions rating of C or better will obtain a higher TC rate as the vessel performs better environmentally compared to the average of its peer group.

In addition to including a categorical variable for each obtainable GHG rating, using D as the reference, we also use two dummies grouping grades better than and worse than the average in two separate regressions. The dummy variable ABC_D will equal 1 if the vessel has received a grade C or better, and the dummy variable EFG_D will equal 1 if the vessel has received a grade E or worse. These dummies are included to analyze whether the market is willing to pay a premium for vessels rated above average or a discount for vessels rated below average, not looking at one specific grade.

In the case of a bust market characterized by oversupply, charterers are expected to be more selective of the vessels they hire, looking at specific features such as energy efficiency. In a booming market, when supply is limited, other vessel characteristics, such as speed and capacity, become the priority (Ådland et al., 2017). To capture any effect market conditions and the GHG ratings combined have on the TC rate, we include interaction terms consisting of the boom dummy with the different GHG rating variables, which will equal 1 for observations within the boom period specified at the beginning of this section.

Lastly, looking at the contract-specific variables, Period, Forward, Option_D, and Atlantic_D are included in the regression analyses. A variable for the duration of the TC contract is incorporated (Period). In a case of backwardation, in which spot rates (at the time of signing the contract) are higher than expected future rates, there is an expected discount for longer-duration contracts. In the opposite case, contango, there is an expected premium for longer-duration contracts as rates are expected to increase (Wahab et al., 2019). It all depends on the slope of the forward curve. The Forward variable represents the delivery lead time, and the sign of the coefficient also depends on the slope of the forward curve at the time of signing the contract (Ådland et al., 2017). The forward curves for the Panamax, Capesize, and Supramax segments in the appendix (figures A2.1-A2.3) are mostly downward sloping, suggesting a negative impact of a longer delivery lead time on the TC rate.

A TC contract with the option to extend the contract offers more flexibility to the charterer; thus, he should be willing to pay more for a contract with this feature. Therefore, we include the dummy variable Option_D in our analysis and expect it to positively impact the contract rate when equal to 1. A dummy variable, Atalantic_D, will equal 1 if the vessel is delivered in the Atlantic. This variable is included because a fronthaul from the Atlantic to the Pacific is expected to obtain a higher TC contract rate, as it can be a better-paid fronthaul. This is due to asymmetric trade flows where the trade volume transported from the Atlantic to the Pacific is higher than that transported in the opposite direction (Ådland & Prochazka, 2021).

Table 1 – All variables with description and data source

Dependent variable

Variables	Units	Exp. Sign	Interpretation	Data source
Rate	$/day		The daily rate agreed upon in the TC contract	Clarksons SIN/Western Bulk

Independent variables

Variables	Units	Exp. Sign	Interpretation	Data source
Market variables				
FuelPrice	$/tonne	-	Average Rotterdam/Singapore price for HSFO and VLSFO	Clarksons SIN
Boom		+	Dummy for boom market period	Baltic Exchange Dry Index (BDI)
Ship specific variables				
DWT	Tonnes	+	Deadweight carrying capacity of ship	Clarksons WFR/Western Bulk
Age	Years	-	Age of ship on contract report date	Clarksons WFR/Western Bulk
Age_sq		-	Squared age to capture non-linear effects	Clarksons WFR/Western Bulk
Flag_D		-	Dummy for black/greylisted Paris MoU flags	Clarksons WFR/Western Bulk + Paris MoU
Japan_D		+	Dummy for Japan-built vessels	Clarksons WFR/Western Bulk
Electronic_D		+	Dummy for vessels with electric engine	Western Bulk/Assumptions
Scrubber_D		+	Dummy for scrubber-fitted vessels	Clarksons WFR/Western Bulk
A		+	Categorical variable for vessels with A GHG rating	RightShip
B		+	Categorical variable for vessels with B GHG rating	RightShip
C		+	Categorical variable for vessels with C GHG rating	RightShip
D		Reference	Categorical variable for vessels with D (average) GHG rating	RightShip
E		-	Categorical variable for vessels with E GHG rating	RightShip
F		-	Categorical variable for vessels with F GHG rating	RightShip
G		-	Categorical variable for vessels with G GHG rating	RightShip
ABC_D		+	Dummy for vessels with GHG rating above average (A, B or C)	RightShip
EFG_D		-	Dummy for vessels with GHG rating below average (E, F or G)	RightShip
Boom:A		-	Interaction term for vessels with A GHG rating under boom period	RightShip/BDI
Boom:B		-	Interaction term for vessels with B GHG rating under boom period	RightShip/BDI
Boom:C		-	Interaction term for vessels with C GHG rating under boom period	RightShip/BDI
Boom:E		+	Interaction term for vessels with E GHG rating under boom period	RightShip/BDI
Boom:F		+	Interaction term for vessels with F GHG rating under boom period	RightShip/BDI
Boom:G		+	Interaction term for vessels with G GHG rating under boom period	RightShip/BDI
Boom:ABC_D		-	Interaction term for vessels with GHG rating above average (A, B or C) under boom period	RightShip/BDI
Boom:EFG_D		+	Interaction term for vessels with GHG rating below average (E, F or G) under boom period	RightShip/BDI
Contract specific variables				
Period	Months	0	Duration of time charter contract	Clarksons SIN/Western Bulk
Forward	Days	-	Days between report date and delivery	Clarksons SIN/Western Bulk
Atlantic_D		+	Dummy for Atlantic ocean delivery at start of TC	Clarksons SIN/Western Bulk
Option_D		+	Dummy for the presence of an extension option	Clarksons SIN/Western Bulk

4.2 Data Cleaning Process

The raw data is collected from Clarksons SIN, Clarksons WFR, Wester Bulk, and RightShip. Initially, 983 TC contracts between 2019 and 2022 were downloaded from SIN, including 12 contract-specific variables, and 1,019 TC contracts between 2013 and 2022 were provided by Wester Bulk, including 11 contract-specific variables. Furthermore, data on more than 5,000 vessels with 33 ship-specific variables were downloaded from WFR, and Western Bulk provided 234 ship-specific variables for ~34,800 vessels. Data provided by RightShip included 96,764 GHG ratings with 11 related variables.

Starting with the SIN data, we removed 45 observations due to missing values under Rate, which is the dependent variable of the analysis. After merging the TC contracts with vessel-specific variables from WFR, first by Name and Built and then by Exname and Built, and lastly merging with GHG ratings by IMO number, we are left with only 397 unique observations. We lose 577 observations in these steps, due to lack of matches with WFR and invalid GHG ratings. Repeating the same process for the data provided by Western Bulk, merging contracts with vessel details and GHG ratings, all by IMO number, we are left with 208 unique observations. All 811 observations lost in this step are due to missing valid GHG ratings. SIN and Western Bulk combined make up 605 contracts. After manually reconstructing another 80 contracts from Western Bulk and 111 contracts from SIN, assuming the last GHG rating is valid for the vessel used in the TC, we have 796 observations.

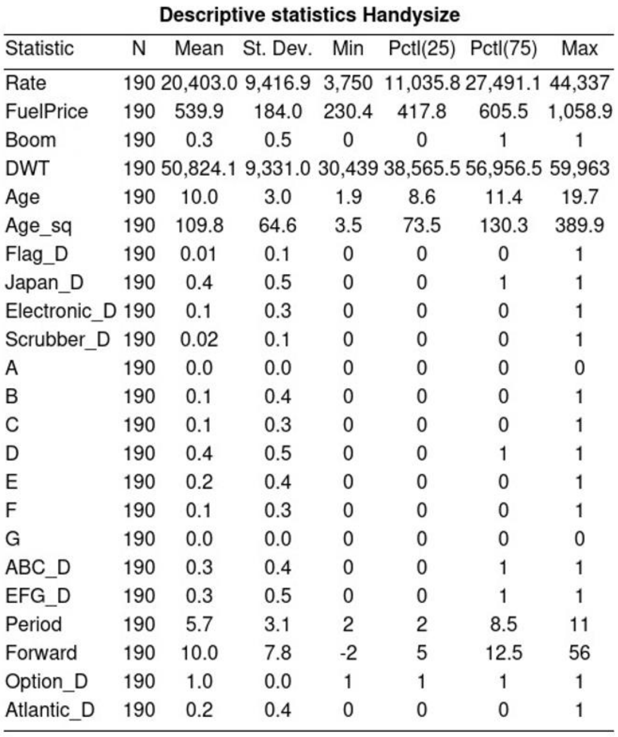
We further remove two observations due to values of “1/1/1900” under Laycan from. This value is not meaningful and is thus removed as we need the laycan information to calculate Forward. Another 12 observations are removed due to missing values under Period, also a crucial variable for the analysis. Finally, we remove three observations with missing values for Forward. As a result, we are left with 194 Handysize, 511 Panamax, and 74 Capesize, a total of 779 observations before further data cleaning.

Due to the low number of observations, a discretionary assessment of data cleaning is applied. For the 194 observations under Handysize, we can see from the scatterplot of the Forward variable in Figure A3.1 in the appendix that there are a couple of outliers. We, therefore, remove observations with Forward higher than 60 days, as this is rather unusual to observe in the market (R.O. Ådland, personal communication, January 31, 2023), resulting in 4 fewer observations. For the Panamax segment, we also remove all observations with Forward above 60 days in addition to observations with Forward below -20 days. Figure A3.2 in the appendix shows that the Panamax segment has two observations with Forward values of less than -500 days, likely representing errors in the data. This results in the total of Panamax observations being reduced to 498. We repeat the same procedure for the Capesize segment, resulting in a total of 73 observations. The scatterplot of Rate vs. Forward for the Capesize segment is presented in Figure A3.3 in the appendix. After data cleaning, observations with DWT between 50,000 and 60,000, qualifying as the Supramax segment, are left with 137 observations.

4.3 Descriptive Statistics

Following the data cleaning process, tables 2-5 show the descriptive statistics for the variables used in the analysis per size segment. Studying all tables, we see that the larger the DWT range, the higher the segment's average TC rate. Moreover, the GHG emissions ratings given to Handysize and Panamax vessels are close to normally distributed over RightShip's scale, while most Capesize vessels are graded to average or just below average in our data sample. The larger the size segment, the greater the share of scrubber-fitted vessels and the longer the average duration of the contracts, which aligns with what can be observed *de facto*.

Table 2 – Descriptive statistics for the Handysize segment

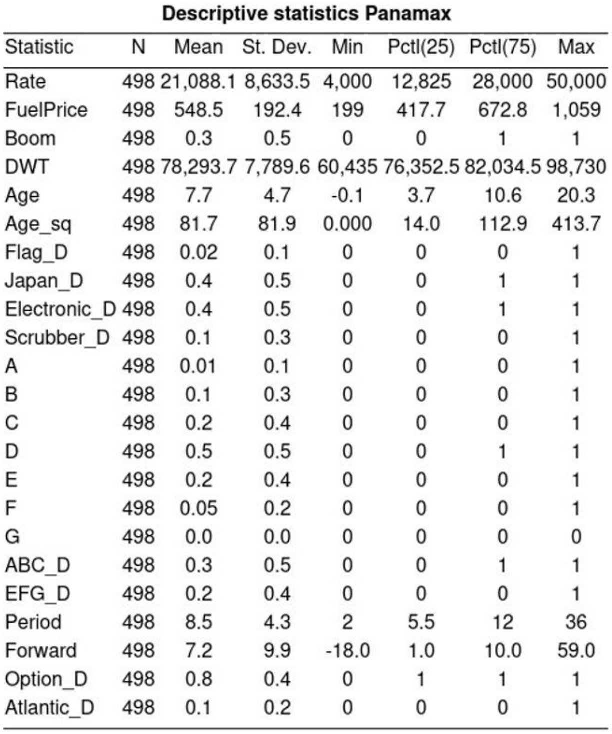


Descriptive statistics Handysize

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Rate	190	20,403.0	9,416.9	3,750	11,035.8	27,491.1	44,337
FuelPrice	190	539.9	184.0	230.4	417.8	605.5	1,058.9
Boom	190	0.3	0.5	0	0	1	1
DWT	190	50,824.1	9,331.0	30,439	38,565.5	56,956.5	59,963
Age	190	10.0	3.0	1.9	8.6	11.4	19.7
Age_sq	190	109.8	64.6	3.5	73.5	130.3	389.9
Flag_D	190	0.01	0.1	0	0	0	1
Japan_D	190	0.4	0.5	0	0	1	1
Electronic_D	190	0.1	0.3	0	0	0	1
Scrubber_D	190	0.02	0.1	0	0	0	1
A	190	0.0	0.0	0	0	0	0
B	190	0.1	0.4	0	0	0	1
C	190	0.1	0.3	0	0	0	1
D	190	0.4	0.5	0	0	1	1
E	190	0.2	0.4	0	0	0	1
F	190	0.1	0.3	0	0	0	1
G	190	0.0	0.0	0	0	0	0
ABC_D	190	0.3	0.4	0	0	1	1
EFG_D	190	0.3	0.5	0	0	1	1
Period	190	5.7	3.1	2	2	8.5	11
Forward	190	10.0	7.8	-2	5	12.5	56
Option_D	190	1.0	0.0	1	1	1	1
Atlantic_D	190	0.2	0.4	0	0	0	1

The Handysize (Table 2) vessels range from ~2 – 20 years of age, 40% are built in Japan, 10% have electronic engines, and only 2% are scrubber-fitted. The GHG emissions ratings are close to normally distributed over the grading scale as intended by RightShip. However, the observations have yet to receive the best (A) or the worst (G) rating. The TC contracts have a duration of between 2 and 11 months, only 10 % have the option to extend, and 20% have Atlantic Ocean delivery of the vessel.

Table 3 – Descriptive statistics for the Panamax segment

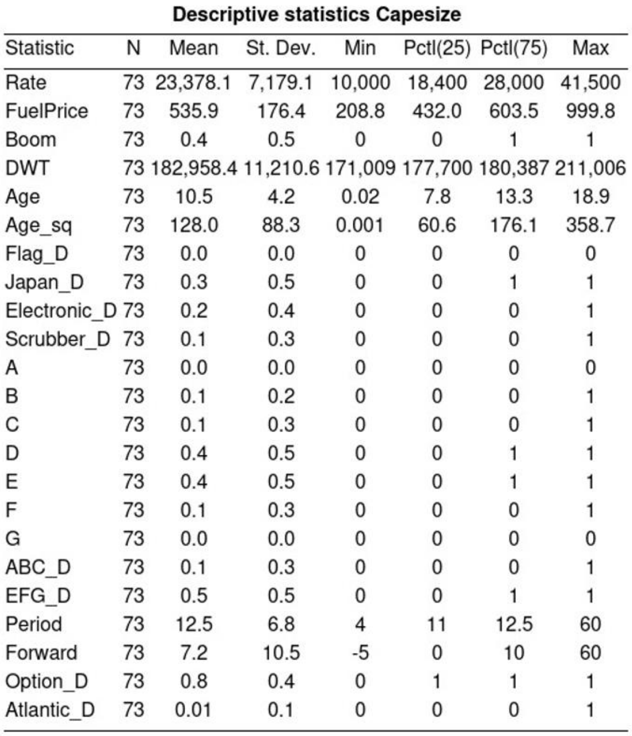


Descriptive statistics Panamax

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Rate	498	21,088.1	8,633.5	4,000	12,825	28,000	50,000
FuelPrice	498	548.5	192.4	199	417.7	672.8	1,059
Boom	498	0.3	0.5	0	0	1	1
DWT	498	78,293.7	7,789.6	60,435	76,352.5	82,034.5	98,730
Age	498	7.7	4.7	-0.1	3.7	10.6	20.3
Age_sq	498	81.7	81.9	0.000	14.0	112.9	413.7
Flag_D	498	0.02	0.1	0	0	0	1
Japan_D	498	0.4	0.5	0	0	1	1
Electronic_D	498	0.4	0.5	0	0	1	1
Scrubber_D	498	0.1	0.3	0	0	0	1
A	498	0.01	0.1	0	0	0	1
B	498	0.1	0.3	0	0	0	1
C	498	0.2	0.4	0	0	0	1
D	498	0.5	0.5	0	0	1	1
E	498	0.2	0.4	0	0	0	1
F	498	0.05	0.2	0	0	0	1
G	498	0.0	0.0	0	0	0	0
ABC_D	498	0.3	0.5	0	0	1	1
EFG_D	498	0.2	0.4	0	0	0	1
Period	498	8.5	4.3	2	5.5	12	36
Forward	498	7.2	9.9	-18.0	1.0	10.0	59.0
Option_D	498	0.8	0.4	0	1	1	1
Atlantic_D	498	0.1	0.2	0	0	0	1

The Panamax (Table 3) vessels range from newbuilds to ~20 years of age, 40% are built in Japan and have electronic engines, and only 10% are scrubber-fitted. Half of the vessels rate average in their peer group on GHG emissions and the remaining vessels are normally distributed on RightShip's grading scale, likely due to the high number of observations within the Panamax segment. The TC contracts have a duration of between two months and three years, 80 % have the option to extend, and 10% have vessel delivery in the Atlantic Ocean.

Table 4 – Descriptive statistics for the Capesize segment

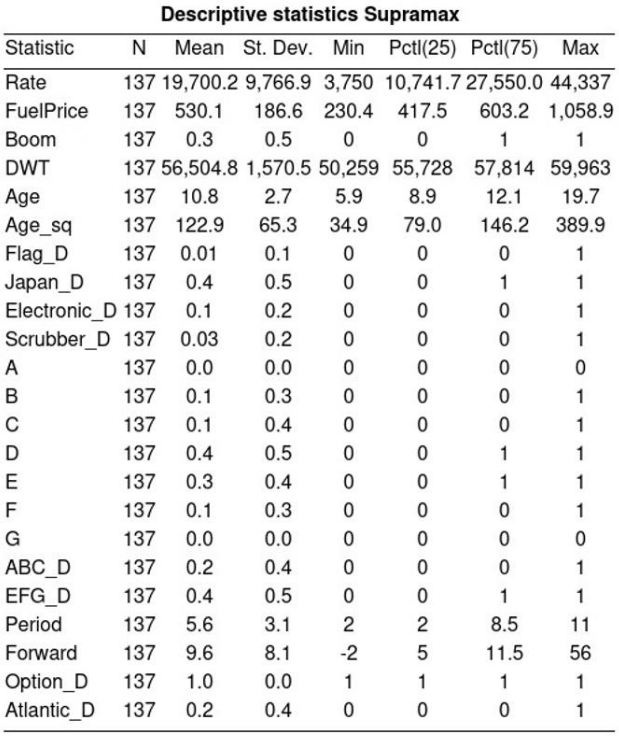


Descriptive statistics Capesize

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Rate	73	23,378.1	7,179.1	10,000	18,400	28,000	41,500
FuelPrice	73	535.9	176.4	208.8	432.0	603.5	999.8
Boom	73	0.4	0.5	0	0	1	1
DWT	73	182,958.4	11,210.6	171,009	177,700	180,387	211,006
Age	73	10.5	4.2	0.02	7.8	13.3	18.9
Age_sq	73	128.0	88.3	0.001	60.6	176.1	358.7
Flag_D	73	0.0	0.0	0	0	0	0
Japan_D	73	0.3	0.5	0	0	1	1
Electronic_D	73	0.2	0.4	0	0	0	1
Scrubber_D	73	0.1	0.3	0	0	0	1
A	73	0.0	0.0	0	0	0	0
B	73	0.1	0.2	0	0	0	1
C	73	0.1	0.3	0	0	0	1
D	73	0.4	0.5	0	0	1	1
E	73	0.4	0.5	0	0	1	1
F	73	0.1	0.3	0	0	0	1
G	73	0.0	0.0	0	0	0	0
ABC_D	73	0.1	0.3	0	0	0	1
EFG_D	73	0.5	0.5	0	0	1	1
Period	73	12.5	6.8	4	11	12.5	60
Forward	73	7.2	10.5	-5	0	10	60
Option_D	73	0.8	0.4	0	1	1	1
Atlantic_D	73	0.01	0.1	0	0	0	1

The Capesize (Table 4) vessels range between newbuilds to ~19 years of age, none of them sails under a blacklisted flag, 30% are built in Japan, 20% have electronic engines, and 10% are scrubber-fitted. Most vessels have received a GHG emission rating of average or below average compared to the peer group, and none have received the best (A) or worst (G) rating. The Capesize vessels obtain an average rate of just above 23,000 $/day in the TC market, the contracts range between four months and five years, 80% have the option to extend, and as little as 1% of the contracts have Atlantic Ocean delivery of the vessel.

Table 5 – Descriptive statistics for the Supramax segment



Descriptive statistics Supramax

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Rate	137	19,700.2	9,766.9	3,750	10,741.7	27,550.0	44,337
FuelPrice	137	530.1	186.6	230.4	417.5	603.2	1,058.9
Boom	137	0.3	0.5	0	0	1	1
DWT	137	56,504.8	1,570.5	50,259	55,728	57,814	59,963
Age	137	10.8	2.7	5.9	8.9	12.1	19.7
Age_sq	137	122.9	65.3	34.9	79.0	146.2	389.9
Flag_D	137	0.01	0.1	0	0	0	1
Japan_D	137	0.4	0.5	0	0	1	1
Electronic_D	137	0.1	0.2	0	0	0	1
Scrubber_D	137	0.03	0.2	0	0	0	1
A	137	0.0	0.0	0	0	0	0
B	137	0.1	0.3	0	0	0	1
C	137	0.1	0.4	0	0	0	1
D	137	0.4	0.5	0	0	1	1
E	137	0.3	0.4	0	0	1	1
F	137	0.1	0.3	0	0	0	1
G	137	0.0	0.0	0	0	0	0
ABC_D	137	0.2	0.4	0	0	0	1
EFG_D	137	0.4	0.5	0	0	1	1
Period	137	5.6	3.1	2	2	8.5	11
Forward	137	9.6	8.1	-2	5	11.5	56
Option_D	137	1.0	0.0	1	1	1	1
Atlantic_D	137	0.2	0.4	0	0	0	1

The Supramax (Table 5) vessels range between approximately 6-20 years of age, 40% of them are built in Japan, 10% have electronic engines, and 3% are scrubber-fitted. Compared to the 2% scrubber-fitted Handysize vessels, most of them are Supramax vessels, showing that larger vessels are more typically scrubber-fitted. The GHG ratings are also close to normally distributed, but most vessels are rated average or below average. The charter contracts range between 2 and 11 months in duration, all contracts include the option to extend, and 20% include Atlantic Ocean delivery.

5 Methodology

In order to study the effect of the proposed determinants on the contract rate in the dry bulk market, a multiple linear regression model was explored. The mathematical expression for multiple linear regressions is given by

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + u_i, i = 1, \dots, n.$$

where Y_i denotes the i^{th} observation of the dependent variable (Stock & Watson, 2015), the contract rate for time charter contracts in the dry bulk market. β_0 is the intercept of the slope, and β_k the coefficients of the independent variables. Further, the observations are given by X_{ki} for each of the k regressors. For each value of $j = 1, \dots, k$, β_j reflect the expected effect of a change in one unit of X_{ki} on Y_i while holding all other regressors constant. Lastly, u_i is the error term of the model.

In addition, our model contains an interaction term between the GHG ratings and the Boom dummy variable indicating whether the contract is signed during a boom period. Interaction terms are incorporated in multiple linear regression models as follows (Stock & Watson, 2015):

$$\beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2$$

For our analysis, the above results in the following model:

$$\begin{aligned} Rate = {} & \beta_0 + \beta_1 FuelPrice + \beta_2 Boom + \beta_3 DWT + \beta_4 Age + \beta_5 Age\_sq + \beta_6 Flag\_D \\ & + \beta_7 Japan\_D + \beta_8 Electronic\_D + \beta_9 Scrubber\_D + \beta_{10} A + \beta_{11} B + \beta_{12} C \\ & + \beta_{13} E + \beta_{14} F + \beta_{15} G + \beta_{16} Boom \cdot A + \beta_{17} Boom \cdot B + \beta_{18} Boom \cdot C \\ & + \beta_{19} Boom \cdot E + \beta_{20} Boom \cdot F + \beta_{21} Boom \cdot G + \beta_{22} Period + \beta_{23} Forward \\ & + \beta_{24} Option\_D + \beta_{25} Atlantic\_D \end{aligned}$$

By omitting the variable for GHG rating D, the effect of all other ratings is presented as relative to vessels with the rating D. As RightShip's GHG rating system is based on a peer group, ratings within groups are normally distributed. Thus, rating D is the baseline for all groups. Although we do not know whether our chosen segments align with the groups RightShip operates with when analyzing and rating vessels, the assumption that D-rated ships are the standard is considered applicable.

Further, two additional regression models, one with the variable ABC_D and one with EFG_D, were applied. By doing this, the model will consider higher rated and lower rated ships rather than the effect of each grade separately. Thus, the model separates the general performance of the ship rather than between the grades individually. We constructed two models, one grouping better performing ships and one grouping worse performing ships.

The model below considers all vessels with GHG ratings D, E, F, and G as the baseline, and vessels with better performing ratings are present through the dummy variable ABC_D. Thus, the dummy variable ABC_D indicates wheatear the market is willing to pay for better performing vessels.

$$\begin{aligned} Rate = \beta_0 + \beta_1 FuelPrice + \beta_2 Boom + \beta_3 DWT + \beta_4 Age + \beta_5 Age\_sq + \beta_6 Flag\_D \\ + \beta_7 Japan\_D + \beta_8 Electronic\_D + \beta_9 Scrubber\_D + \beta_{10} ABC\_D + \beta_{11} Boom \\ \cdot ABC\_D + \beta_{12} Period + \beta_{13} Forward + \beta_{14} Option\_D + \beta_{15} Atlantic\_D \end{aligned}$$

The model below considers the four highest GHG ratings as the baseline rather than the lowest four, resulting in the model being able to examine if the market has a reduced willingness to pay for less energy-efficient vessels.

$$\begin{aligned} Rate = \beta_0 + \beta_1 FuelPrice + \beta_2 Boom + \beta_3 DWT + \beta_4 Age + \beta_5 Age\_sq + \beta_6 Flag\_D \\ + \beta_7 Japan\_D + \beta_8 Electronic\_D + \beta_9 Scrubber\_D + \beta_{10} EFG\_D + \beta_{11} Boom \\ \cdot EFG\_D + \beta_{12} Period + \beta_{13} Forward + \beta_{14} Option\_D + \beta_{15} Atlantic\_D \end{aligned}$$

Residual diagnostics were performed for all multiple linear regression models to detect possible unwanted characteristics. All diagnostics plots are presented in the appendix in sections A4 through A. 15. For multiple linear regression, the following four underlying assumptions must be satisfied: 1) homoskedasticity of variance of the residuals, 2) normally distributed residuals, 3) no large outliers, and 4) independence amongst the independent variables (Stock & Watson, 2015). Lastly, by using a linear regression model, the assumption of linearity between the dependent and independent variables follows naturally.

The residual diagnostics, multicollinearity matrices, and squared scaled GVIF values for all multiple linear models are presented in the appendix sections A4-A15. By studying the Scale-Location plots, we cannot observe any clearly discernible patterns among the observations, indicating that the assumption of homoskedasticity is satisfied. Through examining the histograms, it becomes visible that the assumption of normally distributed residuals is maintained. There are no large outliers visible in the residual diagnostics. These were removed in the “Data Cleaning Process” section, preventing them from influencing the regression model.

Further, we need to check the variables for multicollinearity to ensure independence among the independent variables. As our analysis contain several categorical variables, we calculate the squared scaled GVIF score for all variables. Using the squared scaled GVIF allows us to compare GVIF values across all types of variables. The scaled GVIF corresponds to the square root of the VIF, and therefore, we can use the VIF rule of thumb for the squared scaled GVIF values (Buteikis, 2020). We apply a threshold of 5, which all variables except Age and Age_sq comply with. The Age variable is highly correlated with Age_sq, which is expected as Age_sq is calculated from the Age variable. This results in multicollinearity with squared scaled GVIF values above our chosen threshold in all models. Thus, the assumption of independence amongst the determinants is not upheld. However, as we expect both the vessel's age and squared age to be relevant determinants of the contract rate, we include both. Lastly, by studying the Normal Q-Q plots, it becomes clear that the assumption of linearity is upheld across all models.

6 Results and Discussion

This section will elaborate on the results of the regression models for the different size segments and discuss their statistical significance and economic importance. As we have not included a market rate proxy in the analyses, the explanatory power of the models is limited compared to that achieved in previous research by Ådland et al. (2017). An overall discussion of the results will follow after the segments.

6.1 Handysize

The results of the regression models made for the Handysize segment are displayed in Table 6. A multiple linear regression model is applied to this segment with several interaction terms to account for the effect of boom conditions. The three models have satisfactory explanatory power with adjusted R^2 of between 0.403 and 0.427. The variables largely act as expected, with coefficient signs equal to what economic theory and industry experience would suggest. The macroeconomic variables FuelPrice and Boom are positively significant at a 99% level of confidence in one or more models. Higher bunker prices are often associated with more slow steaming (Kontovas & Psaraftis, 2011), leading to lower supply and higher rates, a potential explanation for the positive effect of the fuel price observed in the models. Moreover, the premium for Handysize vessels during a boom can be explained by increased demand pressuring the availability of vessels and, thus, the rate.

In one of the Handysize models, vessels with an electronic engine are awarded a TC rate premium of ~$5,600/day at a 90% level of confidence (model 2). This is per expectations as an electronically controlled engine has lower consumption and thus lower voyage costs for the charterer. Furthermore, scrubber-fitted vessels also gain a rate premium at a 99% level of confidence in all the Handysize models. This aligns with expectations as scrubber-fitted vessels can use cheaper fuel, also lowering voyage costs. The contract-specific variable for delivery lead time also has a significant positive effect at a 99% level of confidence in all three models. A positive effect of longer delivery lead time implies an upward-sloping forward curve.

Most importantly, and interestingly, there is a significant negative effect of the GHG ratings E and F, and of the dummy for the below average rated vessels (EFG_D). A vessel with a GHG rating of E obtains a discount of ~$4,600/day at a 99% level of confidence. A vessel with a GHG rating of F obtains a discount of ~$4,800/day at a 95% level of confidence, indicating that vessels rated below average on energy efficiency obtain a lower rate in the TC market. However, we do not find that vessels performing above average on energy efficiency are awarded a premium in the market. Although not significant, the B rating has a positive coefficient, and the C rating has a negative coefficient. Counterintuitively, the negative effect of the C rating implies a discount compared to the average rated vessel. Looking at the interaction terms for the GHG ratings, we see that some of the premiums and discounts are adjusted for boom conditions. However, these are not statistically significant.

Table 6 – Regression results for the Handysize segment

Handysize sector results

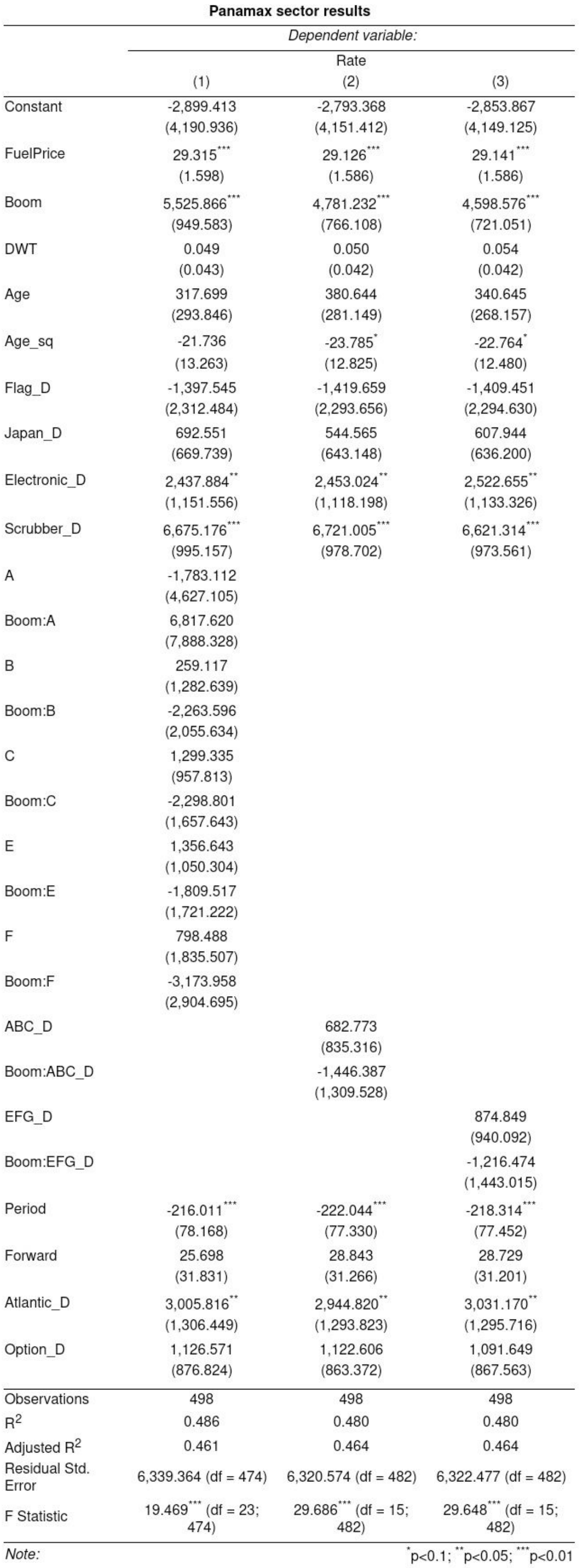
	Dependent variable:		
	Rate		
	(1)	(2)	(3)
Constant	-2,737.901	-4,781.515	-2,614.263
	(6,844.250)	(6,884.969)	(6,719.900)
FuelPrice	27.139***	28.801***	26.842***
	(3.215)	(3.121)	(3.128)
Boom	3,830.303**	5,982.814***	3,577.673**
	(1,868.994)	(1,396.241)	(1,439.309)
DWT	-0.018	-0.025	-0.030
	(0.066)	(0.065)	(0.064)
Age	1,035.891	909.161	1,048.779
	(1,172.072)	(1,165.411)	(1,138.822)
Age_sq	-31.599	-27.849	-31.231
	(46.769)	(46.614)	(45.507)
Flag_D	3,192.152	4,991.261	3,497.844
	(5,494.260)	(5,500.126)	(5,383.819)
Japan_D	-1,604.027	-1,221.501	-1,923.626
	(1,202.851)	(1,192.779)	(1,171.566)
Electronic_D	4,241.053	5,568.671*	4,611.485
	(3,307.030)	(3,115.878)	(2,885.576)
Scrubber_D	10,314.780***	11,702.230***	10,712.030***
	(3,779.831)	(3,768.786)	(3,692.629)
B	103.306		
	(2,287.363)		
Boom:B	-346.004		
	(3,573.531)		
C	-3,449.144		
	(2,273.895)		
Boom:C	370.642		
	(3,634.365)		
E	-4,610.412***		
	(1,750.693)		
Boom:E	3,717.426		
	(2,968.549)		
F	-4,761.738**		
	(2,204.337)		
Boom:F	3,895.226		
	(4,479.336)		
ABC_D		192.419	
		(1,637.066)	
Boom:ABC_D		-2,452.144	
		(2,584.470)	
EFG_D			-4,137.919***
			(1,416.335)
Boom:EFG_D			3,994.524
			(2,438.752)
Period	68.228	62.749	58.416
	(180.955)	(182.812)	(178.960)
Forward	195.985***	192.794***	201.776***
	(72.990)	(73.318)	(71.454)
Atlantic_D	1,033.905	940.562	1,076.535
	(1,364.329)	(1,376.619)	(1,346.522)
Observations	190	190	190
R^2	0.481	0.447	0.469
Adjusted R^2	0.420	0.403	0.427
Residual Std. Error	7,174.126 (df = 169)	7,277.240 (df = 175)	7,128.103 (df = 175)
F Statistic	7.832*** (df = 20; 169)	10.106*** (df = 14; 175)	11.061*** (df = 14; 175)
Note:			*p<0.1; **p<0.05; ***p<0.01

6.2 Panamax

The Panamax models (Table 7) have higher explanatory power than the Handysize models, with adjusted R^2 between 0.461 and 0.464. The variables mostly behave as expected per economic theory, and as for the Handysize segment, the FuelPrice and the Boom variables are positively significant at a 99% level of confidence. Vessels with electronically controlled engines and scrubbers obtain rate premiums at a 95% and a 99% level of confidence, respectively. Unlike the Handysize segment, the Panamax segment obtains a premium for Atlantic vessel delivery of ~$3,000/day at a 95% level of confidence, aligned with the higher value fronthaul possibilities associated with Atlantic vessel delivery.

The nonlinear age variable has a significant negative effect at a 90% level of confidence in two Panamax models. A vessel is expected to obtain a lower rate as it ages but at an accelerated pace, explaining the negative nonlinear effect found in the models. Furthermore, a discount for longer-duration contracts is significant at a 99% level of confidence, suggesting backwardation when signing the contract, as implied by the contango/backwardation curve in Figure A2.1 in the appendix. Regarding energy efficiency, we see no significant effect of the GHG ratings on the TC rate in the Panamax segment. The ratings, B-F, have positive coefficients, suggesting they all obtain premiums compared to the reference rating D, while A obtain a discount.

Table 7 – Regression results for the Panamax segment



Panamax sector results

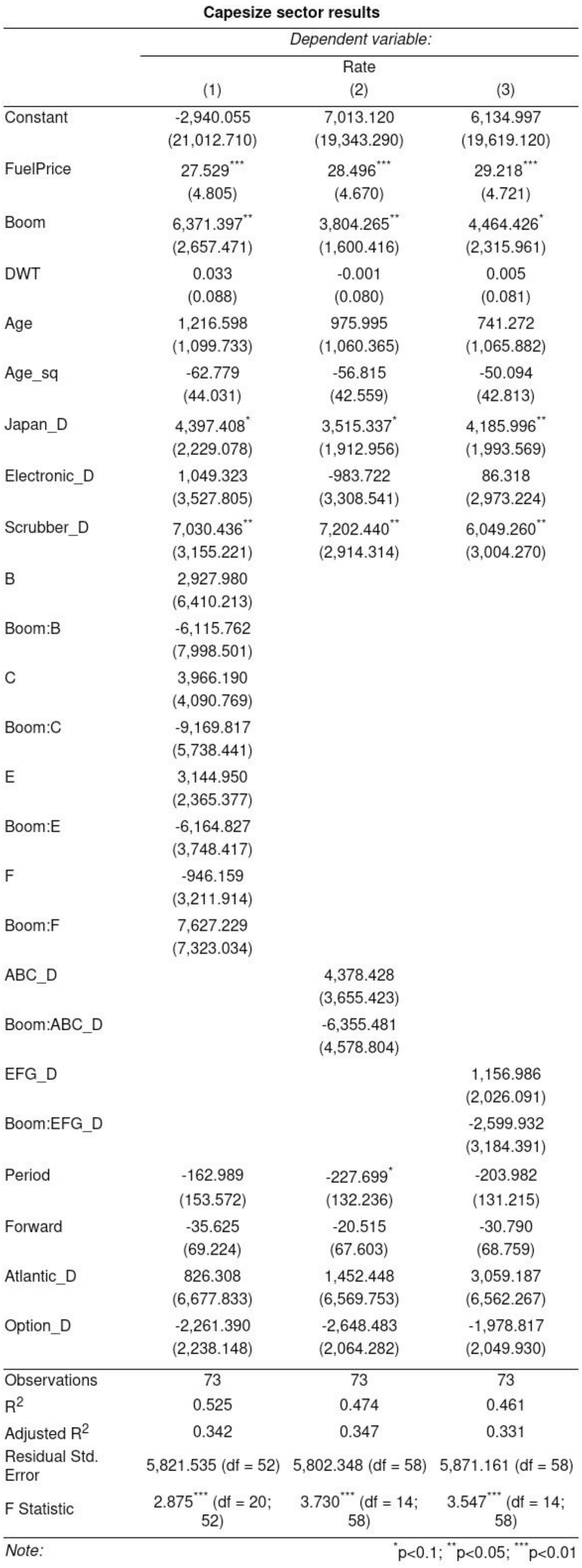
	Dependent variable:		
	Rate		
	(1)	(2)	(3)
Constant	-2,899.413 (4,190.936)	-2,793.368 (4,151.412)	-2,853.867 (4,149.125)
FuelPrice	29.315*** (1.598)	29.126*** (1.586)	29.141*** (1.586)
Boom	5,525.866*** (949.583)	4,781.232*** (766.108)	4,598.576*** (721.051)
DWT	0.049 (0.043)	0.050 (0.042)	0.054 (0.042)
Age	317.699 (293.846)	380.644 (281.149)	340.645 (268.157)
Age_sq	-21.736 (13.263)	-23.785* (12.825)	-22.764* (12.480)
Flag_D	-1,397.545 (2,312.484)	-1,419.659 (2,293.656)	-1,409.451 (2,294.630)
Japan_D	692.551 (669.739)	544.565 (643.148)	607.944 (636.200)
Electronic_D	2,437.884** (1,151.556)	2,453.024** (1,118.198)	2,522.655** (1,133.326)
Scrubber_D	6,675.176*** (995.157)	6,721.005*** (978.702)	6,621.314*** (973.561)
A	-1,783.112 (4,627.105)		
Boom:A	6,817.620 (7,888.328)		
B	259.117 (1,282.639)		
Boom:B	-2,263.596 (2,055.634)		
C	1,299.335 (957.813)		
Boom:C	-2,298.801 (1,657.643)		
E	1,356.643 (1,050.304)		
Boom:E	-1,809.517 (1,721.222)		
F	798.488 (1,835.507)		
Boom:F	-3,173.958 (2,904.695)		
ABC_D		682.773 (835.316)	
Boom:ABC_D		-1,446.387 (1,309.528)	
EFG_D			874.849 (940.092)
Boom:EFG_D			-1,216.474 (1,443.015)
Period	-216.011*** (78.168)	-222.044*** (77.330)	-218.314*** (77.452)
Forward	25.698 (31.831)	28.843 (31.266)	28.729 (31.201)
Atlantic_D	3,005.816** (1,306.449)	2,944.820** (1,293.823)	3,031.170** (1,295.716)
Option_D	1,126.571 (876.824)	1,122.606 (863.372)	1,091.649 (867.563)
Observations	498	498	498
R^2	0.486	0.480	0.480
Adjusted R^2	0.461	0.464	0.464
Residual Std. Error	6,339.364 (df = 474)	6,320.574 (df = 482)	6,322.477 (df = 482)
F Statistic	19.469*** (df = 23; 474)	29.686*** (df = 15; 482)	29.648*** (df = 15; 482)
Note:			*p<0.1; **p<0.05; ***p<0.01

6.3 Capesize

The Capesize models (Table 8) have decent explanatory power with adjusted R^2 between 0.331 and 0.347. Most of the variables behave as expected in terms of the coefficient sign, except for some of the GHG ratings, although none are statistically significant. Like the other segments, the fuel price, the boom, and the scrubber variables show significant effects with the expected coefficient signs. In addition, vessels built in Japan obtain a premium of ~$4,200/day at a 95% level of confidence (model 3). This aligns with industry experience as Japanese-built vessels are typically of higher quality and thus consume less fuel than other vessels, decreasing voyage costs (Husby, 2023). Moreover, there is a significant negative effect of Period on the contract rate, at a 90% level of confidence in one of the models, implying backwardation (Appendix A2.2).

The GHG ratings B and C have positive coefficient signs, which is expected, given that charterers care about a vessel's relative energy efficiency performance. However, the E GHG rating also positively affects the contract rate, suggesting that charterers also value below average energy efficiency performance. On the other hand, F-rated vessels obtain a discount of ~$946/day according to model 1, but this effect is not significant either. B- and C-rated vessels are penalized during boom conditions, obtaining a discount compared to an average rated vessel. Further, F-rated vessels obtain a premium during the boom period, while E-rated vessels get a discount. A possible explanation for these results is that other parameters become much more critical when supply is limited, particularly when and where the vessel is available (Husby, 2023).

Table 8 – Regression results for the Capesize segment



Capesize sector results

	Dependent variable:		
	Rate		
	(1)	(2)	(3)
Constant	-2,940.055 (21,012.710)	7,013.120 (19,343.290)	6,134.997 (19,619.120)
FuelPrice	27.529*** (4.805)	28.496*** (4.670)	29.218*** (4.721)
Boom	6,371.397** (2,657.471)	3,804.265** (1,600.416)	4,464.426* (2,315.961)
DWT	0.033 (0.088)	-0.001 (0.080)	0.005 (0.081)
Age	1,216.598 (1,099.733)	975.995 (1,060.365)	741.272 (1,065.882)
Age_sq	-62.779 (44.031)	-56.815 (42.559)	-50.094 (42.813)
Japan_D	4,397.408* (2,229.078)	3,515.337* (1,912.956)	4,185.996** (1,993.569)
Electronic_D	1,049.323 (3,527.805)	-983.722 (3,308.541)	86.318 (2,973.224)
Scrubber_D	7,030.436** (3,155.221)	7,202.440** (2,914.314)	6,049.260** (3,004.270)
B	2,927.980 (6,410.213)		
Boom:B	-6,115.762 (7,998.501)		
C	3,966.190 (4,090.769)		
Boom:C	-9,169.817 (5,738.441)		
E	3,144.950 (2,365.377)		
Boom:E	-6,164.827 (3,748.417)		
F	-946.159 (3,211.914)		
Boom:F	7,627.229 (7,323.034)		
ABC_D		4,378.428 (3,655.423)	
Boom:ABC_D		-6,355.481 (4,578.804)	
EFG_D			1,156.986 (2,026.091)
Boom:EFG_D			-2,599.932 (3,184.391)
Period	-162.989 (153.572)	-227.699* (132.236)	-203.982 (131.215)
Forward	-35.625 (69.224)	-20.515 (67.603)	-30.790 (68.759)
Atlantic_D	826.308 (6,677.833)	1,452.448 (6,569.753)	3,059.187 (6,562.267)
Option_D	-2,261.390 (2,238.148)	-2,648.483 (2,064.282)	-1,978.817 (2,049.930)
Observations	73	73	73
R^2	0.525	0.474	0.461
Adjusted R^2	0.342	0.347	0.331
Residual Std. Error	5,821.535 (df = 52)	5,802.348 (df = 58)	5,871.161 (df = 58)
F Statistic	2.875*** (df = 20; 52)	3.730*** (df = 14; 58)	3.547*** (df = 14; 58)
Note:			*p<0.1; **p<0.05; ***p<0.01

6.4 Supramax

The Supramax models (Table 9) have satisfactory explanatory power with adjusted R^2 between 0.440 and 0.489. As the Supramax models are made based on a lot of the same data as the Handysize models, the regression results are similar. The FuelPrice, Boom, scrubber, and Forward variables are also statistically significant for the Supramax segment. However, not the dummy for vessels with electronically controlled engines. We find a positive effect of the Forward variable that is statistically significant at a 90% level of confidence, suggesting contango. This does not align with the downward-sloping contango/backwardation curve in Figure A2.3 in the appendix. The GHG ratings also have the same results as the Handysize segment. There is a significant negative effect of the GHG ratings E and F, and of the dummy for the below average rated vessels (EFG_D). A vessel with a GHG rating of E obtains a discount of ~$4,200/day at a 95% level of confidence. A vessel with a GHG rating of F obtains a discount of ~$9,400/day at a 99% level of confidence. These results imply that Supramax vessels rated below average on energy efficiency obtain a discount in the TC market.

Table 9 – Regression results for the Supramax segment

Supramax sector results

	Dependent variable:		
	Rate		
	(1)	(2)	(3)
Constant	-29,876.220	-35,056.570	-24,145.500
	(30,683.300)	(31,140.890)	(30,340.490)
FuelPrice	29.517***	31.082***	27.462***
	(3.893)	(3.887)	(3.853)
Boom	4,672.059**	6,833.734***	4,229.657**
	(2,168.712)	(1,630.831)	(1,712.354)
DWT	0.428	0.493	0.321
	(0.539)	(0.544)	(0.531)
Age	1,079.979	719.380	1,198.039
	(1,663.338)	(1,678.360)	(1,636.984)
Age_sq	-25.719	-12.767	-31.433
	(66.424)	(67.166)	(65.658)
Flag_D	-3,273.130	-242.317	-2,637.503
	(7,353.817)	(7,617.726)	(7,411.139)
Japan_D	-918.971	-478.678	-1,819.965
	(1,544.609)	(1,533.756)	(1,501.428)
Electronic_D	3,715.980	3,943.167	2,874.492
	(4,223.097)	(3,931.160)	(3,626.045)
Scrubber_D	11,473.780***	12,126.040***	10,904.000***
	(3,727.559)	(3,805.566)	(3,692.228)
B	-1,852.111		
	(3,092.511)		
Boom:B	510.713		
	(4,602.592)		
C	-3,550.345		
	(2,386.759)		
Boom:C	-955.467		
	(3,948.927)		
E	-4,221.851**		
	(1,969.511)		
Boom:E	3,596.895		
	(3,273.938)		
F	-9,361.208***		
	(2,636.646)		
Boom:F	831.242		
	(5,920.016)		
ABC_D		-409.843	
		(1,996.566)	
Boom:ABC_D		-2,397.565	
		(3,139.171)	
EFG_D			-4,992.505***
			(1,646.804)
Boom:EFG_D			4,120.157
			(2,802.484)
Period	136.319	101.754	122.978
	(213.386)	(221.324)	(213.885)
Forward	98.737	127.261	145.437*
	(84.913)	(86.782)	(83.154)
Atlantic_D	1,029.254	754.908	1,462.283
	(1,750.090)	(1,796.974)	(1,738.200)
Observations	137	137	137
R^2	0.564	0.497	0.528
Adjusted R^2	0.489	0.440	0.474
Residual Std. Error	6,983.263 (df = 116)	7,311.076 (df = 122)	7,081.068 (df = 122)
F Statistic	7.502*** (df = 20; 116)	8.622*** (df = 14; 122)	9.767*** (df = 14; 122)
Note:			*p<0.1; **p<0.05; ***p<0.01

6.5 Overall Discussion

As discussed under the segments above, we find a discount for vessels with below average GHG ratings in the Handysize and Supramax segments, implying that vessels with relatively poorer energy efficiency obtain a lower TC rate. E- and F-rated vessels are penalized, suggesting a potential cut-off by some charterers on a GHG rating of D, meaning that vessels rated below are in lower demand, earning a lower rate. However, no publicly available evidence of such a cut-off in the charter market exists. Operators are willing to charter any vessel, even those performing poorly environmentally, if it makes sense financially (Husby, 2023). One can observe a gradual transition to applying cut-offs as charterers wish to use this GHG rating requirement as a marketing effect. Thus, they are willing to compromise flexibility to show customers they consider the environment when chartering vessels (Husby, 2023). Shipping segments with longer duration contracts have stricter requirements for certain vessel attributes, including energy efficiency. Cut-offs are, therefore, more commonly observed in, for example, the car carrier market (Husby, 2023).

Vessels of all sizes can carry much of the same cargo, are thus interchangeable, and will change between the segments for changes in the freight rate to increase their earnings potential (Stopford, 2009). Yet, Panamax and Capesize trade patterns differ somewhat from those of the Handysize and Supramax vessels. Handysize and Supramax vessels operate more frequently in Europe (Husby, 2023). In European waters vessels are required to burn lighter fuel than the standard VLSFO, which is also more expensive (Husby, 2023). This implies that fuel efficiency may have some extra value in terms of lowering fuel costs, which will have a more significant effect on the Handysize and Supramax segments as these vessels are more exposed to these regulations. On the other hand, these fuel-burning requirements only apply to a small share of European waters and are therefore not likely the main reason we observe this discount. However, it might contribute to the divide in results we find between the smaller and larger size segments. Moreover, the larger size segments typically have more standard and fixed cargo agreements (Husby, 2023), giving less room for a vessel parameter like energy efficiency to carry much weight in determining the contract rate.

Over the four size segments analyzed in the models, we find no premium for energy efficiency of statistical significance in the dry bulk TC market. Conversely, charterers in the freight market show no willingness to pay for energy efficiency despite reductions in voyage costs and environmental footprint. A possible explanation for these results may be principal-agent problems in the shipowner-charterer relationship under a TC contract, ultimately resulting in market failure. As discussed in the theory section, this will involve split incentives, information asymmetries between the two contract parties, and a lack of information. As we are focusing on the TC market, we have established that there are split incentives as the shipowner invests in energy efficiency measures for the vessel while the charterer pays for the fuel cost. These contract dynamics mean that the charterer benefits from any cost savings from the energy efficiency technology paid for by the shipowner, splitting their incentives.

In terms of information, charterers observe either the EVDI/EEDI score or RightShips' GHG rating of the vessel. However, these metrics only inform on the *technical* energy efficiency of a vessel and thus only provide an estimate of the energy efficiency potential, given the vessel's design, engine, and equipment (Transport & Environment, 2012). The actual fuel and cost savings accrued from the energy efficiency potential will depend heavily on the vessel's *operational* efficiency, which can differ vastly from the technical. While the technical energy efficiency is calculated based on assumptions about the fuel consumption, the operational energy efficiency is calculated using actual fuel consumption, which is influenced by weather conditions, transport work, and how the vessel is operated (Transport & Environment, 2012).

Furthermore, charterers generally receive little information from shipowners and have little confidence in the information they receive (Husby, 2023). In terms of energy efficiency, they typically get a short description, including a few points on the speed performance curve. Shipowners guarantee a certain fuel efficiency performance but always subject to a certain level of variance (typically +/- 5% for both speed and consumption) and very often subject to strict rules on what weather conditions need to be in place for the warranty to be valid (Husby, 2023). Unless the shipowner has an outstandingly well performing vessel in terms of energy efficiency, he will not disclose this information willingly. This is typical information dynamics in a charter market with relatively short contracts, such as the dry bulk market (Husby, 2023).

The degree of information asymmetry between the shipowner and charterer will depend on how well the owner knows his vessel(s), which will vary with how much control he has over the asset(s)

(Husby, 2023). However, most shipowners know their vessel(s) quite well. Moreover, the vessels may differ vastly in energy efficiency performance, which the shipowners are aware of. However, they are not incentivized to share this with potential charterers as they are willing to pay for the vessel either way. Any vessel information in favor of the shipowner he is not incentivized to disclose to the charterer (Husby, 2023).

We find no statistically significant effect of any of the interaction terms consisting of the GHG ratings and the boom dummy. Moreover, their coefficient signs in the different models for the segments are inconsistent. For the Handysize segment, we can observe that the B- and C-rated vessels obtain freight rate premiums under normal market conditions while they obtain discounts during boom conditions. Moreover, fuel-inefficient vessels, rated E and F, obtain freight rate premiums during boom conditions. These findings are similar to those of Ådland et al. (2017) and can potentially be explained by differing market characteristics under the boom and normal conditions. Boom market periods are characterized by a shorter supply of vessels, limiting the availability and pressuring rates upwards. Facing such circumstances, charterers primarily focus on profitability-related vessel features such as speed, capacity, and current location rather than energy efficiency (Husby, 2023).

In sum, it is reasonable to assume that charterers lack adequate information about a vessel's actual fuel and cost savings from energy efficiency, because of information asymmetry, to be willing to pay a premium. As we can identify both split incentives and lack of information/information asymmetries between the parties, it is not unlikely that the principal-agent relationship results in market failure. This is a possible explanation as to why we do not observe an energy efficiency premium in the size segments and slow investments in energy efficiency by shipowners.

The absence of satisfactory measurement and verification methods for operating the energy efficiency equipment and technology on a vessel (Longarela-Ares et al., 2020) contributes to an incomplete information problem for charterers. Data collection and transparency are vital to equalizing the information asymmetry between the shipowner and the charterer. RightShip is one of the few organizations that collect and share data on energy efficiency (Ådland et al., 2017). Implementing a regulation requiring data collection on operational factors related to vessel energy efficiency technology would allow charterers to make more informed decisions (Ådland et al., 2017). The data collected should remove the variance and uncertainty related to, for example, weather conditions, making vessel comparisons easier. As part of the IMO 2023 regulation, IMO implemented the EEXI metric for existing ships and the CII with a related grading scale A (good)-E (poor) that will require improvement from vessels in the lower range (IMO, 2023). In addition to the design efficiency of the vessel, the CII is calculated based on operational factors such as fuel type, fuel consumption, speed, cargo transported, and weather conditions (DNV, 2023), providing an operational CO_2 efficiency indicator to charterers.

The European Union (EU) has a Monitoring, Reporting, and Verification (MRV) regulation requiring vessels above 5,000 gross tonnages (GT) to report on bunkering and voyage data for EU-related voyages to collect and analyze ship emission data (DNV, 2023). An amendment to the current policy affecting the definition of the regulated “company” has been suggested, which will transfer the reporting responsibility to the party paying the fuel cost (Sørås, 2021). In the case of a TC contract this is the charterer. Currently, the shipowner is formally responsible for emissions, while in reality, the charterer is responsible for affecting the level of emission through operational decisions (Husby, 2023). If the amendment is approved and taken into effect, it will likely affect charterers’ willingness to pay for energy efficiency, as they would be formally responsible and bear the cost. However, the amendment is being fought by many charterers (Sørås, 2021).

Our analysis shows no freight rate premium for energy-efficient ships in the dry bulk TC market. Thus, shipowners do not recoup their investment in energy efficiency measures, resulting in fewer investments due to a lack of financial incentives. However, other factors besides recouping the investment may affect the investment decision. One potential factor is the risk and uncertainty related to large, long-term investments in decarbonization technology. Ship technology is developing rapidly, and with constantly stricter regulations and requirements, shipowners risk investing in technology that becomes outdated long before the lifetime of the technology. As the world seeks to reduce carbon emissions, phasing out fossil fuels is critical, which requires innovation and improvements to the current fleet. The industry consensus is that technology and alternative fuels that has any real potential to decarbonize the shipping industry has yet to be proven at scale (Lin, 2020), which inevitably halts investments.

The risk involved when investing in energy efficiency technology also varies with the length of the charter contracts and customer characteristics. In the car carrier segment, for example, contracts are typically of long duration, and a shipowner usually has fewer, more loyal customers (Husby, 2023). Longer contracts can help equalize asymmetric information when charterers observe the vessel in operation over several years, providing a data foundation not much different from that of the shipowner. The dry bulk TC market is characterized by contracts lasting a maximum of a few years and a large group of smaller customers (Husby, 2023). This means that it is much harder to find customers that are willing to pay for better than average vessels, for investments in fuel-saving technology, or that is willing to pay for a sufficiently long period (Husby, 2023). This makes the investment case for shipowners highly uncertain.

Lastly, this analysis only investigates whether an energy efficiency premium can be identified in the TC market. Energy efficiency may pay in other markets, such as the VC market, the newbuild market, or the secondhand market. Owning an asset involves a different risk profile than operating it, affecting what vessel characteristics are the main priority and the willingness to pay for them (Husby, 2023).

7 Limitations and Further Research

7.1 Limitations

The limitations of this analysis are divided into three: a small, unrepresentative data sample, biased data sources, and the frequent use of assumptions.

When conducting a multiple linear regression, the sample size should include at least 300 subjects to make accurate inferences about the population (Bujang et al., 2017). Data on GHG emissions from RightShip is limited to grades given between January 2020 and November 2022. Matched with the remaining data and cleaned for analysis; a total of 779 observations makes up the entire data sample. As we conduct separate analyses for each size segment, each one alone should preferably have at least 300 observations. Out of the four segments, only Panamax upholds this requirement. The Handysize segment has 190 observations, the Capesize segment has 73 observations, and the Supramax segment has 137 observations. The most extensive regression model on all segments includes around 20 explanatory variables, many compared to the size of the sample. Too small sample sizes reduce the likelihood that a statistically significant effect in the analysis reflects an actual effect, creating inflated effects (Button et al., 2013). Thus, one must be cautious when interpreting the results.

The small data sample also fails to cover a complete freight market cycle, which typically lasts three to twelve years (Stopford, 2009). The observations in this analysis are between 2020 and 2022, limiting the model's ability to investigate changes over time and the effects of these cycles in a pleasing way. Agnolucci et al. (2014) included four years of data in their analysis and encountered the same problem. Moreover, the period analyzed in this thesis is characterized by a boom and turbulent markets because of the covid19 pandemic. As discussed in the "Presentation av variables" section, the market's willingness to pay for energy efficiency can depend on the underlying market conditions, which Ådland et al. (2017) found in their study, making a limited data sample increasingly disadvantageous.

To make reliable inferences about the population, a sample chosen at random is essential (Agresti et al., 2018). As Western Bulk fixtures are overrepresented in the Handysize (189/190) and Panamax (82/498) samples, and make out the full Supramax sample, it is a case of sampling bias, which occur when the randomness in the sampling process is compromised (Agresti et al., 2018). As this study intends to investigate the charter market's willingness to pay for energy efficiency, the target population is all charterers in the four size segments within the dry bulk TC market. Thus, our sample should ideally include a random selection of charterers, which is only the case for fixtures from Clarksons SIN. The regression results from the Handysize and Supramax segments should be interpreted as Western Bulk's willingness to pay for energy efficiency and other parameters, as the results are not representative of the market. The regression results for the Panamax segment do not specifically represent Western Bulk's willingness to pay for energy efficiency. However, the significant bias in the data may still lead to a faulty conclusion when considering the market. All Capesize fixtures come from Clarksons SIN; therefore, this sample is random and representative of the market, looking only at this criterion.

Finally, a set of assumptions had to be made to create specific variables used in the analysis and add more observations to the data sample. These assumptions have been outlined in the "Presentation of Variables" and "Data Cleaning Process" sections of this thesis and ultimately affect the analysis's correctness and robustness. For example, the assumptions made for the dummy for black-/grey-listed flags do not align with what we observe. The list is assumed constant but is dynamic over time. Further, we have assumed GHG ratings for the manually created observations, giving a second example. These assumptions are not unlikely but cannot be verified, thus weakening the analysis.

7.2 Further Research

Based on the limitations of this analysis, further research should expand the time horizon of the data in this analysis. A satisfactory time horizon for investigating the intended aspects would be similar to that included in the study by Ådland et al. (2017). Their study includes 15 years of data, allowing for analysis that includes complete market cycles and changes over time.

Moreover, further research could investigate other groups of the RightShip GHG emissions ratings, which might reveal other patterns of willingness to pay for energy efficiency than we have uncovered in this analysis. However, this will require a larger data sample with a rating distribution more representative of RightShip's system.

Lastly, further research should investigate whether the EU MRV and IMO 2023 policies affect charterers' willingness to pay in the following years. Given that the EU MRV amendment gets approved, it will make charterers responsible for reporting on emissions in a TC contract (Sørås, 2021). Moreover, when the IMO 2023, which imposes reporting requirements for operational carbon intensity indicators (IMO, 2023), has been in effect for a few years from 2024, it will be interesting to do a similar analysis as this thesis. As the policies combined will increase information and transparency, and move some of the cost of emissions to charterers, they are thus likely to increase the weight of fuel efficiency in the pool of components that determines TC rate, thereby rewarding shipowners that have invested in fuel efficiency.

8 Conclusion

This thesis has investigated whether charterers are willing to pay for energy efficiency in the dry bulk TC market. In the Handysize and Supramax segments, we identify a statistically significant discount for vessels with below average energy efficiency performance compared to their peer group. This result suggests that charterers in these size segments have less willingness to pay for poor energy efficiency performance, implying minimum requirements. If this is the case, it is a step towards more environmentally concerned decision making by charterers. Moreover, as poor performing vessels get penalized, it might increase the pressure of adapting such technology amongst shipowners. Specific segment market dynamics may explain why we do not find similar results for the Panamax and Capesize segments. However, a small data sample, mainly consisting of Western Bulk contracts, makes inferences about the whole market biased and potentially unreliable.

We have discussed how split incentives and information asymmetries can be identified between the two parties and how these conditions lay the foundation for charterers to act opportunistically. The lack of any statistically significant premium for energy efficiency in any segment can be due to market failure caused by principal-agent problems in the shipowner-charterer relationship. Charterers lack accurate information about the performance of the energy efficiency technology to give this vessel attribute any real weight in determining the freight rate. The consequence of charterers not being willing to pay for energy efficiency is that shipowners do not recoup their investment in related technology, incentivizing them not to undertake such investments. This outcome is discouraging, looking at shipping's share of global emissions.

It becomes evident that policy and regulations related to emissions from shipping are key to adjusting for the market failure we observe in the industry concerning energy efficiency. Beneficial policies will help equalize the information asymmetries between the shipowner and charterer by introducing data collection and transparency requirements. Moreover, they should shift the reporting responsibility to the party responsible for fuel and operational decisions, uniting the current split incentives. The IMO 2023 regulation and the EU MRV amendment are candidates to achieve this and help the shipping industry contribute to the global emissions reduction objectives. Given that the EU MRV amendment is approved, further research should include quantifying these policies' effect on a potential energy efficiency premium in a few years.

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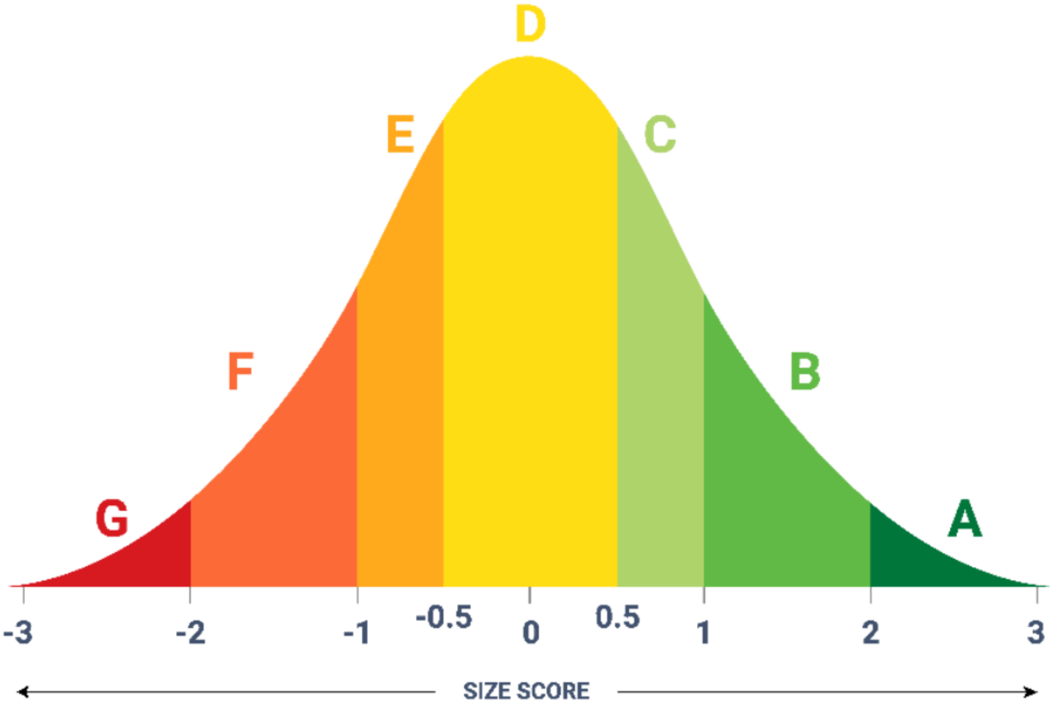
Appendix

A1 RightShip's GHG Rating Band

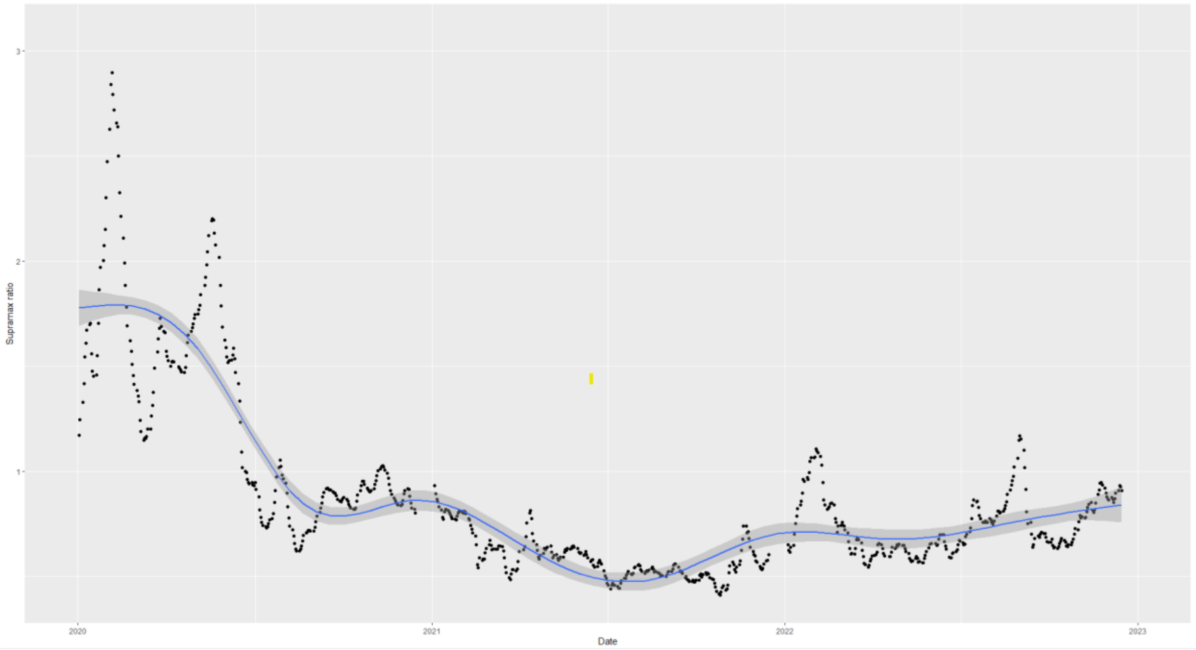
Source: RightShip, 2023



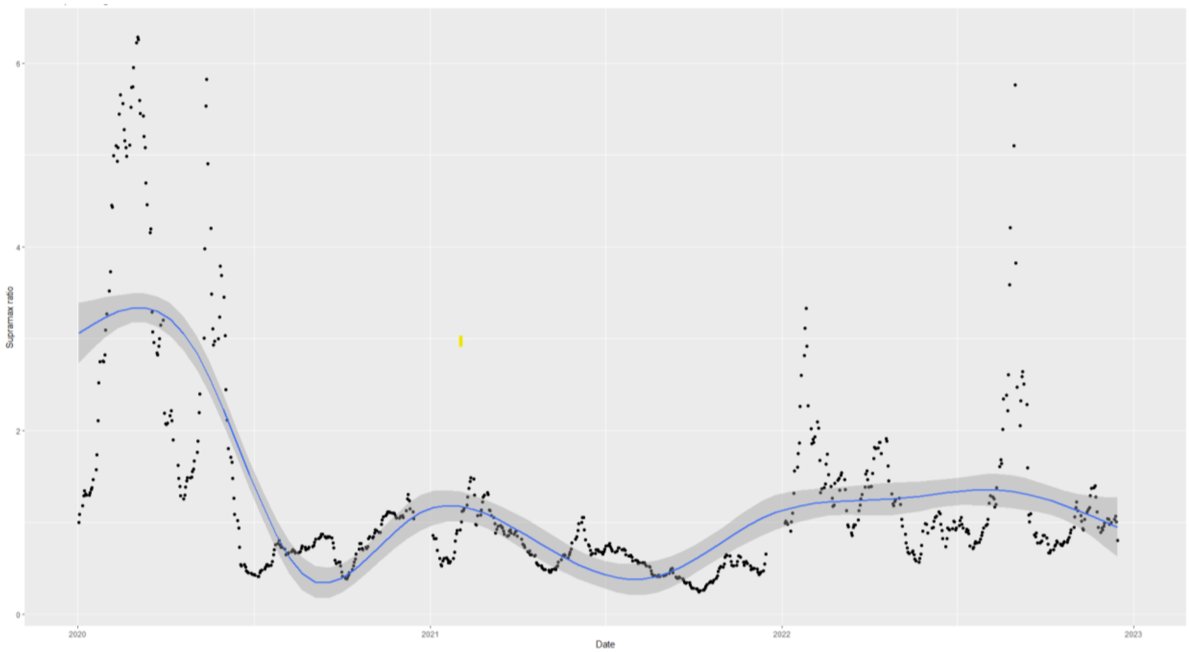
A2 Contango/Backwardation Curve

Source: Constructed based on data provided by Western Bulk.

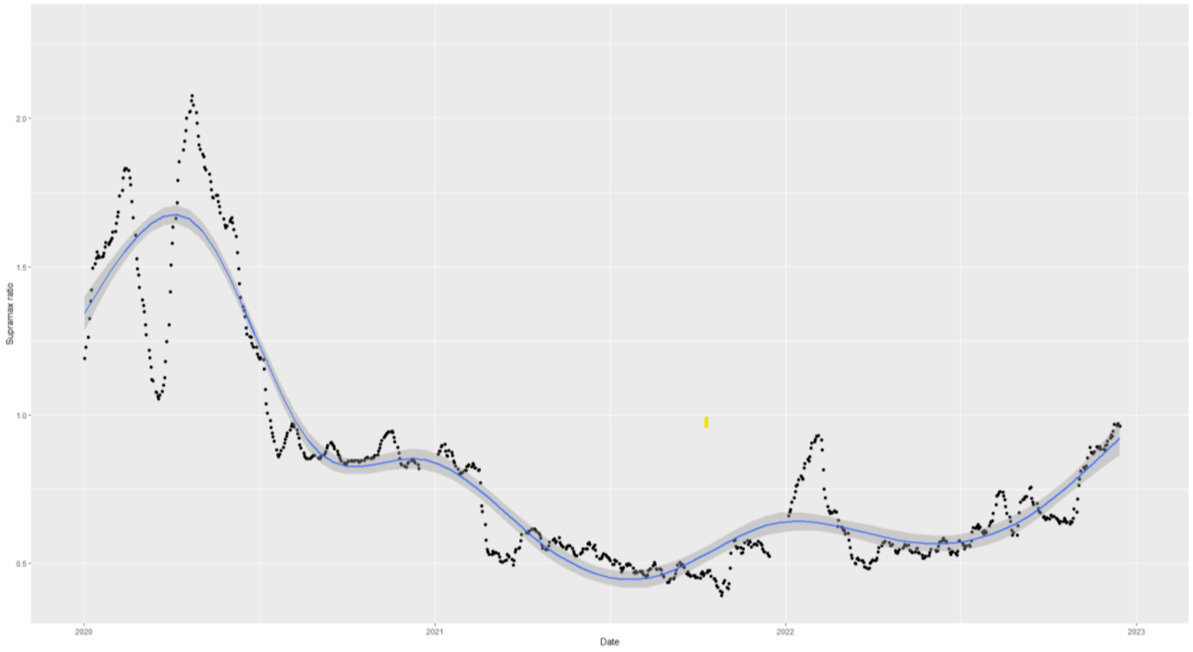
A2.1 Panamax



A2.2 Capesize

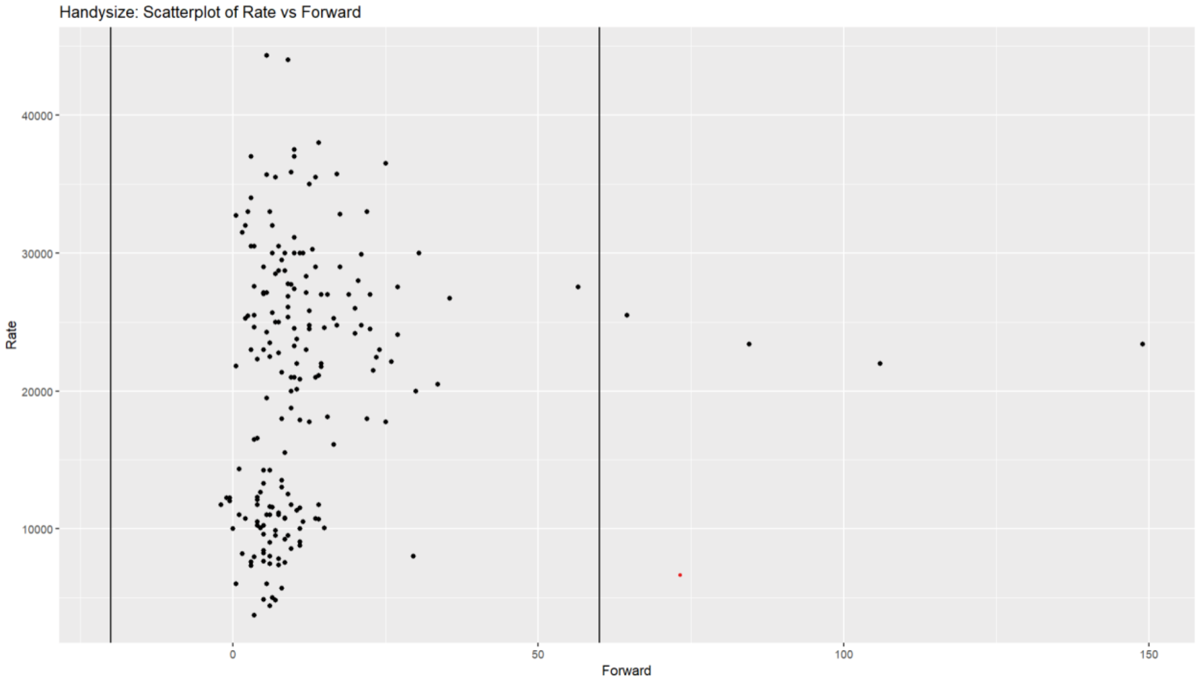


A2.3 Supramax

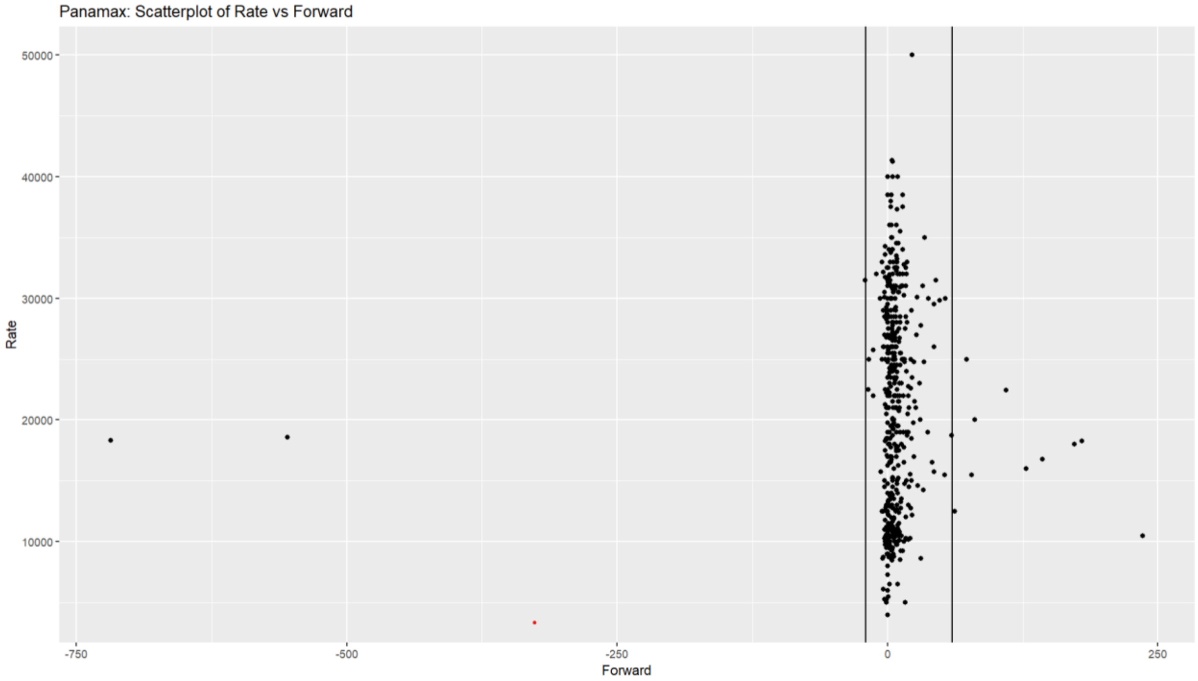


A3 Scatterplots of Rate vs Forward

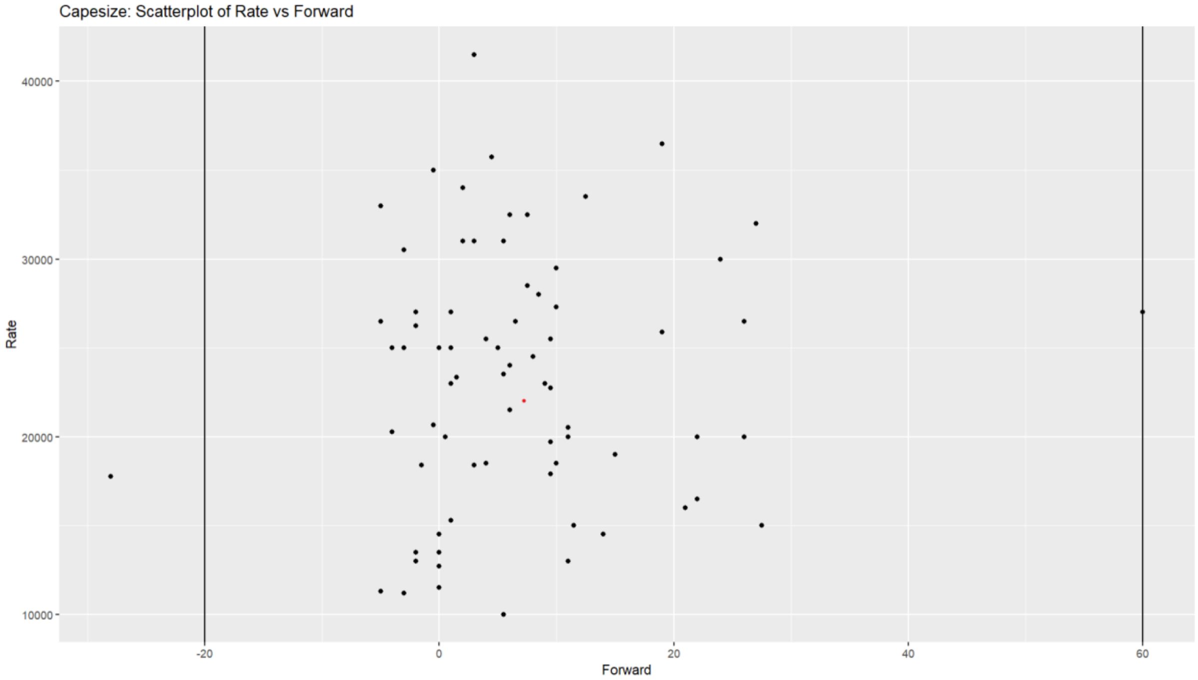
A3.1 Handysize



A3.2 Panamax

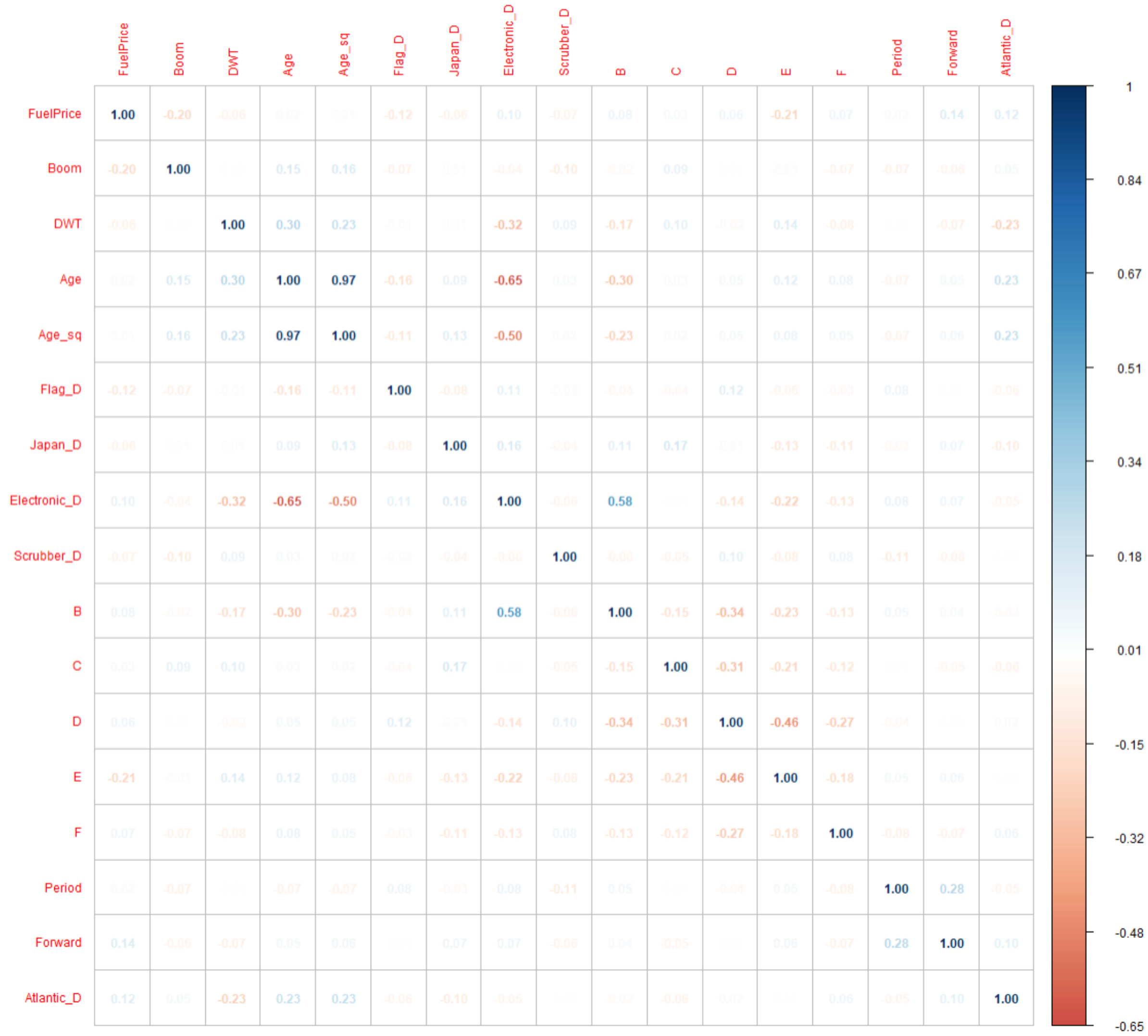


A3.3 Capesize



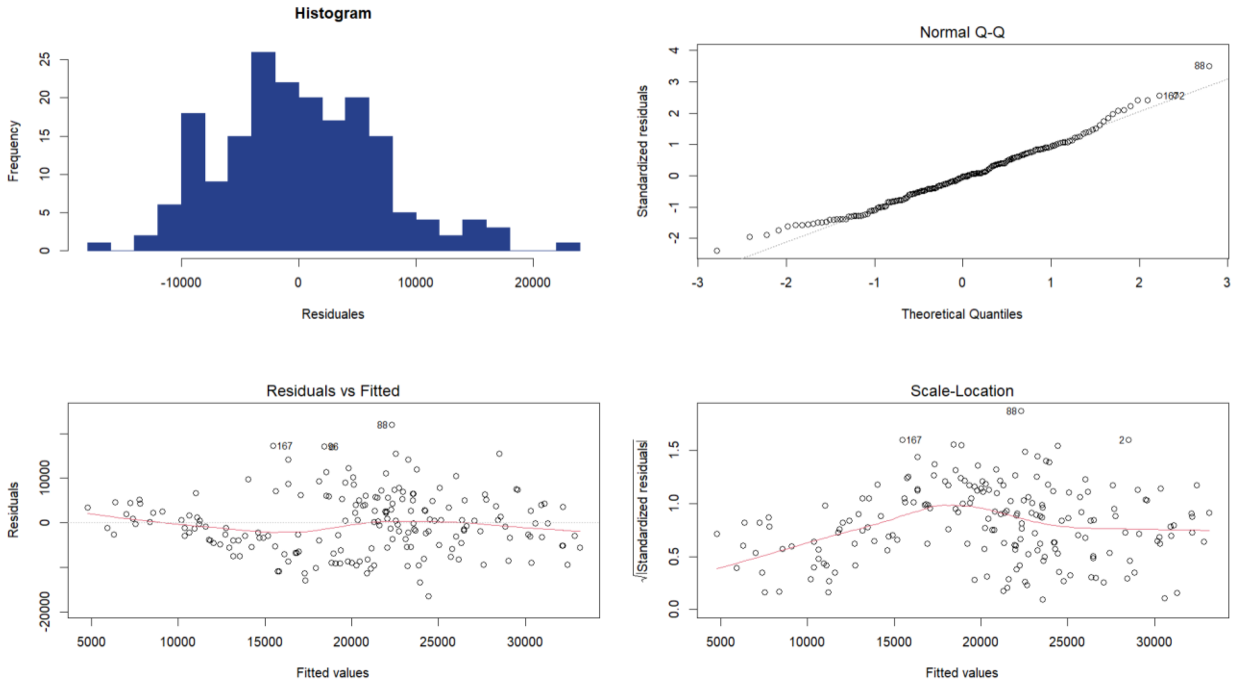
A4 Regression Diagnostics for Model with all GHG Ratings in the Handysize Segment

A4.1 Multicollinearity Matrix

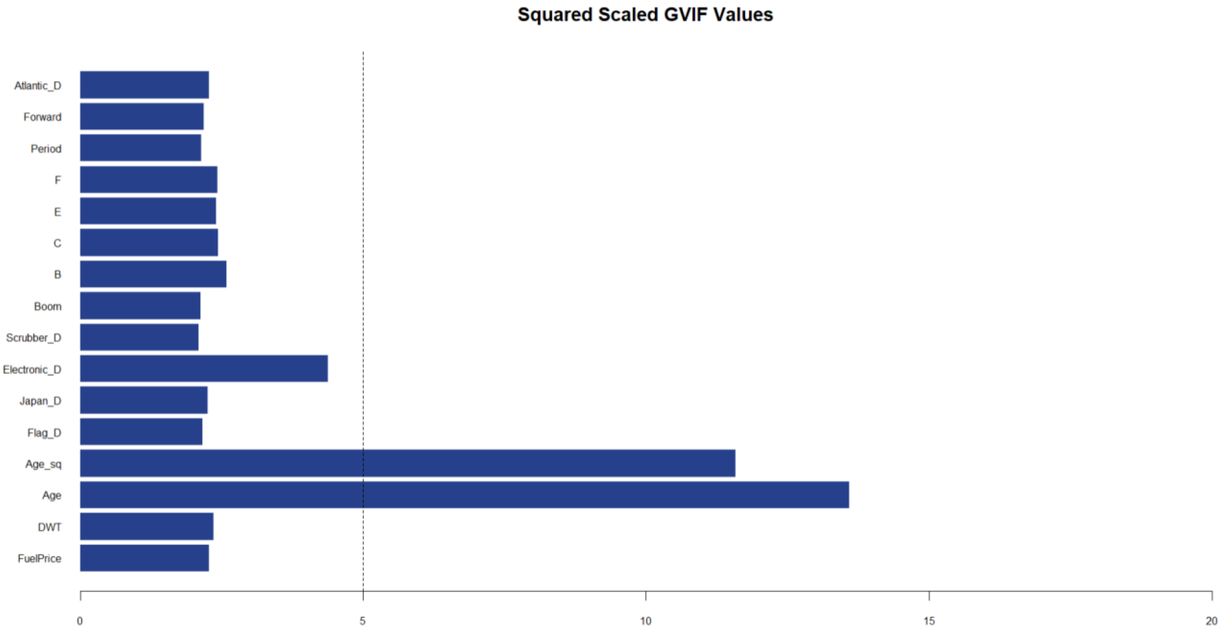


	FuelPrice	Boom	DWT	Age	Age_sq	Flag_D	Japan_D	Electronic_D	Scrubber_D	B	C	D	E	F	Period	Forward	Atlantic_D
FuelPrice	1.00	-0.20	-0.06	0.02	0.01	-0.12	-0.06	0.10	-0.07	0.08	0.03	0.06	-0.21	0.07	0.02	0.14	0.12
Boom	-0.20	1.00	0.00	0.15	0.16	-0.07	0.01	-0.04	-0.10	-0.02	0.09	0.01	-0.01	-0.07	-0.07	-0.06	0.05
DWT	-0.06	0.00	1.00	0.30	0.23	-0.01	0.01	-0.32	0.09	-0.17	0.10	-0.02	0.14	-0.08	0.01	-0.07	-0.23
Age	0.02	0.15	0.30	1.00	0.97	-0.16	0.09	-0.65	0.03	-0.30	0.03	0.05	0.12	0.08	-0.07	0.05	0.23
Age_sq	0.01	0.16	0.23	0.97	1.00	-0.11	0.13	-0.50	0.02	-0.23	0.02	0.05	0.08	0.05	-0.07	0.06	0.23
Flag_D	-0.12	-0.07	-0.01	-0.16	-0.11	1.00	-0.08	0.11	-0.02	-0.04	-0.04	0.12	-0.06	-0.03	0.08	0.01	-0.06
Japan_D	-0.06	0.01	0.01	0.09	0.13	-0.08	1.00	0.16	-0.04	0.11	0.17	-0.01	-0.13	-0.11	-0.03	0.07	-0.10
Electronic_D	0.10	-0.04	-0.32	-0.65	-0.50	0.11	0.16	1.00	-0.06	0.58	-0.01	-0.14	-0.22	-0.13	0.08	0.07	-0.05
Scrubber_D	-0.07	-0.10	0.09	0.03	0.02	-0.02	-0.04	-0.06	1.00	-0.06	-0.05	0.10	-0.08	0.08	-0.11	-0.06	0.00
B	0.08	-0.02	-0.17	-0.30	-0.23	-0.04	0.11	0.58	-0.06	1.00	-0.15	-0.34	-0.23	-0.13	0.05	0.04	-0.02
C	0.03	0.09	0.10	0.03	0.02	-0.04	0.17	-0.01	-0.05	-0.15	1.00	-0.31	-0.21	-0.12	0.01	-0.05	-0.06
D	0.06	0.01	-0.02	0.05	0.05	0.12	-0.01	-0.14	0.10	-0.34	-0.31	1.00	-0.46	-0.27	-0.04	0.00	0.02
E	-0.21	-0.01	0.14	0.12	0.08	-0.06	-0.13	-0.22	-0.08	-0.23	-0.21	-0.46	1.00	-0.18	0.05	0.06	0.01
F	0.07	-0.07	-0.08	0.08	0.05	-0.03	-0.11	-0.13	0.08	-0.13	-0.12	-0.27	-0.18	1.00	-0.08	-0.07	0.06
Period	0.02	-0.07	0.01	-0.07	-0.07	0.08	-0.03	0.08	-0.11	0.05	0.01	-0.04	0.05	-0.08	1.00	0.28	-0.05
Forward	0.14	-0.06	-0.07	0.05	0.06	0.01	0.07	0.07	-0.06	0.04	-0.05	0.00	0.06	-0.07	0.28	1.00	0.10
Atlantic_D	0.12	0.05	-0.23	0.23	0.23	-0.06	-0.10	-0.05	0.00	-0.02	-0.06	0.02	0.01	0.06	-0.05	0.10	1.00

A4.2 Residual Diagnostics

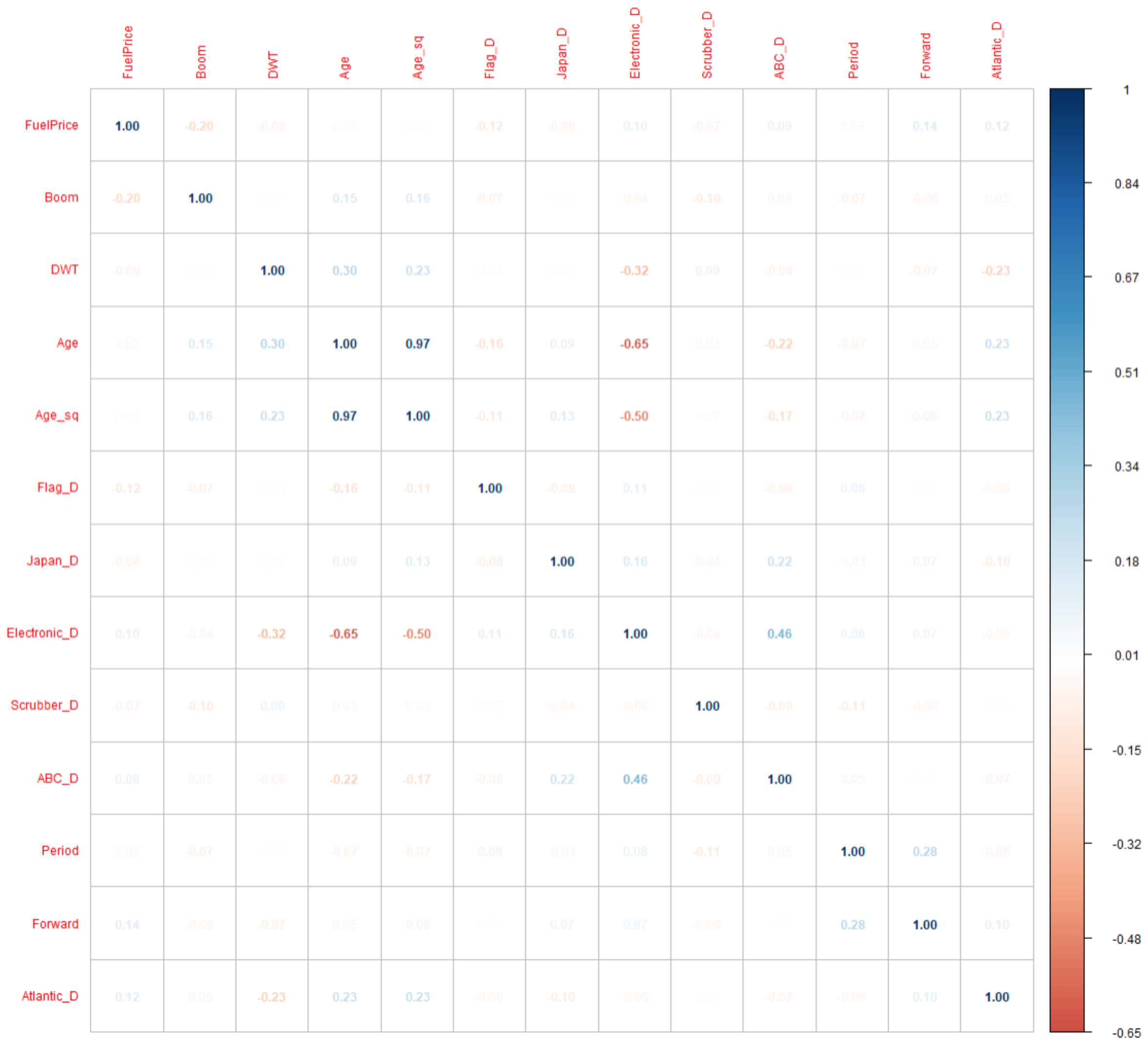


A4.3 Squared Scaled GVIF Values



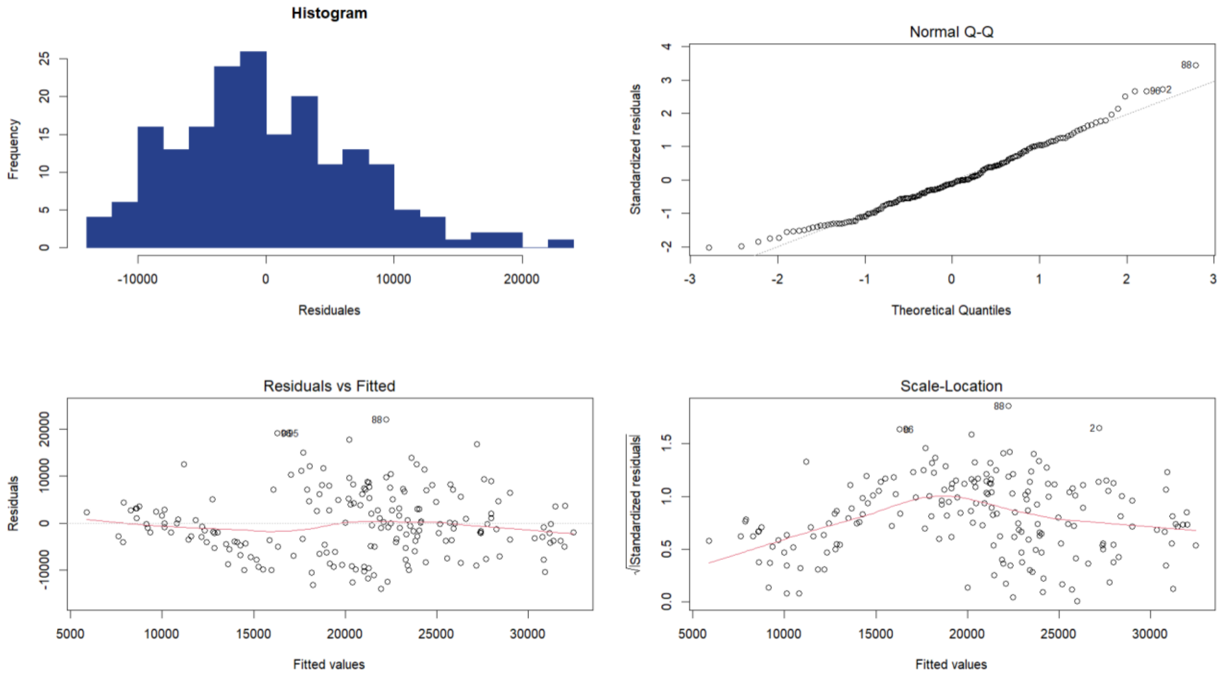
A5 Regression Diagnostics for Model with ABC_D in the Handysize Segment

A5.1 Multicollinearity Matrix

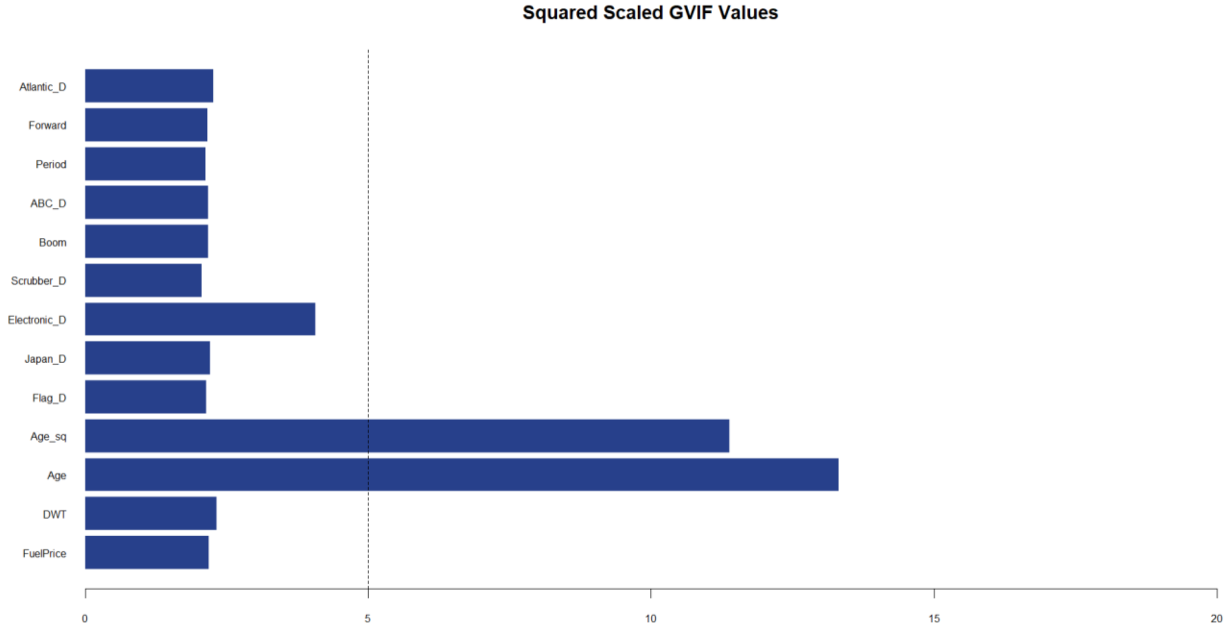


	FuelPrice	Boom	DWT	Age	Age_sq	Flag_D	Japan_D	Electronic_D	Scrubber_D	ABC_D	Period	Forward	Atlantic_D
FuelPrice	1.00	-0.20	-0.06	0.02	0.01	-0.12	-0.06	0.10	-0.07	0.09	0.02	0.14	0.12
Boom	-0.20	1.00	0.00	0.15	0.16	-0.07	0.01	-0.04	-0.10	0.05	-0.07	-0.06	0.05
DWT	-0.06	0.00	1.00	0.30	0.23	-0.01	0.01	-0.32	0.09	-0.06	-0.01	-0.07	-0.23
Age	0.02	0.15	0.30	1.00	0.97	-0.16	0.09	-0.65	0.03	-0.22	-0.07	0.05	0.23
Age_sq	0.01	0.16	0.23	0.97	1.00	-0.11	0.13	-0.50	0.02	-0.17	-0.07	0.06	0.23
Flag_D	-0.12	-0.07	-0.01	-0.16	-0.11	1.00	-0.08	0.11	-0.02	-0.06	0.08	0.01	-0.06
Japan_D	-0.06	0.01	0.01	0.09	0.13	-0.08	1.00	0.16	-0.04	0.22	-0.03	0.07	-0.10
Electronic_D	0.10	-0.04	-0.32	-0.65	-0.50	0.11	0.16	1.00	-0.06	0.46	0.08	0.07	-0.05
Scrubber_D	-0.07	-0.10	0.09	0.03	0.02	-0.02	-0.04	-0.06	1.00	-0.09	-0.11	-0.06	0.00
ABC_D	0.09	0.05	-0.06	-0.22	-0.17	-0.06	0.22	0.46	-0.09	1.00	0.05	0.01	-0.07
Period	0.02	-0.07	-0.01	-0.07	-0.07	0.08	-0.03	0.08	-0.11	0.05	1.00	0.28	-0.05
Forward	0.14	-0.06	-0.07	0.05	0.06	0.01	0.07	0.07	-0.06	0.01	0.28	1.00	0.10
Atlantic_D	0.12	0.05	-0.23	0.23	0.23	-0.06	-0.10	-0.05	0.00	-0.07	-0.05	0.10	1.00

A5.2 Residual Diagnostics

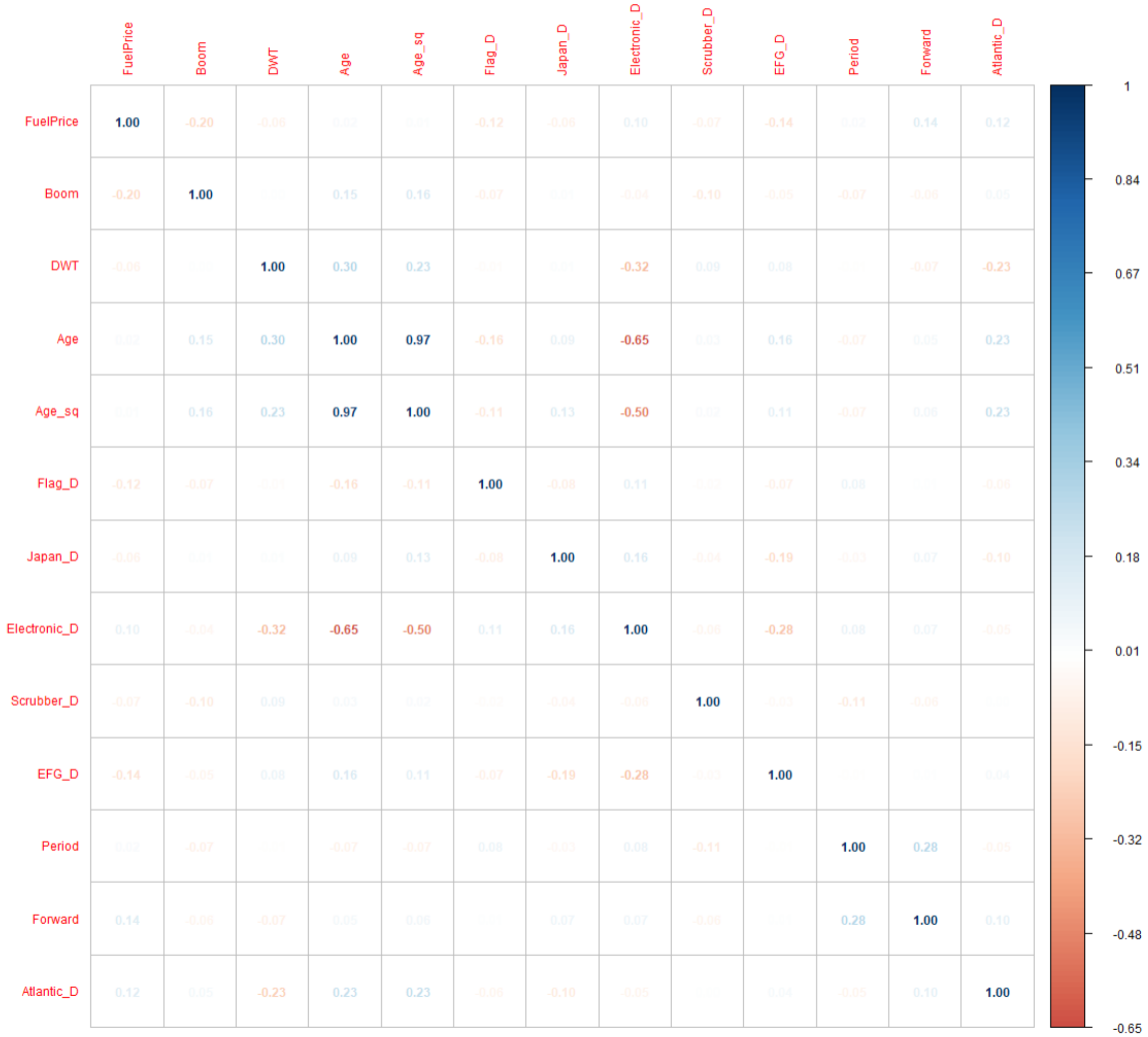


A5.3 Squared Scaled GVIF Values



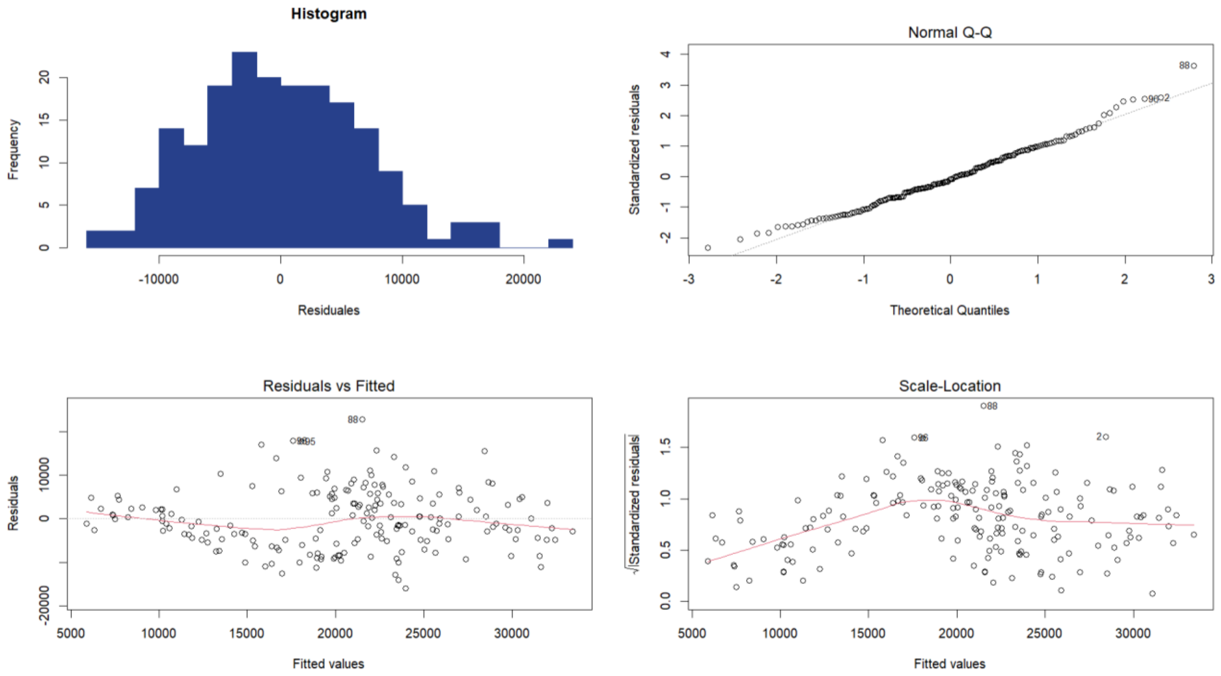
A6 Regression Diagnostics for Model with EFG_D in the Handysize Segment

A6.1 Multicollinearity Matrix

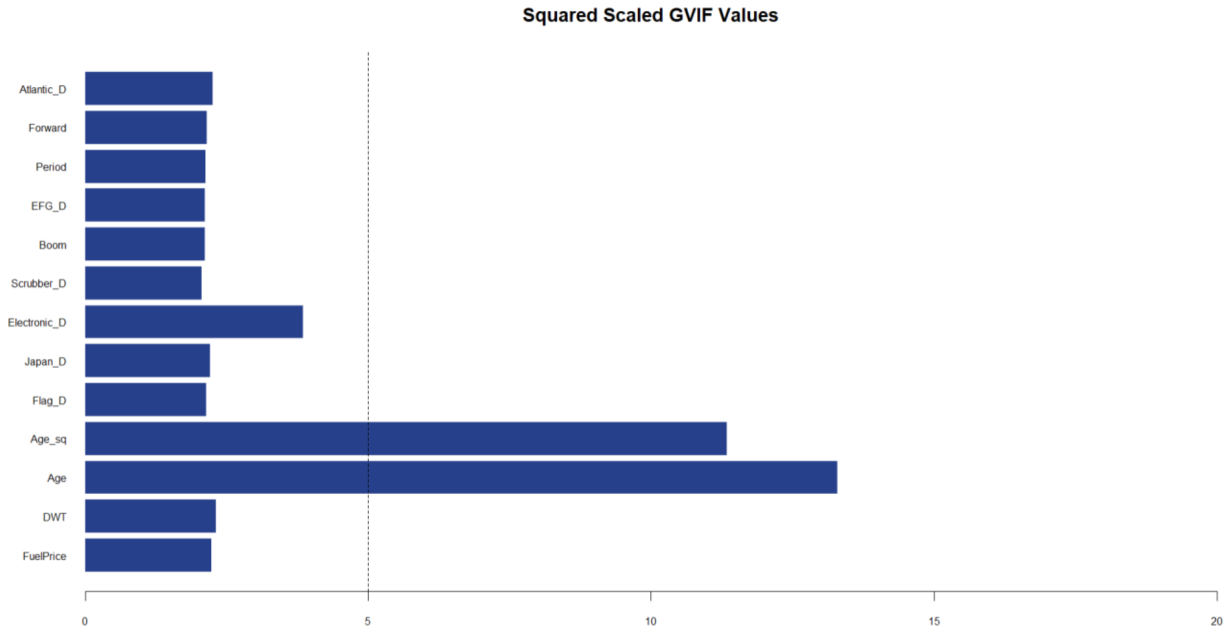


	FuelPrice	Boom	DWT	Age	Age_sq	Flag_D	Japan_D	Electronic_D	Scrubber_D	EFG_D	Period	Forward	Atlantic_D
FuelPrice	1.00	-0.20	-0.06	0.02	0.01	-0.12	-0.06	0.10	-0.07	-0.14	0.02	0.14	0.12
Boom	-0.20	1.00	0.00	0.15	0.16	-0.07	0.01	-0.04	-0.10	-0.05	-0.07	-0.06	0.05
DWT	-0.06	0.00	1.00	0.30	0.23	-0.01	0.01	-0.32	0.09	0.08	-0.01	-0.07	-0.23
Age	0.02	0.15	0.30	1.00	0.97	-0.16	0.09	-0.65	0.03	0.16	-0.07	0.05	0.23
Age_sq	0.01	0.16	0.23	0.97	1.00	-0.11	0.13	-0.50	0.02	0.11	-0.07	0.06	0.23
Flag_D	-0.12	-0.07	-0.01	-0.16	-0.11	1.00	-0.08	0.11	-0.02	-0.07	0.08	0.01	-0.06
Japan_D	-0.06	0.01	0.01	0.09	0.13	-0.08	1.00	0.16	-0.04	-0.19	-0.03	0.07	-0.10
Electronic_D	0.10	-0.04	-0.32	-0.65	-0.50	0.11	0.16	1.00	-0.06	-0.28	0.08	0.07	-0.05
Scrubber_D	-0.07	-0.10	0.09	0.03	0.02	-0.02	-0.04	-0.06	1.00	-0.03	-0.11	-0.06	0.00
EFG_D	-0.14	-0.05	0.08	0.16	0.11	-0.07	-0.19	-0.28	-0.03	1.00	-0.01	0.01	0.04
Period	0.02	-0.07	-0.01	-0.07	-0.07	0.08	-0.03	0.08	-0.11	-0.01	1.00	0.28	-0.05
Forward	0.14	-0.06	-0.07	0.05	0.06	0.01	0.07	0.07	-0.06	0.01	0.28	1.00	0.10
Atlantic_D	0.12	0.05	-0.23	0.23	0.23	-0.06	-0.10	-0.05	0.00	0.04	-0.05	0.10	1.00

A6.2 Residual Diagnostics

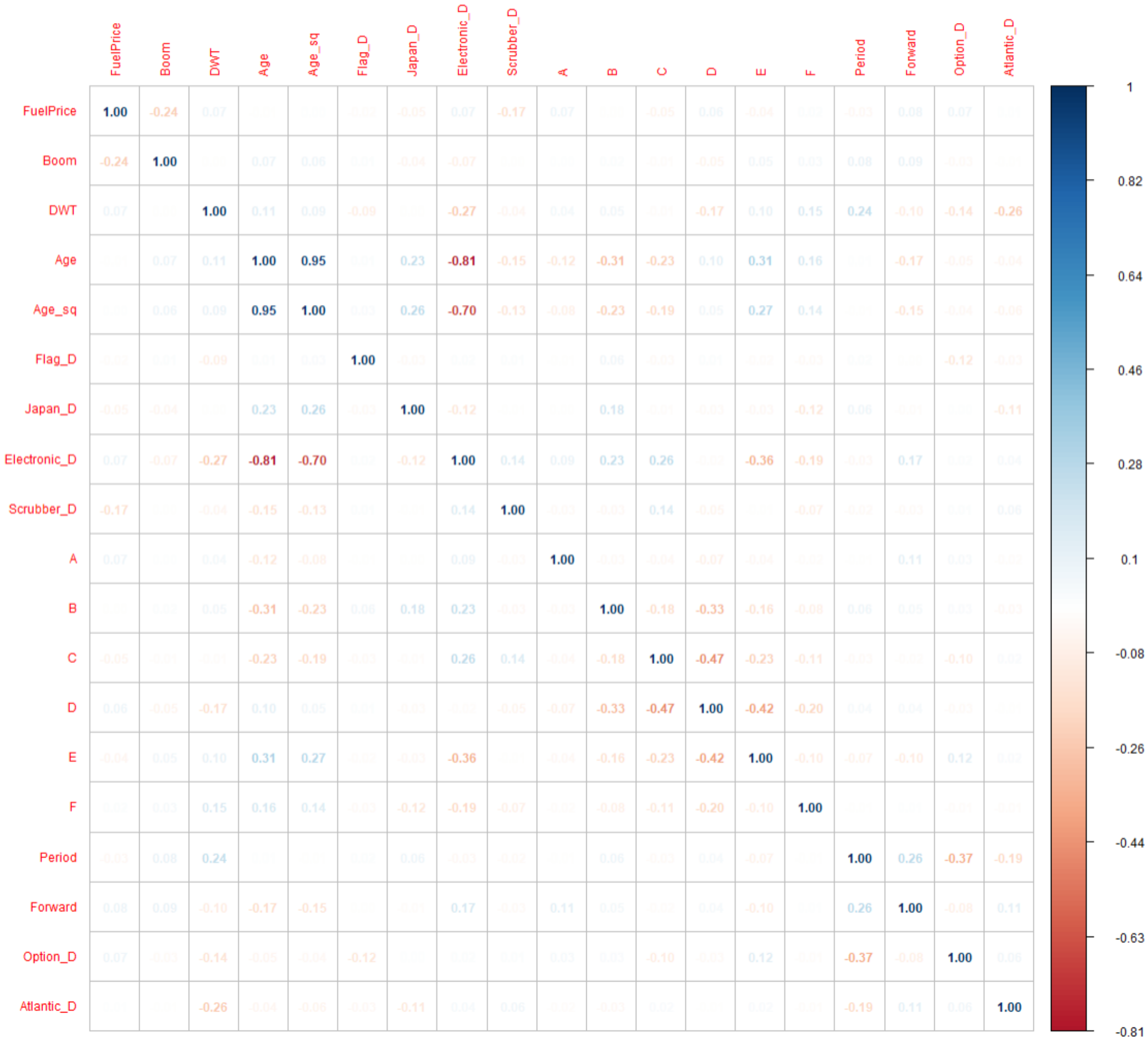


A6.3 Squared Scaled GVIF Values



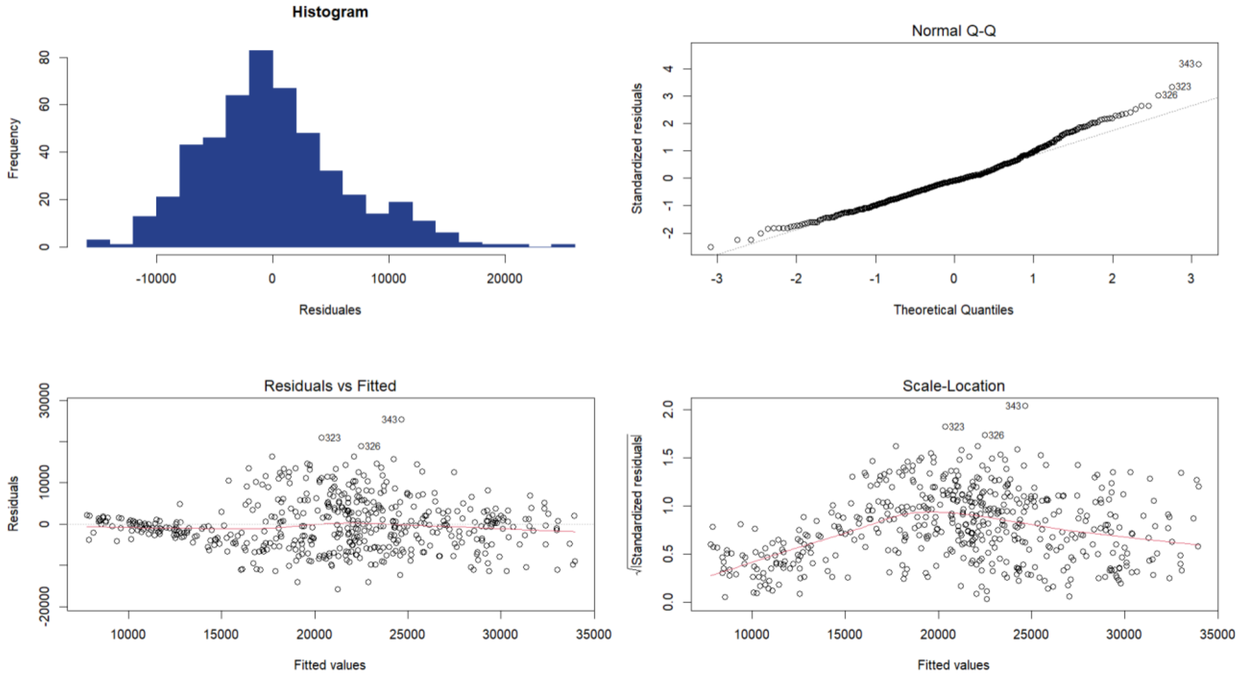
A7 Regression Diagnostics for Model with all GHG Ratings in the Panamax Segment

A7.1 Multicollinearity Matrix

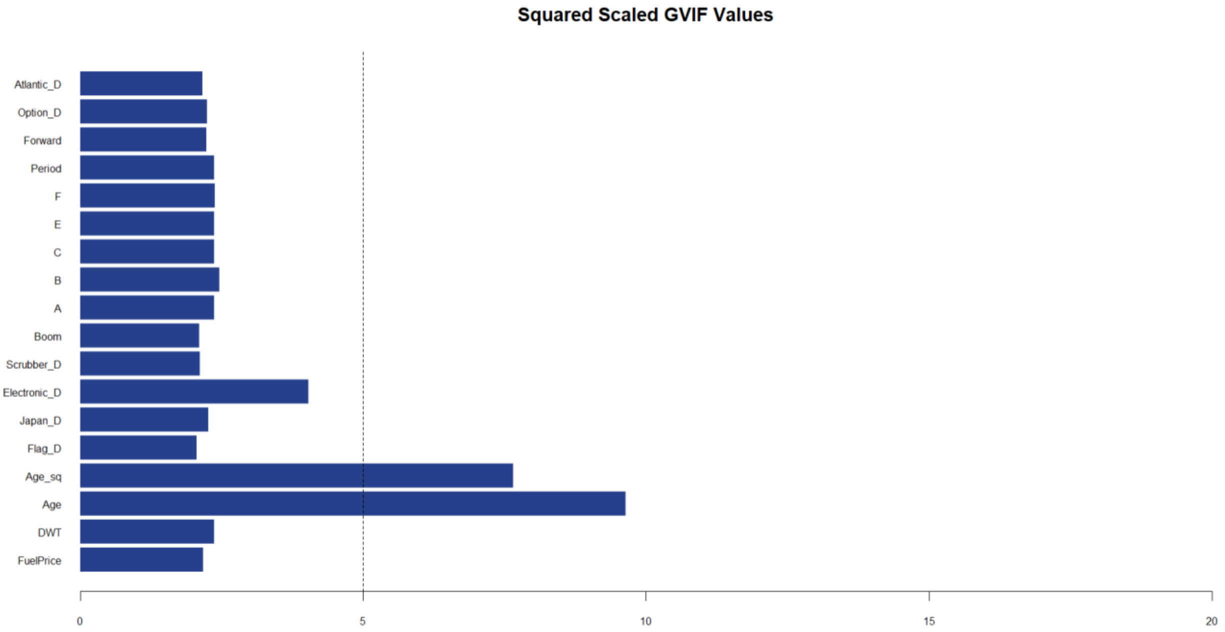


	FuelPrice	Boom	DWT	Age	Age_sq	Flag_D	Japan_D	Electronic_D	Scrubber_D	A	B	C	D	E	F	Period	Forward	Option_D	Atlantic_D
FuelPrice	1.00	-0.24	0.07	-0.01	0.00	-0.02	-0.05	0.07	-0.17	0.07	0.02	-0.05	0.06	-0.04	0.02	-0.03	0.08	0.07	0.01
Boom	-0.24	1.00	0.00	0.07	0.06	0.01	-0.04	-0.07	0.00	0.00	0.02	-0.01	-0.05	0.05	0.03	0.08	0.09	-0.03	-0.01
DWT	0.07	0.00	1.00	0.11	0.09	-0.09	0.00	-0.27	-0.04	0.04	0.05	-0.01	-0.17	0.10	0.15	0.24	-0.10	-0.14	-0.26
Age	-0.01	0.07	0.11	1.00	0.95	0.01	0.23	-0.81	-0.15	-0.12	-0.31	-0.23	0.10	0.31	0.16	0.01	-0.17	-0.05	-0.04
Age_sq	0.00	0.06	0.09	0.95	1.00	0.03	0.26	-0.70	-0.13	-0.08	-0.23	-0.19	0.05	0.27	0.14	-0.01	-0.15	-0.04	-0.06
Flag_D	-0.02	0.01	-0.09	0.01	0.03	1.00	-0.03	0.02	0.01	-0.01	0.06	-0.03	0.01	-0.02	-0.03	0.02	0.00	-0.12	-0.03
Japan_D	-0.05	-0.04	0.00	0.23	0.26	-0.03	1.00	-0.12	-0.01	0.00	0.18	-0.01	-0.03	-0.03	-0.12	0.06	-0.01	0.00	-0.11
Electronic_D	0.07	-0.07	-0.27	-0.81	-0.70	0.02	-0.12	1.00	0.14	0.09	0.23	0.26	-0.02	-0.36	-0.19	-0.03	0.17	0.02	0.04
Scrubber_D	-0.17	0.00	-0.04	-0.15	-0.13	0.01	-0.01	0.14	1.00	-0.03	-0.03	0.14	-0.05	-0.01	-0.07	-0.02	-0.03	0.01	0.06
A	0.07	0.00	0.04	-0.12	-0.08	-0.01	0.00	0.09	-0.03	1.00	-0.03	-0.04	-0.07	-0.04	-0.02	-0.01	0.11	0.03	-0.02
B	0.02	0.02	0.05	-0.31	-0.23	0.06	0.18	0.23	-0.03	-0.03	1.00	-0.18	-0.33	-0.16	-0.08	0.06	0.05	0.03	-0.03
C	-0.05	-0.01	-0.01	-0.23	-0.19	-0.03	-0.01	0.26	0.14	-0.04	-0.18	1.00	-0.47	-0.23	-0.11	-0.03	-0.02	-0.10	0.02
D	0.06	-0.05	-0.17	0.10	0.05	0.01	-0.03	-0.02	-0.05	-0.07	-0.33	-0.47	1.00	-0.42	-0.20	0.04	0.04	-0.03	-0.01
E	-0.04	0.05	0.10	0.31	0.27	-0.02	-0.03	-0.36	-0.01	-0.04	-0.16	-0.23	-0.42	1.00	-0.10	-0.07	-0.10	0.12	0.02
F	0.02	0.03	0.15	0.16	0.14	-0.03	-0.12	-0.19	-0.07	-0.02	-0.08	-0.11	-0.20	-0.10	1.00	-0.01	0.01	-0.01	-0.01
Period	-0.03	0.08	0.24	0.01	-0.01	0.02	0.06	-0.03	-0.02	-0.01	0.06	-0.03	0.04	-0.07	-0.01	1.00	0.26	-0.37	-0.19
Forward	0.08	0.09	-0.10	-0.17	-0.15	0.00	-0.01	0.17	-0.03	0.11	0.05	-0.02	0.04	-0.10	0.01	0.26	1.00	-0.08	0.11
Option_D	0.07	-0.03	-0.14	-0.05	-0.04	-0.12	0.00	0.02	0.01	0.03	0.03	-0.10	-0.03	0.12	-0.01	-0.37	-0.08	1.00	0.06
Atlantic_D	0.01	-0.01	-0.26	-0.04	-0.06	-0.03	-0.11	0.04	0.06	-0.02	-0.03	0.02	-0.01	0.02	-0.01	-0.19	0.11	0.06	1.00

A7.2 Residual Diagnostics

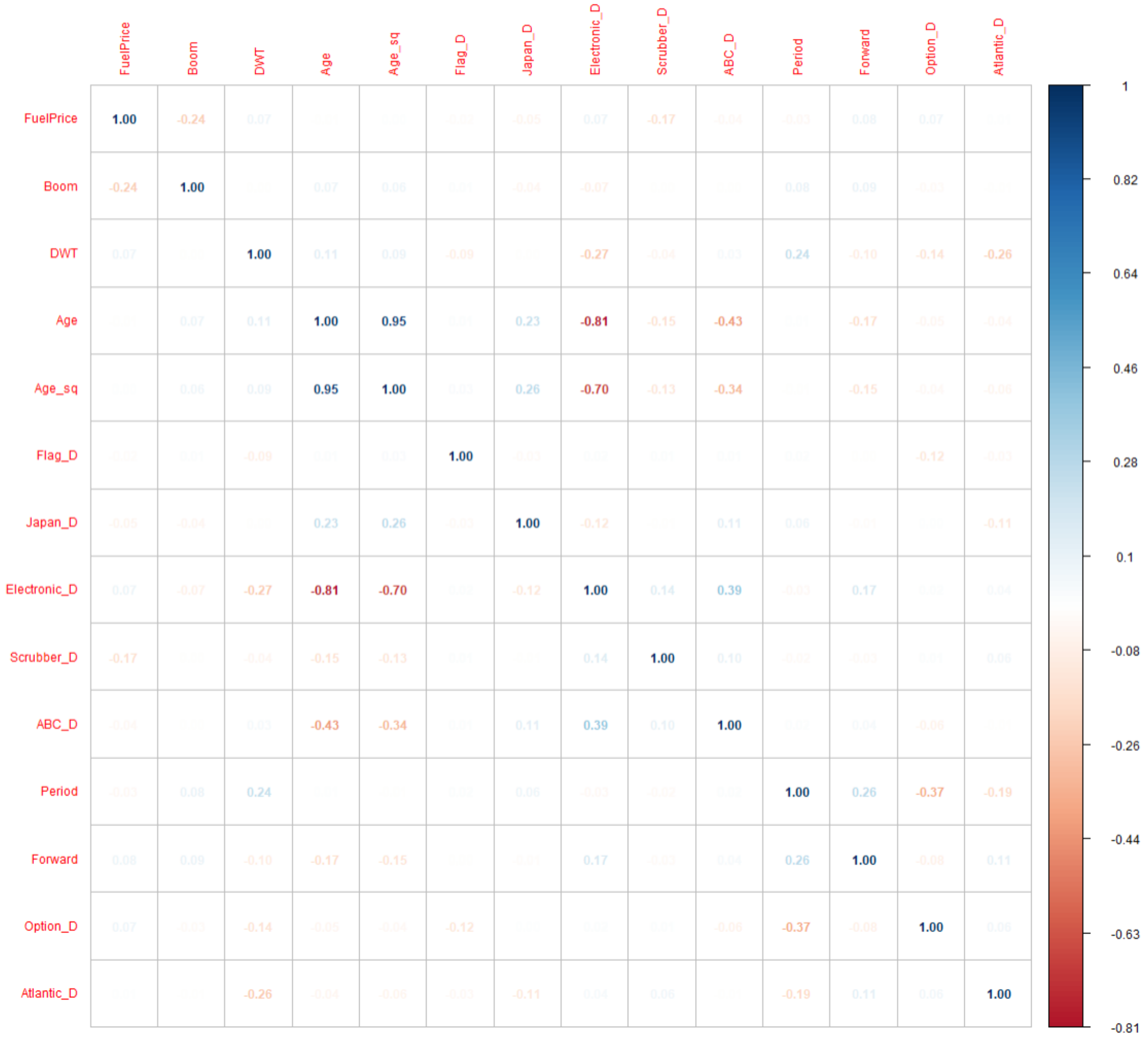


A7.3 Squared Scaled GVIF Values



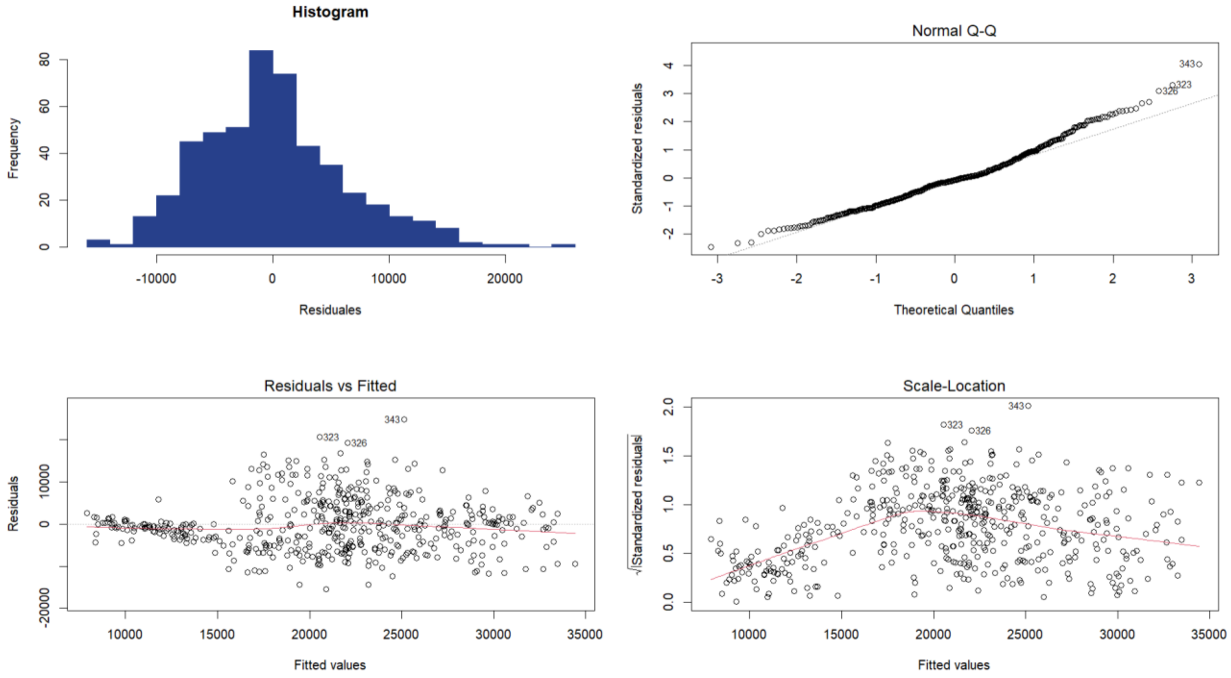
A8 Regression Diagnostics for Model with ABC_D in the Panamax Segment

A8.1 Multicollinearity Matrix

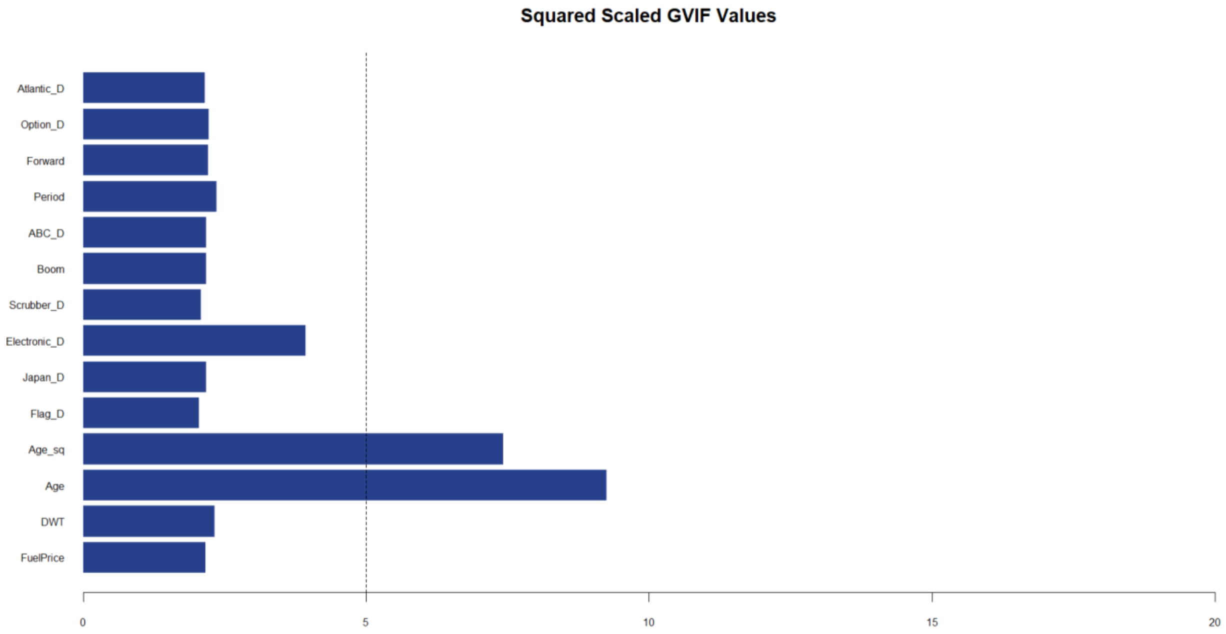


	FuelPrice	Boom	DWT	Age	Age_sq	Flag_D	Japan_D	Electronic_D	Scrubber_D	ABC_D	Period	Forward	Option_D	Atlantic_D
FuelPrice	1.00	-0.24	0.07	0.01	0.02	-0.02	-0.05	0.07	-0.17	-0.04	-0.03	0.08	0.07	0.01
Boom	-0.24	1.00	0.02	0.07	0.06	0.01	-0.04	-0.07	0.00	0.02	0.08	0.09	-0.03	-0.01
DWT	0.07	0.02	1.00	0.11	0.09	-0.09	0.02	-0.27	-0.04	0.03	0.24	-0.10	-0.14	-0.26
Age	0.01	0.07	0.11	1.00	0.95	0.01	0.23	-0.81	-0.15	-0.43	0.01	-0.17	-0.05	-0.04
Age_sq	0.02	0.06	0.09	0.95	1.00	0.03	0.26	-0.70	-0.13	-0.34	0.01	-0.15	-0.04	-0.06
Flag_D	-0.02	0.01	-0.09	0.01	0.03	1.00	-0.03	0.02	0.01	0.01	0.02	0.00	-0.12	-0.03
Japan_D	-0.05	-0.04	0.02	0.23	0.26	-0.03	1.00	-0.12	-0.01	0.11	0.06	-0.01	0.00	-0.11
Electronic_D	0.07	-0.07	-0.27	-0.81	-0.70	0.02	-0.12	1.00	0.14	0.39	-0.03	0.17	0.02	0.04
Scrubber_D	-0.17	0.00	-0.04	-0.15	-0.13	0.01	-0.01	0.14	1.00	0.10	-0.02	-0.03	0.01	0.06
ABC_D	-0.04	0.02	0.03	-0.43	-0.34	0.01	0.11	0.39	0.10	1.00	0.02	0.04	-0.06	0.01
Period	-0.03	0.08	0.24	0.01	0.01	0.02	0.06	-0.03	-0.02	0.02	1.00	0.26	-0.37	-0.19
Forward	0.08	0.09	-0.10	-0.17	-0.15	0.00	-0.01	0.17	-0.03	0.04	0.26	1.00	-0.08	0.11
Option_D	0.07	-0.03	-0.14	-0.05	-0.04	-0.12	0.00	0.02	0.01	-0.06	-0.37	-0.08	1.00	0.06
Atlantic_D	0.01	-0.01	-0.26	-0.04	-0.06	-0.03	-0.11	0.04	0.06	0.01	-0.19	0.11	0.06	1.00

A8.2 Residual Diagnostics

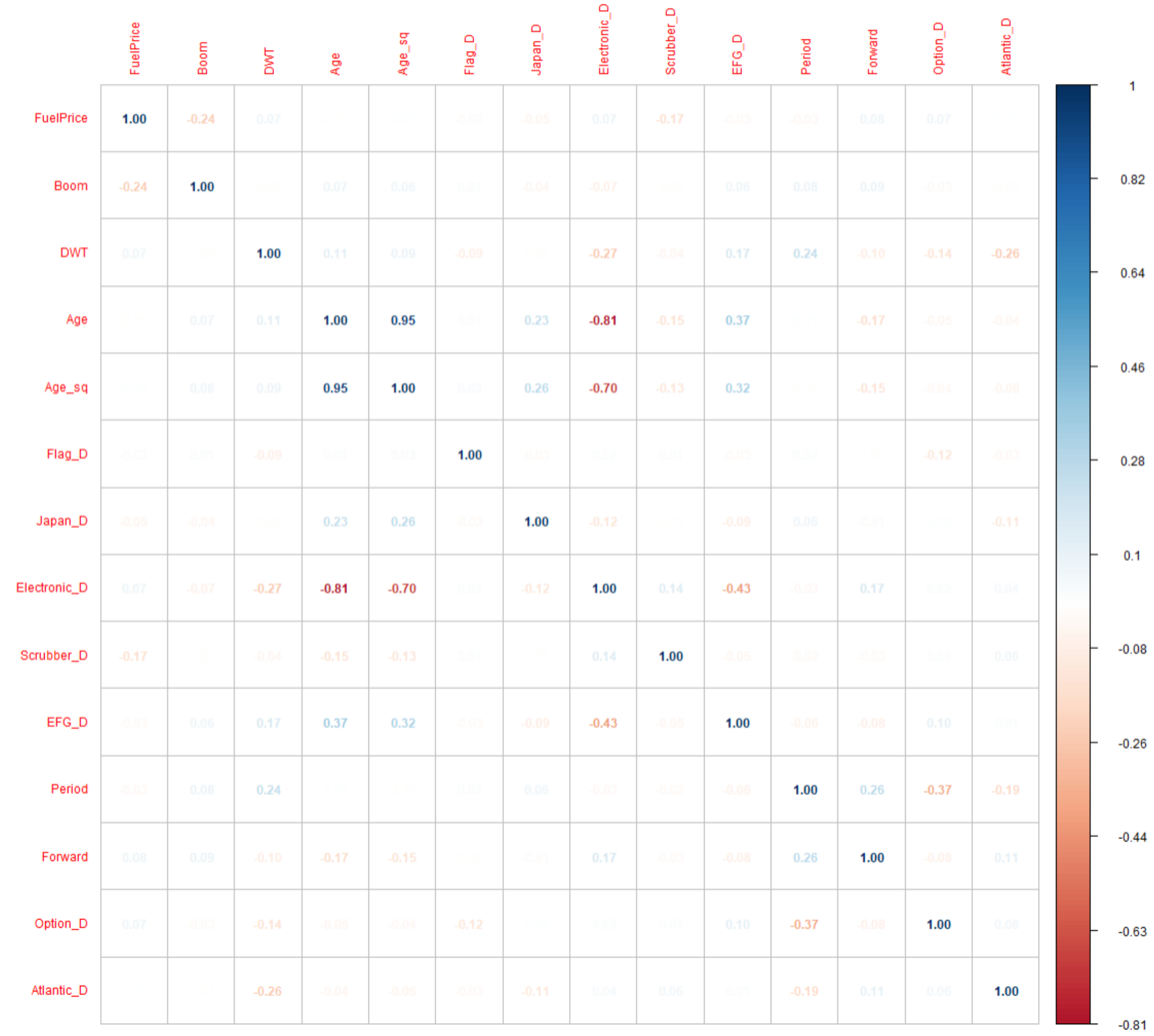


A8.3 Squared Scaled GVIF Values



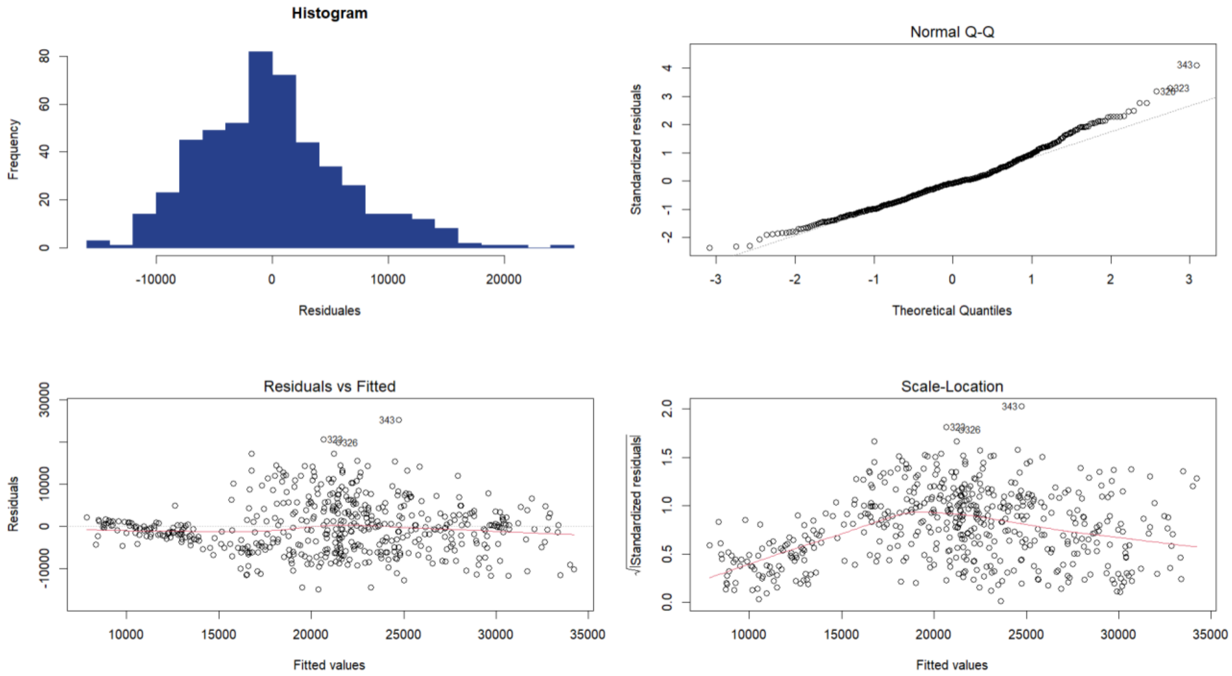
A9 Regression Diagnostics for Model with EFG_D in the Panamax Segment

A9.1 Multicollinearity Matrix

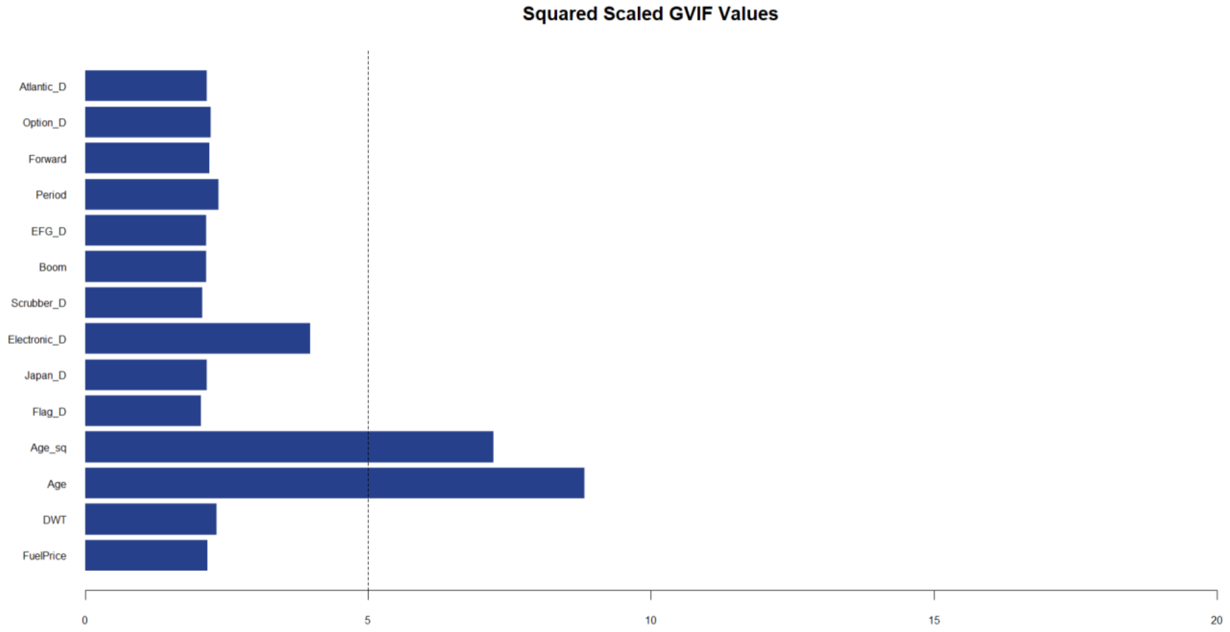


	FuelPrice	Boom	DWT	Age	Age_sq	Flag_D	Japan_D	Electronic_D	Scrubber_D	EFG_D	Period	Forward	Option_D	Atlantic_D
FuelPrice	1.00	-0.24	0.07	-0.01	0.00	-0.02	-0.05	0.07	-0.17	-0.03	-0.03	0.08	0.07	0.01
Boom	-0.24	1.00	0.00	0.07	0.06	0.01	-0.04	-0.07	0.00	0.06	0.08	0.09	-0.03	-0.01
DWT	0.07	0.00	1.00	0.11	0.09	-0.09	0.00	-0.27	-0.04	0.17	0.24	-0.10	-0.14	-0.26
Age	-0.01	0.07	0.11	1.00	0.95	0.01	0.23	-0.81	-0.15	0.37	0.01	-0.17	-0.05	-0.04
Age_sq	0.00	0.06	0.09	0.95	1.00	0.03	0.26	-0.70	-0.13	0.32	-0.01	-0.15	-0.04	-0.06
Flag_D	-0.02	0.01	-0.09	0.01	0.03	1.00	-0.03	0.02	0.01	-0.03	0.02	0.00	-0.12	-0.03
Japan_D	-0.05	-0.04	0.00	0.23	0.26	-0.03	1.00	-0.12	-0.01	-0.09	0.06	-0.01	0.00	-0.11
Electronic_D	0.07	-0.07	-0.27	-0.81	-0.70	0.02	-0.12	1.00	0.14	-0.43	-0.03	0.17	0.02	0.04
Scrubber_D	-0.17	0.00	-0.04	-0.15	-0.13	0.01	-0.01	0.14	1.00	-0.05	-0.02	-0.03	0.01	0.06
EFG_D	-0.03	0.06	0.17	0.37	0.32	-0.03	-0.09	-0.43	-0.05	1.00	-0.06	-0.08	0.10	0.01
Period	-0.03	0.08	0.24	0.01	-0.01	0.02	0.06	-0.03	-0.02	-0.06	1.00	0.26	-0.37	-0.19
Forward	0.08	0.09	-0.10	-0.17	-0.15	0.00	-0.01	0.17	-0.03	-0.08	0.26	1.00	-0.08	0.11
Option_D	0.07	-0.03	-0.14	-0.05	-0.04	-0.12	0.00	0.02	0.01	0.10	-0.37	-0.08	1.00	0.06
Atlantic_D	0.01	-0.01	-0.26	-0.04	-0.06	-0.03	-0.11	0.04	0.06	0.01	-0.19	0.11	0.06	1.00

A9.2 Residual Diagnostics

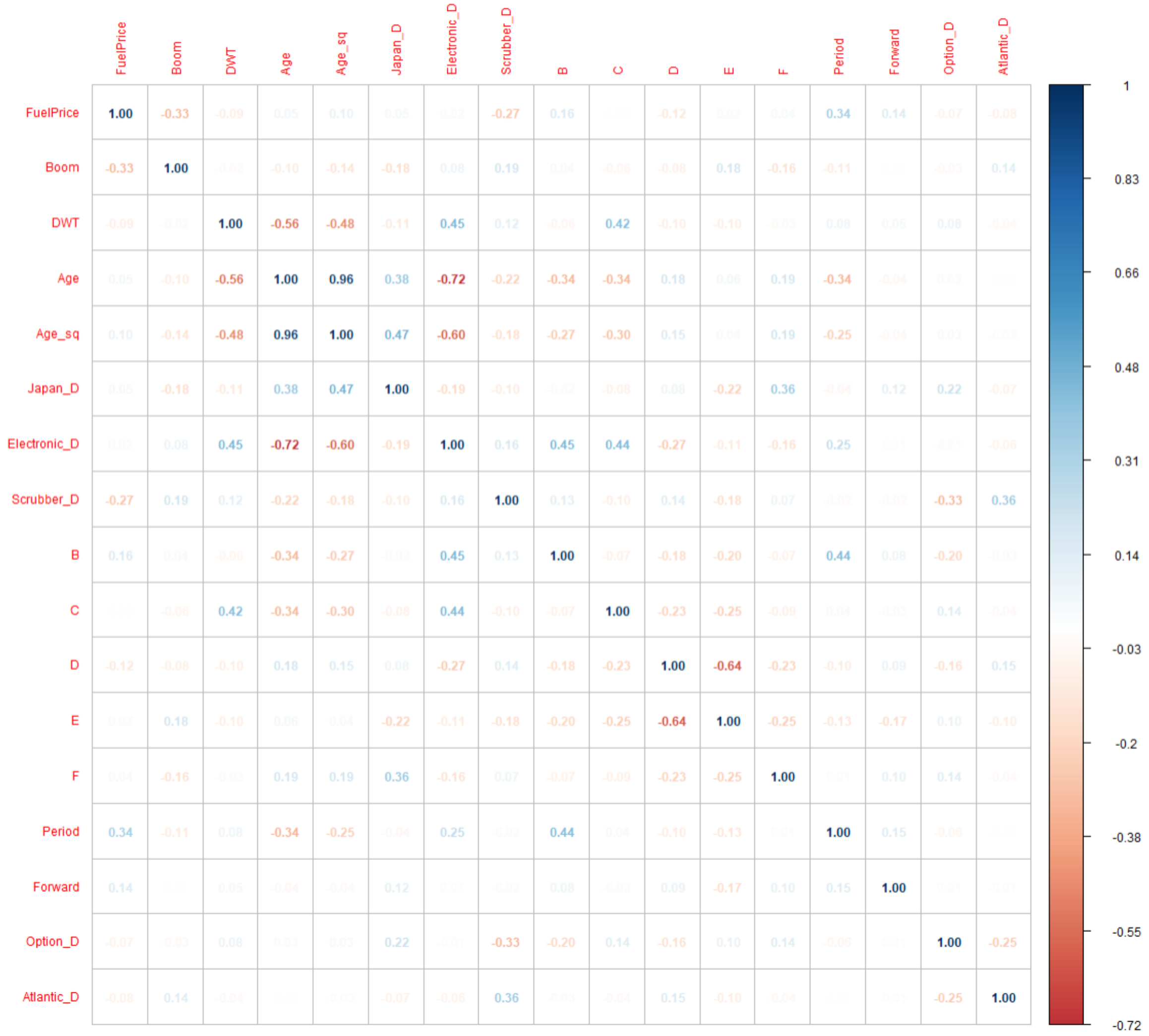


A9.3 Squared Scaled GVIF Values



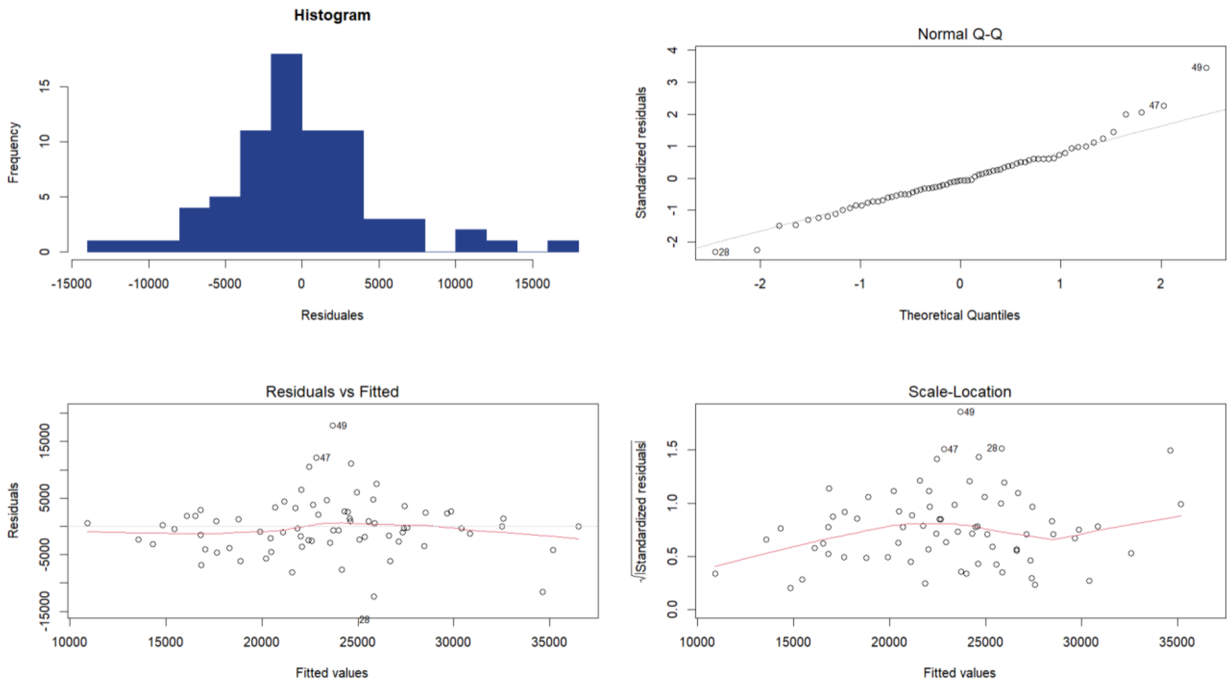
A10 Regression Diagnostics for Model with all GHG Ratings in the Capesize Segment

A10.1 Multicollinearity Matrix

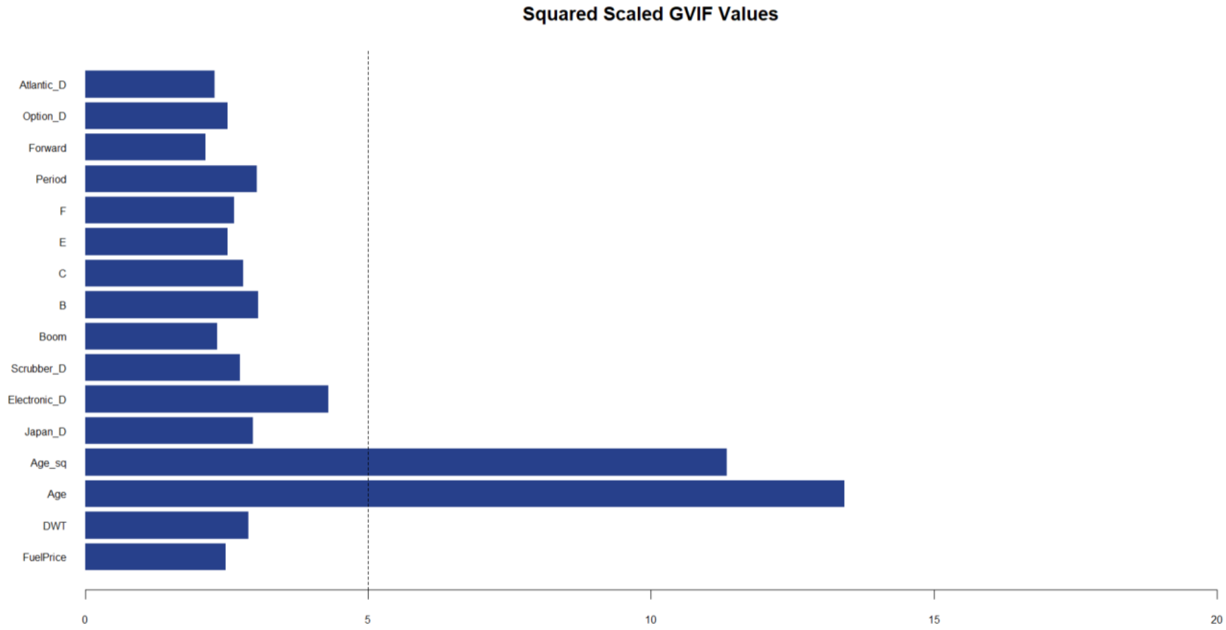


	FuelPrice	Boom	DWT	Age	Age_sq	Japan_D	Electronic_D	Scrubber_D	B	C	D	E	F	Period	Forward	Option_D	Atlantic_D
FuelPrice	1.00	-0.33	-0.09	0.05	0.10	0.05	0.02	-0.27	0.16	0.00	-0.12	0.02	0.04	0.34	0.14	-0.07	-0.08
Boom	-0.33	1.00	-0.02	-0.10	-0.14	-0.18	0.08	0.19	0.04	-0.06	-0.08	0.18	-0.16	-0.11	0.00	-0.03	0.14
DWT	-0.09	-0.02	1.00	-0.56	-0.48	-0.11	0.45	0.12	-0.06	0.42	-0.10	-0.10	-0.03	0.08	0.05	0.08	-0.04
Age	0.05	-0.10	-0.56	1.00	0.96	0.38	-0.72	-0.22	-0.34	-0.34	0.18	0.06	0.19	-0.34	-0.04	0.03	0.00
Age_sq	0.10	-0.14	-0.48	0.96	1.00	0.47	-0.60	-0.18	-0.27	-0.30	0.15	0.04	0.19	-0.25	-0.04	0.03	-0.02
Japan_D	0.05	-0.18	-0.11	0.38	0.47	1.00	-0.19	-0.10	-0.02	-0.08	0.08	-0.22	0.36	-0.04	0.12	0.22	-0.07
Electronic_D	0.02	0.08	0.45	-0.72	-0.60	-0.19	1.00	0.16	0.45	0.44	-0.27	-0.11	-0.16	0.25	0.01	-0.01	-0.06
Scrubber_D	-0.27	0.19	0.12	-0.22	-0.18	-0.10	0.16	1.00	0.13	-0.10	0.14	-0.18	0.07	-0.02	-0.02	-0.33	0.36
B	0.16	0.04	-0.06	-0.34	-0.27	-0.02	0.45	0.13	1.00	-0.07	-0.18	-0.20	-0.07	0.44	0.08	-0.20	-0.03
C	0.00	-0.06	0.42	-0.34	-0.30	-0.08	0.44	-0.10	-0.07	1.00	-0.23	-0.25	-0.09	0.04	-0.03	0.14	-0.04
D	-0.12	-0.08	-0.10	0.18	0.15	0.08	-0.27	0.14	-0.18	-0.23	1.00	-0.64	-0.23	-0.10	0.09	-0.16	0.15
E	0.02	0.18	-0.10	0.06	0.04	-0.22	-0.11	-0.18	-0.20	-0.25	-0.64	1.00	-0.25	-0.13	-0.17	0.10	-0.10
F	0.04	-0.16	-0.03	0.19	0.19	0.36	-0.16	0.07	-0.07	-0.09	-0.23	-0.25	1.00	0.01	0.10	0.14	-0.04
Period	0.34	-0.11	0.08	-0.34	-0.25	-0.04	0.25	-0.02	0.44	0.04	-0.10	-0.13	0.01	1.00	0.15	-0.06	-0.01
Forward	0.14	0.00	0.05	-0.04	-0.04	0.12	0.01	-0.02	0.08	-0.03	0.09	-0.17	0.10	0.15	1.00	0.01	-0.01
Option_D	-0.07	-0.03	0.08	0.03	0.03	0.22	-0.01	-0.33	-0.20	0.14	-0.16	0.10	0.14	-0.06	0.01	1.00	-0.25
Atlantic_D	-0.08	0.14	-0.04	0.00	-0.02	-0.07	-0.06	0.36	-0.03	-0.04	0.15	-0.10	-0.04	-0.01	-0.01	-0.25	1.00

A10.2 Residual Diagnostics

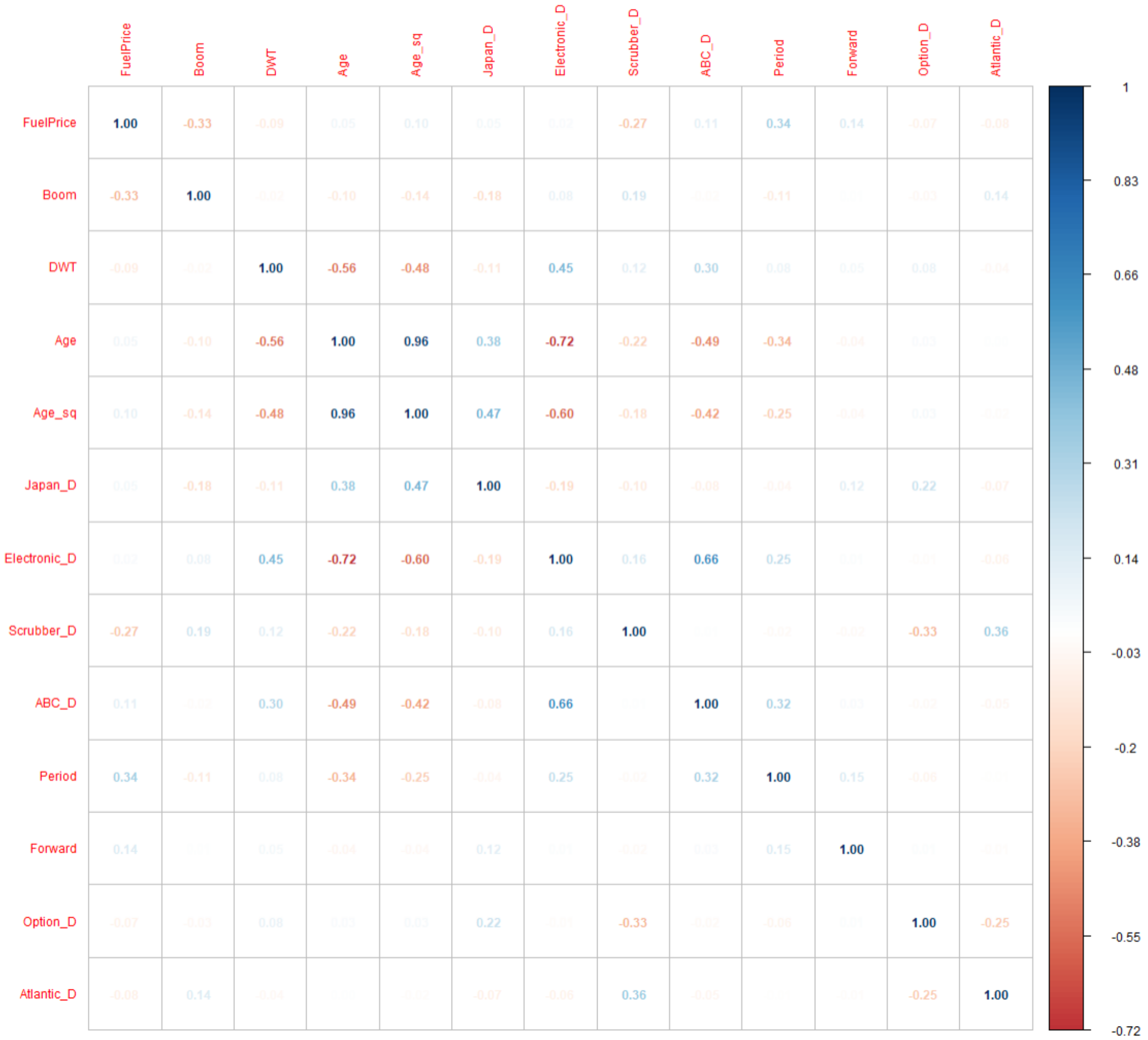


A10.3 Squared Scaled GVIF Values



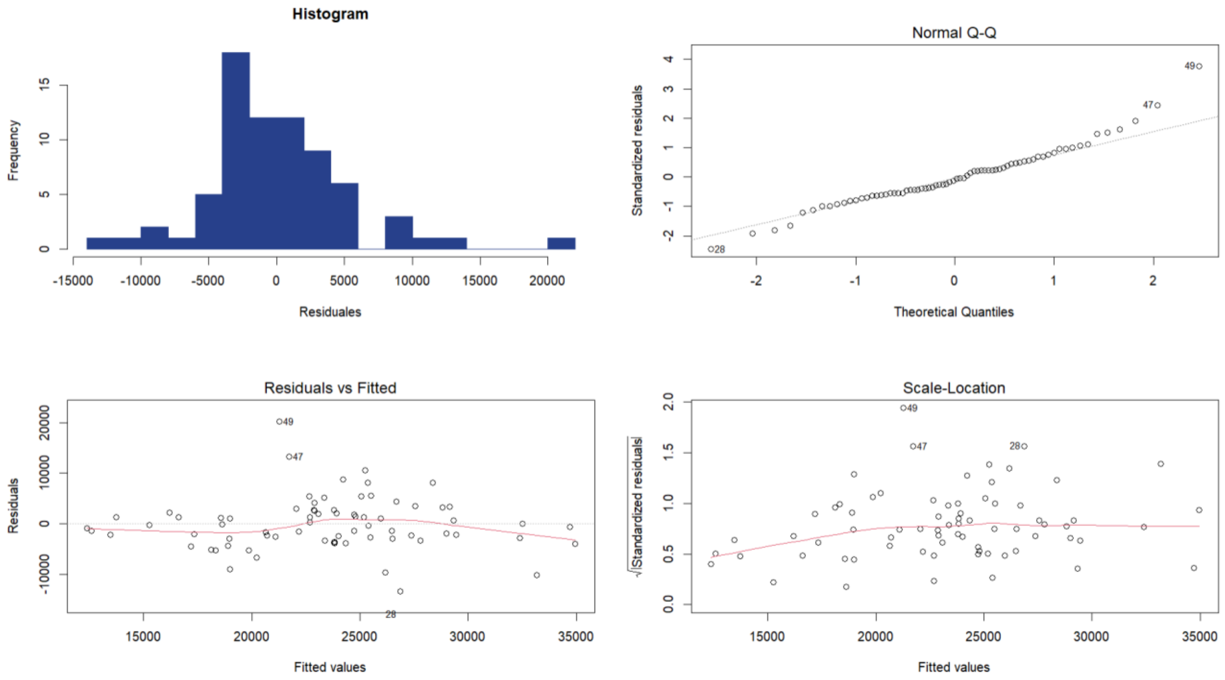
A11 Regression Diagnostics for Model with ABC_D in the Capesize Segment

A11.1 Multicollinearity Matrix

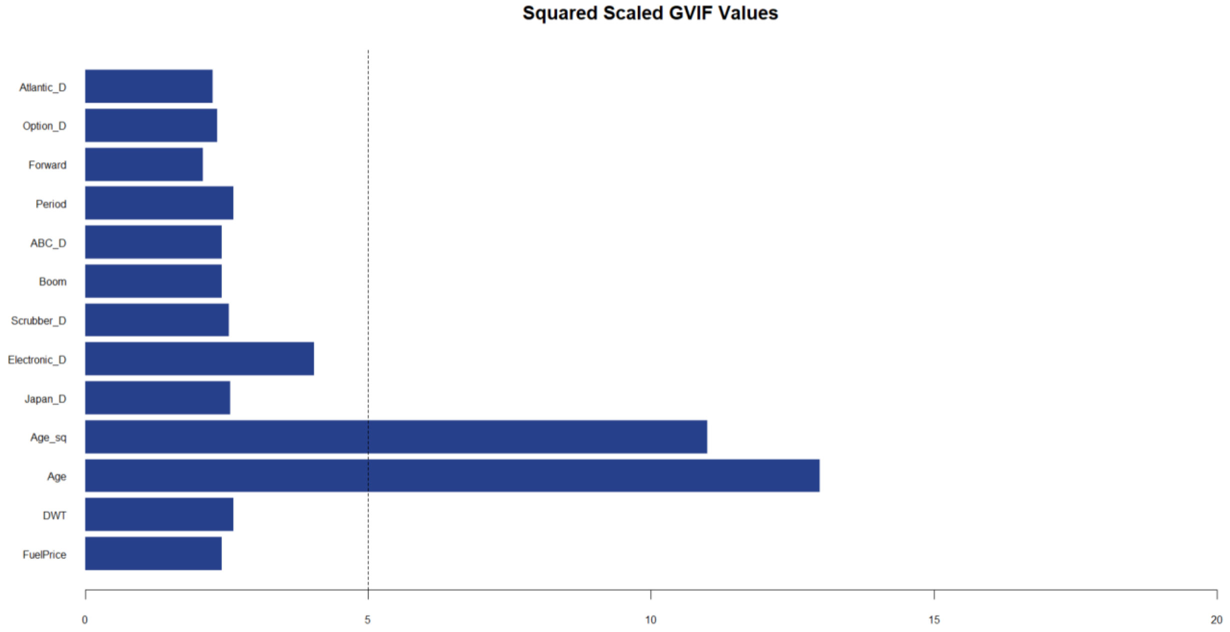


	FuelPrice	Boom	DWT	Age	Age_sq	Japan_D	Electronic_D	Scrubber_D	ABC_D	Period	Forward	Option_D	Atlantic_D
FuelPrice	1.00	-0.33	-0.09	0.05	0.10	0.05	0.02	-0.27	0.11	0.34	0.14	-0.07	-0.08
Boom	-0.33	1.00	-0.02	-0.10	-0.14	-0.18	0.08	0.19	-0.02	-0.11	0.01	-0.03	0.14
DWT	-0.09	-0.02	1.00	-0.56	-0.48	-0.11	0.45	0.12	0.30	0.08	0.05	0.08	-0.04
Age	0.05	-0.10	-0.56	1.00	0.96	0.38	-0.72	-0.22	-0.49	-0.34	-0.04	0.03	0.00
Age_sq	0.10	-0.14	-0.48	0.96	1.00	0.47	-0.60	-0.18	-0.42	-0.25	-0.04	0.03	-0.02
Japan_D	0.05	-0.18	-0.11	0.38	0.47	1.00	-0.19	-0.10	-0.08	-0.04	0.12	0.22	-0.07
Electronic_D	0.02	0.08	0.45	-0.72	-0.60	-0.19	1.00	0.16	0.66	0.25	0.01	-0.01	-0.06
Scrubber_D	-0.27	0.19	0.12	-0.22	-0.18	-0.10	0.16	1.00	0.01	-0.02	-0.02	-0.33	0.36
ABC_D	0.11	-0.02	0.30	-0.49	-0.42	-0.08	0.66	0.01	1.00	0.32	0.03	-0.02	-0.05
Period	0.34	-0.11	0.08	-0.34	-0.25	-0.04	0.25	-0.02	0.32	1.00	0.15	-0.06	0.01
Forward	0.14	0.01	0.05	-0.04	-0.04	0.12	0.01	-0.02	0.03	0.15	1.00	0.01	-0.01
Option_D	-0.07	-0.03	0.08	0.03	0.03	0.22	-0.01	-0.33	-0.02	-0.06	0.01	1.00	-0.25
Atlantic_D	-0.08	0.14	-0.04	0.00	-0.02	-0.07	-0.06	0.36	-0.05	0.01	-0.01	-0.25	1.00

A11.2 Residual Diagnostics

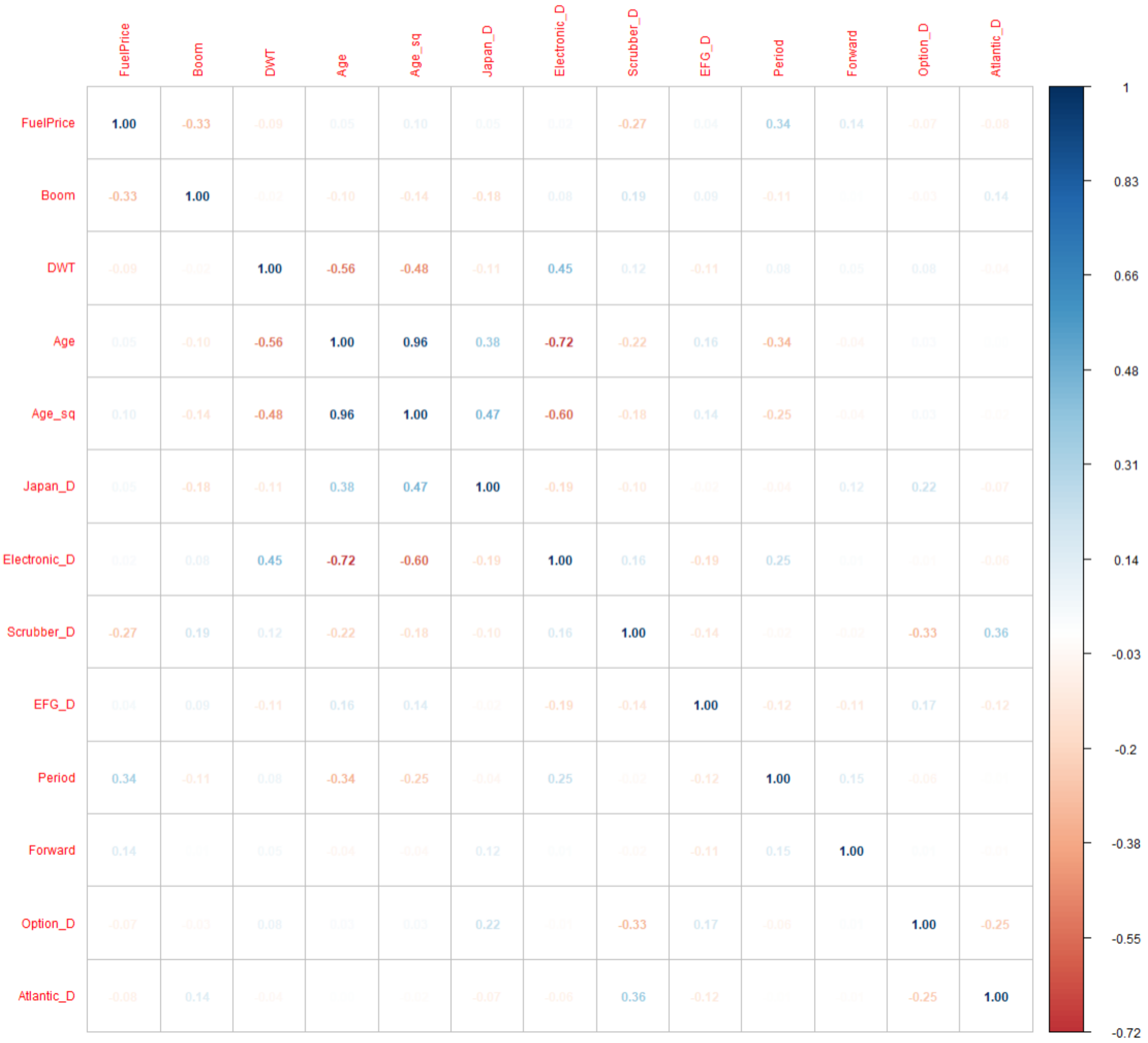


A11.3 Squared Scaled GVIF Values



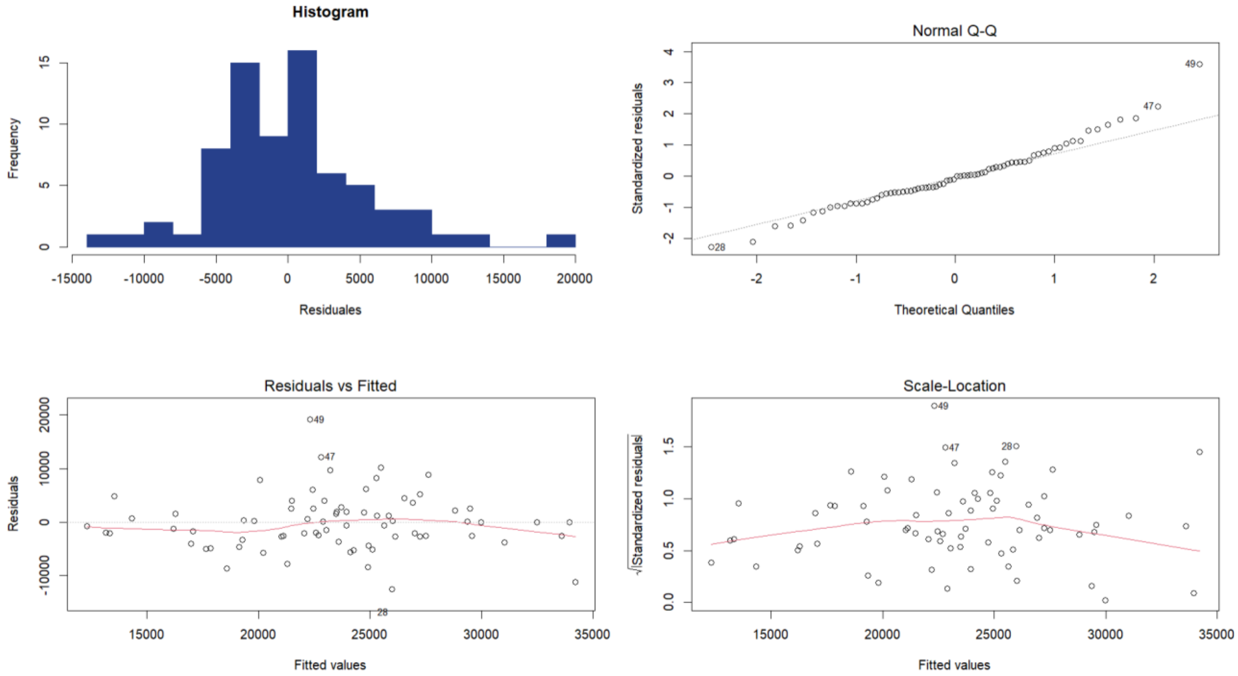
A12 Regression Diagnostics for Model with EFG_D in the Capesize Segment

A12.1 Multicollinearity Matrix

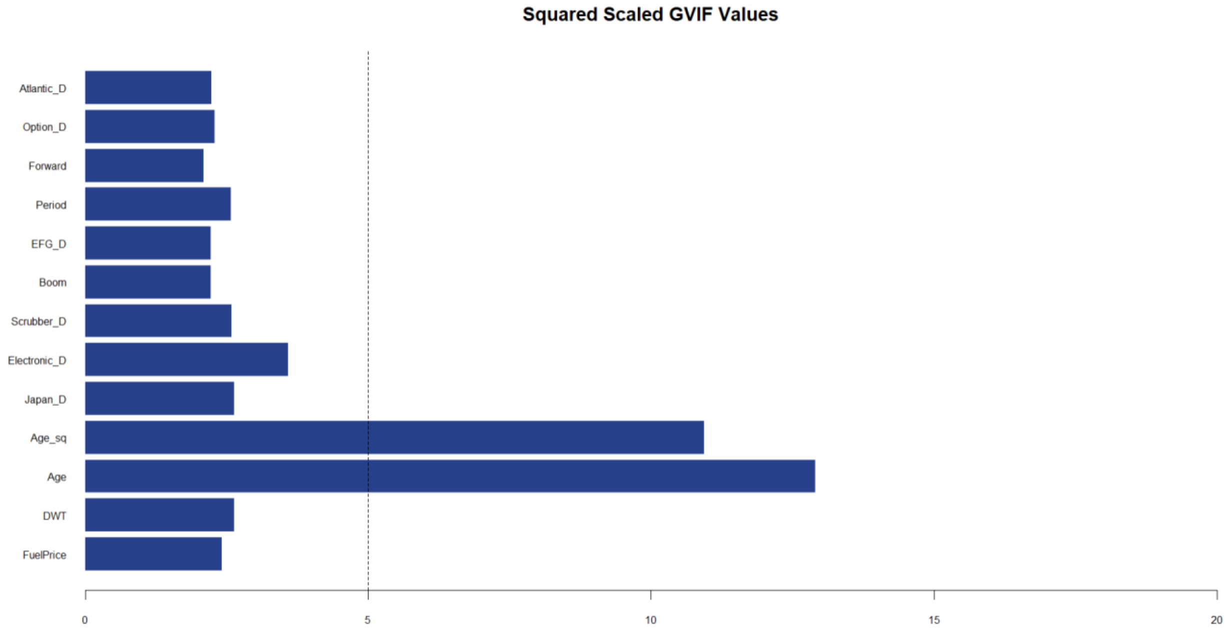


	FuelPrice	Boom	DWT	Age	Age_sq	Japan_D	Electronic_D	Scrubber_D	EFG_D	Period	Forward	Option_D	Atlantic_D
FuelPrice	1.00	-0.33	-0.09	0.05	0.10	0.05	0.02	-0.27	0.04	0.34	0.14	-0.07	-0.08
Boom	-0.33	1.00	-0.02	-0.10	-0.14	-0.18	0.08	0.19	0.09	-0.11	0.01	-0.03	0.14
DWT	-0.09	-0.02	1.00	-0.56	-0.48	-0.11	0.45	0.12	-0.11	0.08	0.05	0.08	-0.04
Age	0.05	-0.10	-0.56	1.00	0.96	0.38	-0.72	-0.22	0.16	-0.34	-0.04	0.03	[illegible]
Age_sq	0.10	-0.14	-0.48	0.96	1.00	0.47	-0.60	-0.18	0.14	-0.25	-0.04	0.03	-0.02
Japan_D	0.05	-0.18	-0.11	0.38	0.47	1.00	-0.19	-0.10	-0.02	-0.04	0.12	0.22	-0.07
Electronic_D	0.02	0.08	0.45	-0.72	-0.60	-0.19	1.00	0.16	-0.19	0.25	0.01	-0.01	-0.06
Scrubber_D	-0.27	0.19	0.12	-0.22	-0.18	-0.10	0.16	1.00	-0.14	-0.02	-0.02	-0.33	0.36
EFG_D	0.04	0.09	-0.11	0.16	0.14	-0.02	-0.19	-0.14	1.00	-0.12	-0.11	0.17	-0.12
Period	0.34	-0.11	0.08	-0.34	-0.25	-0.04	0.25	-0.02	-0.12	1.00	0.15	-0.06	-0.01
Forward	0.14	0.01	0.05	-0.04	-0.04	0.12	0.01	-0.02	-0.11	0.15	1.00	0.01	-0.01
Option_D	-0.07	-0.03	0.08	0.03	0.03	0.22	-0.01	-0.33	0.17	-0.06	0.01	1.00	-0.25
Atlantic_D	-0.08	0.14	-0.04	[illegible]	-0.02	-0.07	-0.06	0.36	-0.12	-0.01	-0.01	-0.25	1.00

A12.2 Residual Diagnostics

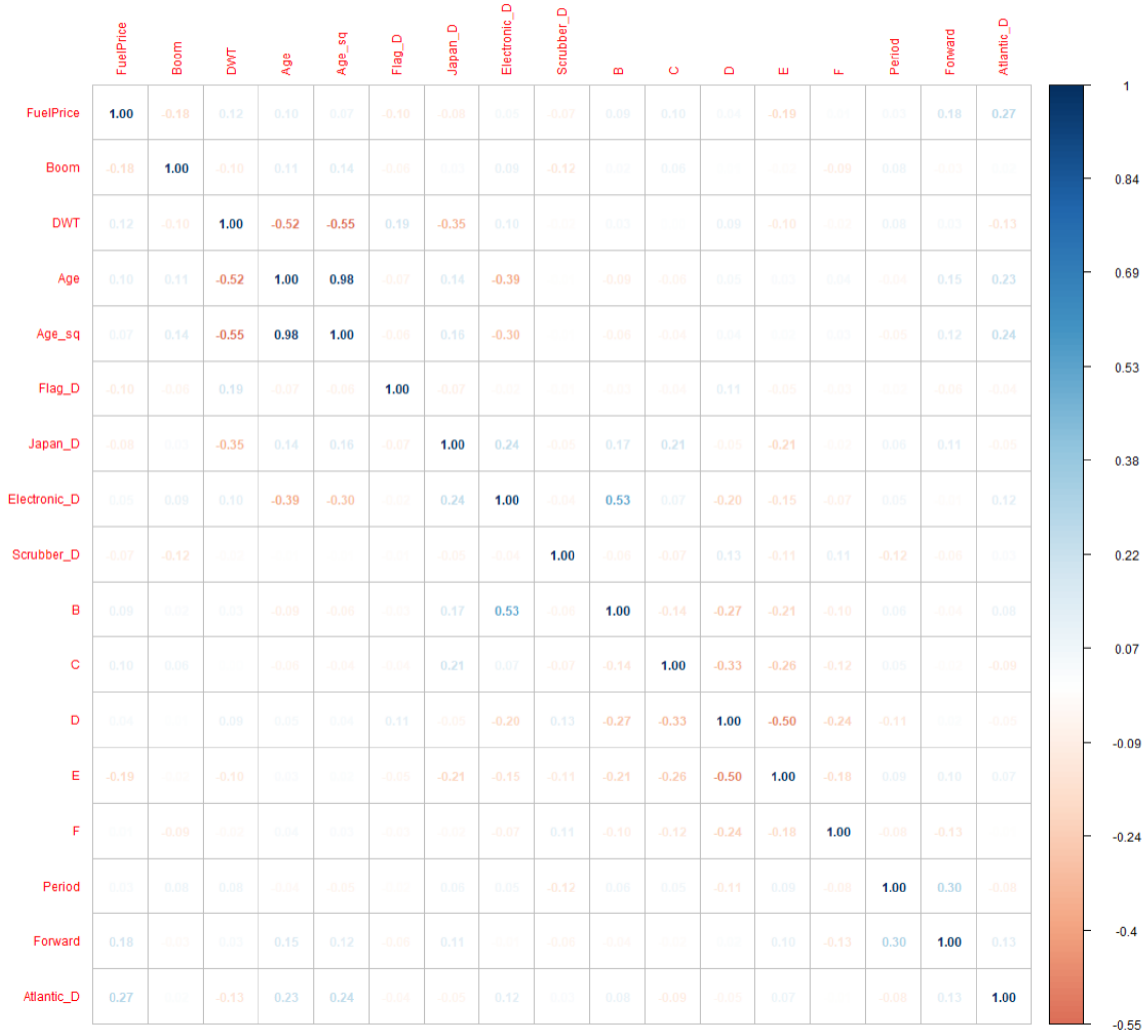


A12.3 Squared Scaled GVIF Values



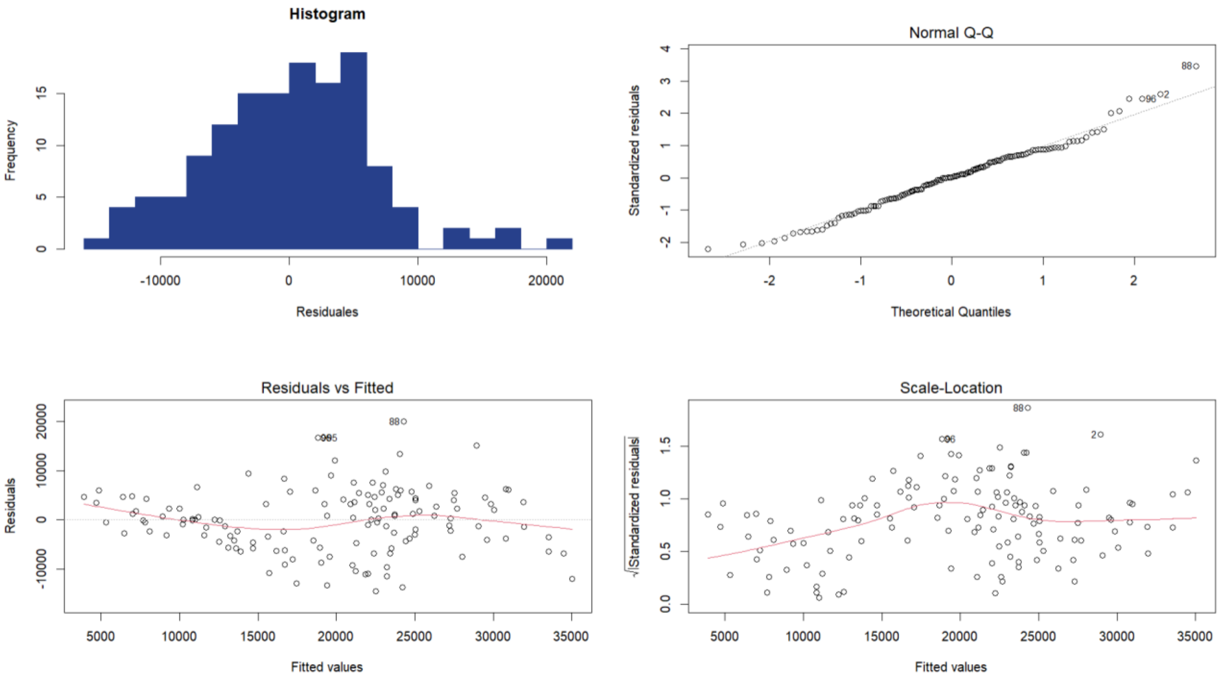
A13 Regression Diagnostics for Model with all GHG Ratings in the Supramax Segment

A13.1 Multicollinearity Matrix

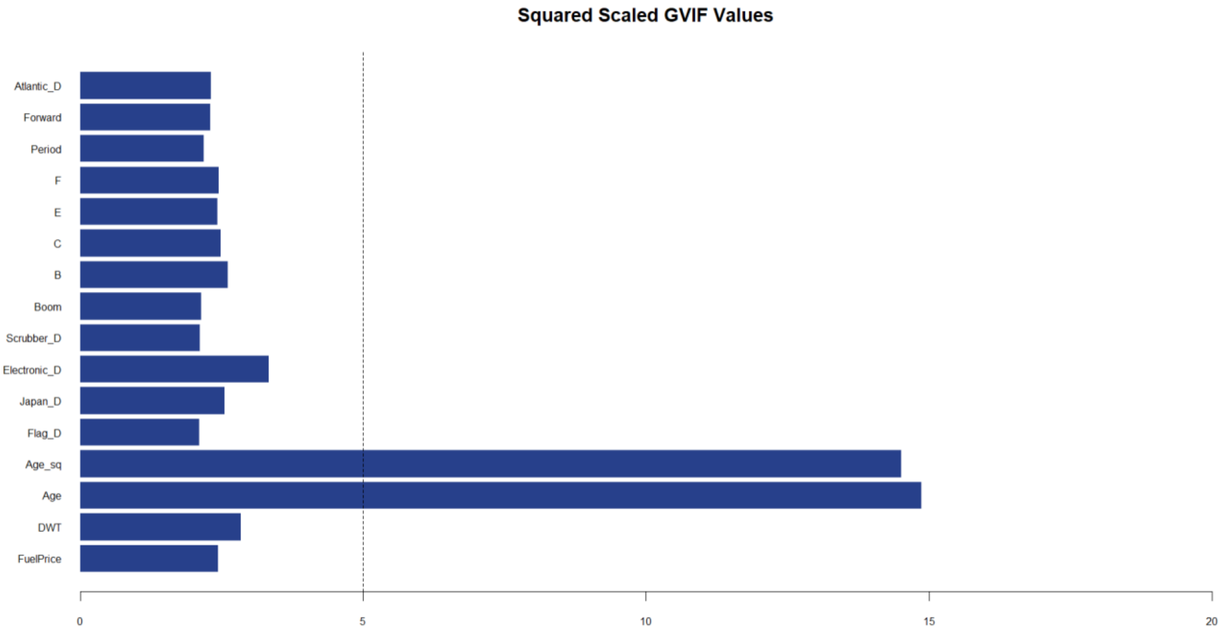


	FuelPrice	Boom	DWT	Age	Age_sq	Flag_D	Japan_D	Electronic_D	Scrubber_D	B	C	D	E	F	Period	Forward	Atlantic_D
FuelPrice	1.00	-0.18	0.12	0.10	0.07	-0.10	-0.08	0.05	-0.07	0.09	0.10	0.04	-0.19	0.01	0.03	0.18	0.27
Boom	-0.18	1.00	-0.10	0.11	0.14	-0.06	0.03	0.09	-0.12	0.02	0.06	0.01	-0.02	-0.09	0.08	-0.03	0.02
DWT	0.12	-0.10	1.00	-0.52	-0.55	0.19	-0.35	0.10	-0.02	0.03	0.00	0.09	-0.10	-0.02	0.08	0.03	-0.13
Age	0.10	0.11	-0.52	1.00	0.98	-0.07	0.14	-0.39	-0.01	-0.09	-0.06	0.05	0.03	0.04	-0.04	0.15	0.23
Age_sq	0.07	0.14	-0.55	0.98	1.00	-0.06	0.16	-0.30	-0.01	-0.06	-0.04	0.04	0.02	0.03	-0.05	0.12	0.24
Flag_D	-0.10	-0.06	0.19	-0.07	-0.06	1.00	-0.07	-0.02	-0.01	-0.03	-0.04	0.11	-0.05	-0.03	-0.02	-0.06	-0.04
Japan_D	-0.08	0.03	-0.35	0.14	0.16	-0.07	1.00	0.24	-0.05	0.17	0.21	-0.05	-0.21	-0.02	0.06	0.11	-0.05
Electronic_D	0.05	0.09	0.10	-0.39	-0.30	-0.02	0.24	1.00	-0.04	0.53	0.07	-0.20	-0.15	-0.07	0.05	-0.01	0.12
Scrubber_D	-0.07	-0.12	-0.02	-0.01	-0.01	-0.01	-0.05	-0.04	1.00	-0.06	-0.07	0.13	-0.11	0.11	-0.12	-0.06	0.03
B	0.09	0.02	0.03	-0.09	-0.06	-0.03	0.17	0.53	-0.06	1.00	-0.14	-0.27	-0.21	-0.10	0.06	-0.04	0.08
C	0.10	0.06	0.00	-0.06	-0.04	-0.04	0.21	0.07	-0.07	-0.14	1.00	-0.33	-0.26	-0.12	0.05	-0.02	-0.09
D	0.04	0.01	0.09	0.05	0.04	0.11	-0.05	-0.20	0.13	-0.27	-0.33	1.00	-0.50	-0.24	-0.11	0.02	-0.05
E	-0.19	-0.02	-0.10	0.03	0.02	-0.05	-0.21	-0.15	-0.11	-0.21	-0.26	-0.50	1.00	-0.18	0.09	0.10	0.07
F	0.01	-0.09	-0.02	0.04	0.03	-0.03	-0.02	-0.07	0.11	-0.10	-0.12	-0.24	-0.18	1.00	-0.08	-0.13	-0.01
Period	0.03	0.08	0.08	-0.04	-0.05	-0.02	0.06	0.05	-0.12	0.06	0.05	-0.11	0.09	-0.08	1.00	0.30	-0.08
Forward	0.18	-0.03	0.03	0.15	0.12	-0.06	0.11	-0.01	-0.06	-0.04	-0.02	0.02	0.10	-0.13	0.30	1.00	0.13
Atlantic_D	0.27	0.02	-0.13	0.23	0.24	-0.04	-0.05	0.12	0.03	0.08	-0.09	-0.05	0.07	-0.01	-0.08	0.13	1.00

A13.2 Residual Diagnostics

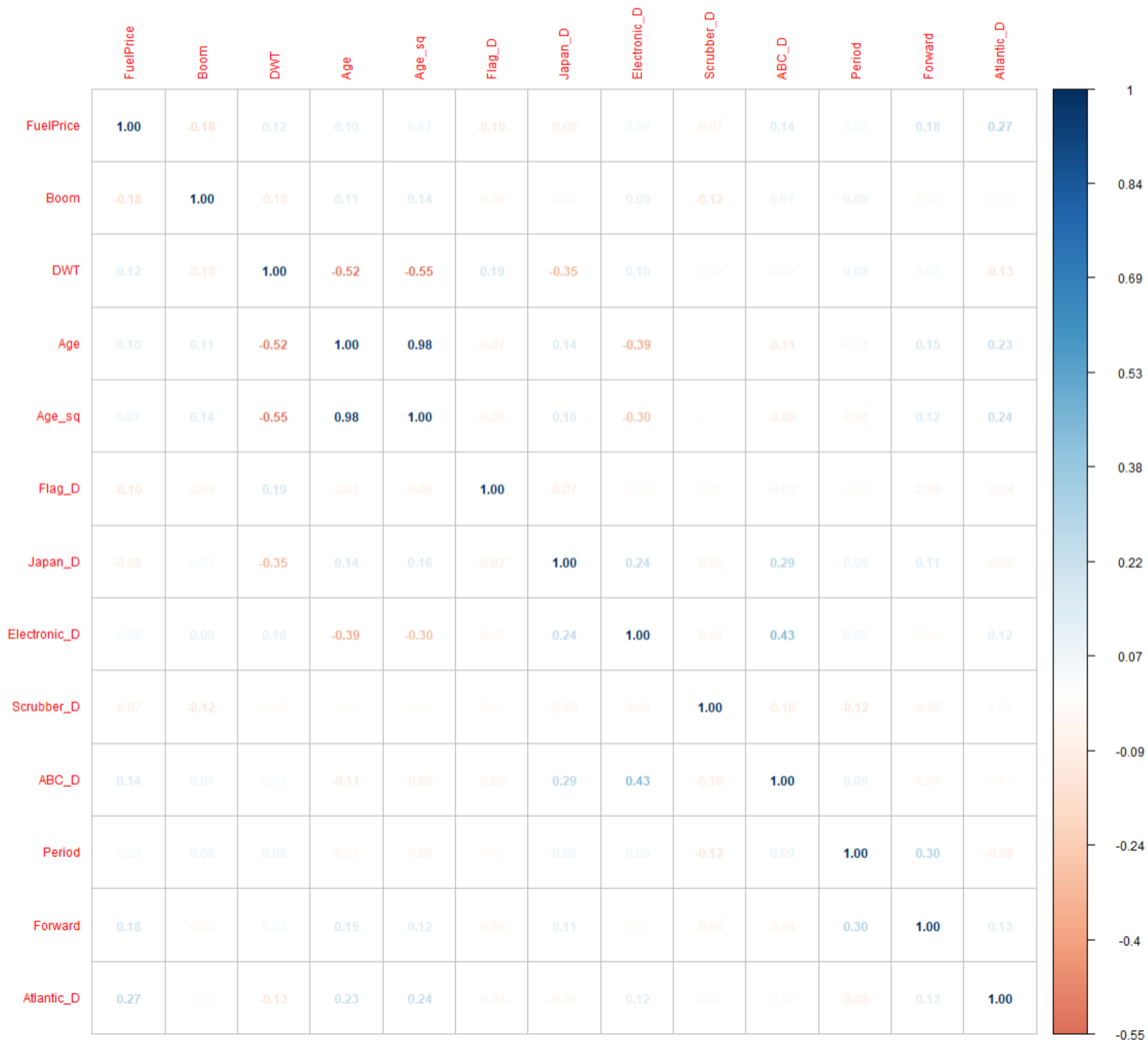


A13.3 Squared Scaled GVIF Values



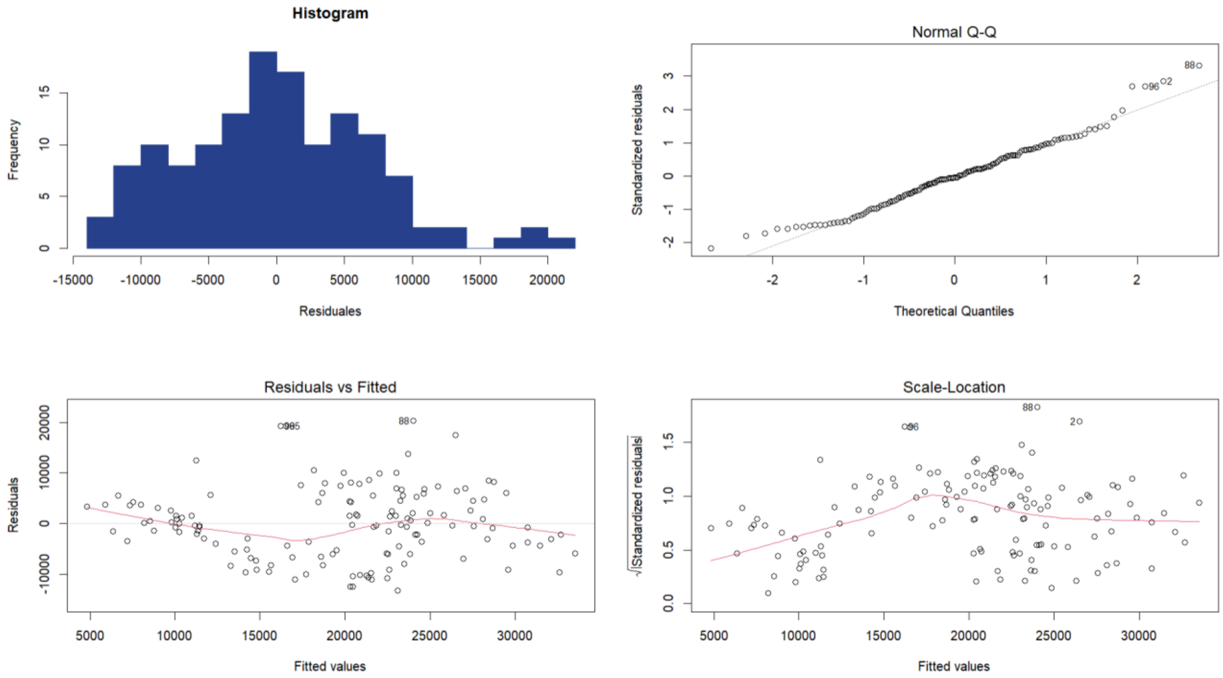
A14 Regression Diagnostics for Model with ABC_D in the Supramax Segment

A14.1 Multicollinearity Matrix

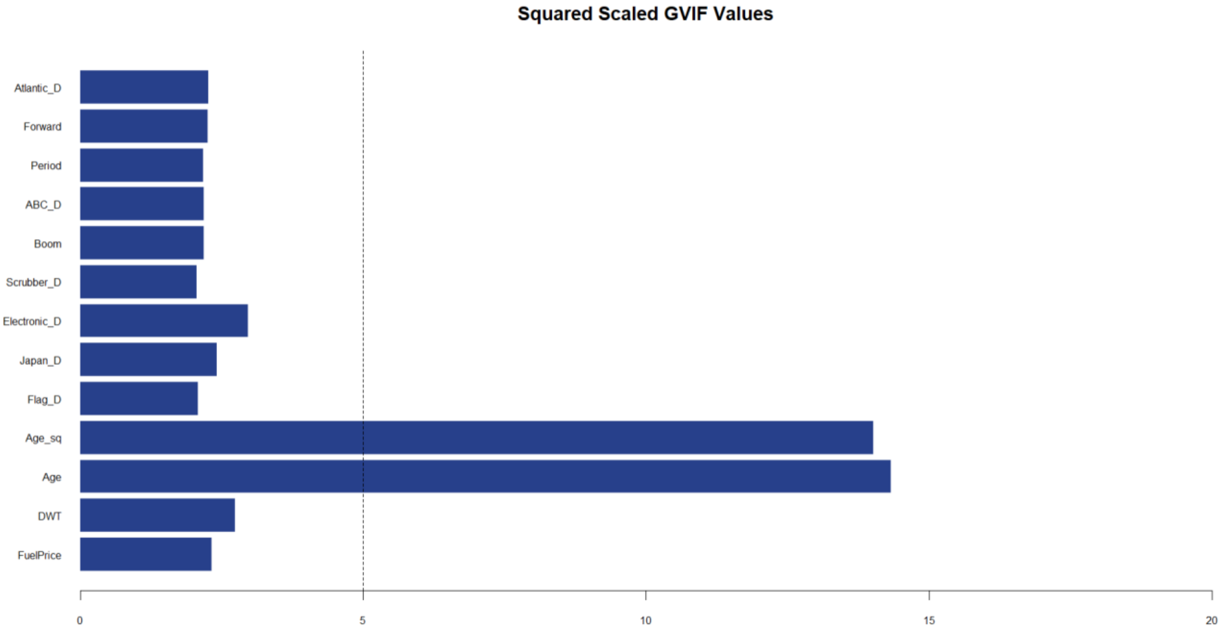


	FuelPrice	Boom	DWT	Age	Age_sq	Flag_D	Japan_D	Electronic_D	Scrubber_D	ABC_D	Period	Forward	Atlantic_D
FuelPrice	1.00	-0.18	0.12	0.10	0.07	-0.10	-0.08	0.05	-0.07	0.14	0.03	0.18	0.27
Boom	-0.18	1.00	-0.10	0.11	0.14	-0.06	0.03	0.09	-0.12	0.07	0.08	-0.03	0.02
DWT	0.12	-0.10	1.00	-0.52	-0.55	0.19	-0.35	0.10	-0.02	0.02	0.08	0.03	-0.13
Age	0.10	0.11	-0.52	1.00	0.98	-0.07	0.14	-0.39	-0.01	-0.11	-0.04	0.15	0.23
Age_sq	0.07	0.14	-0.55	0.98	1.00	-0.06	0.16	-0.30	-0.01	-0.08	-0.05	0.12	0.24
Flag_D	-0.10	-0.06	0.19	-0.07	-0.06	1.00	-0.07	-0.02	-0.01	-0.05	-0.02	-0.06	-0.04
Japan_D	-0.08	0.03	-0.35	0.14	0.16	-0.07	1.00	0.24	-0.05	0.29	0.06	0.11	-0.05
Electronic_D	0.05	0.09	0.10	-0.39	-0.30	-0.02	0.24	1.00	-0.04	0.43	0.05	-0.01	0.12
Scrubber_D	-0.07	-0.12	-0.02	-0.01	-0.01	-0.01	-0.05	-0.04	1.00	-0.10	-0.12	-0.06	0.03
ABC_D	0.14	0.07	0.02	-0.11	-0.08	-0.05	0.29	0.43	-0.10	1.00	0.09	-0.04	-0.02
Period	0.03	0.08	0.08	-0.04	-0.05	-0.02	0.06	0.05	-0.12	0.09	1.00	0.30	-0.08
Forward	0.18	-0.03	0.03	0.15	0.12	-0.06	0.11	-0.01	-0.06	-0.04	0.30	1.00	0.13
Atlantic_D	0.27	0.02	-0.13	0.23	0.24	-0.04	-0.05	0.12	0.03	-0.02	-0.08	0.13	1.00

A14.2 Residual Diagnostics

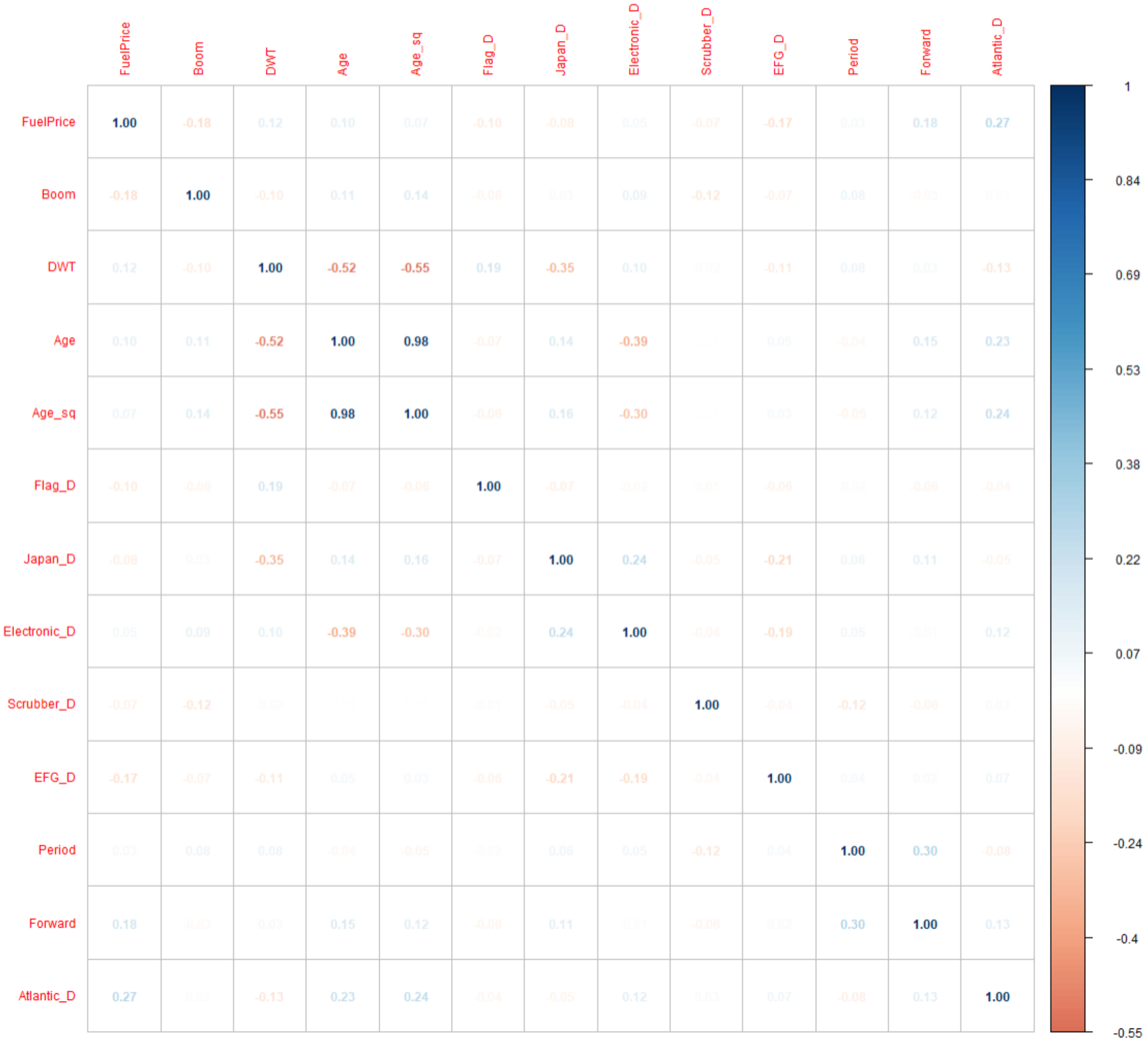


A14.3 Squared Scaled GVIF Values



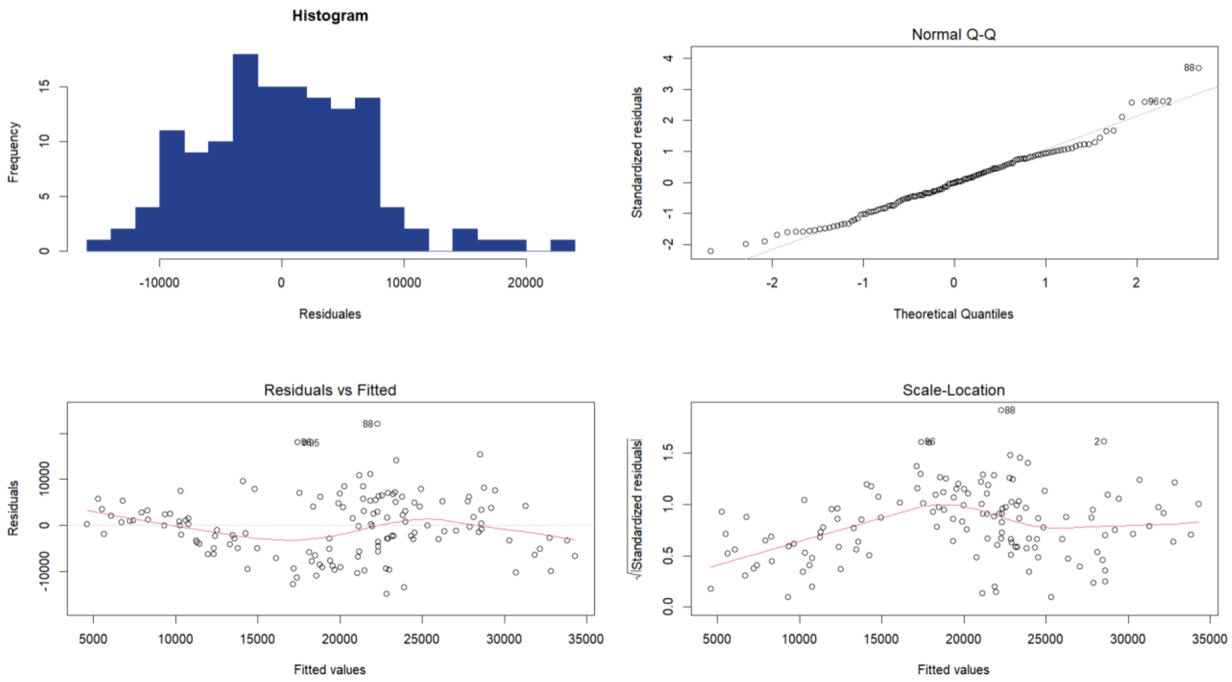
A15 Regression Diagnostics for Model with EFG_D in the Supramax Segment

A15.1 Multicollinearity Matrix



	FuelPrice	Boom	DWT	Age	Age_sq	Flag_D	Japan_D	Electronic_D	Scrubber_D	EFG_D	Period	Forward	Atlantic_D
FuelPrice	1.00	-0.18	0.12	0.10	0.07	-0.10	-0.08	0.05	-0.07	-0.17	0.03	0.18	0.27
Boom	-0.18	1.00	-0.10	0.11	0.14	-0.06	0.03	0.09	-0.12	-0.07	0.08	-0.03	0.02
DWT	0.12	-0.10	1.00	-0.52	-0.55	0.19	-0.35	0.10	-0.02	-0.11	0.08	0.03	-0.13
Age	0.10	0.11	-0.52	1.00	0.98	-0.07	0.14	-0.39	-0.01	0.05	-0.04	0.15	0.23
Age_sq	0.07	0.14	-0.55	0.98	1.00	-0.06	0.16	-0.30	-0.01	0.03	-0.05	0.12	0.24
Flag_D	-0.10	-0.06	0.19	-0.07	-0.06	1.00	-0.07	-0.02	-0.01	-0.06	-0.02	-0.06	-0.04
Japan_D	-0.08	0.03	-0.35	0.14	0.16	-0.07	1.00	0.24	-0.05	-0.21	0.06	0.11	-0.05
Electronic_D	0.05	0.09	0.10	-0.39	-0.30	-0.02	0.24	1.00	-0.04	-0.19	0.05	-0.01	0.12
Scrubber_D	-0.07	-0.12	-0.02	-0.01	-0.01	-0.01	-0.05	-0.04	1.00	-0.04	-0.12	-0.06	0.03
EFG_D	-0.17	-0.07	-0.11	0.05	0.03	-0.06	-0.21	-0.19	-0.04	1.00	0.04	0.02	0.07
Period	0.03	0.08	0.08	-0.04	-0.05	-0.02	0.06	0.05	-0.12	0.04	1.00	0.30	-0.08
Forward	0.18	-0.03	0.03	0.15	0.12	-0.06	0.11	-0.01	-0.06	0.02	0.30	1.00	0.13
Atlantic_D	0.27	0.02	-0.13	0.23	0.24	-0.04	-0.05	0.12	0.03	0.07	-0.08	0.13	1.00

A15.2 Residual Diagnostics



A15.3 Squared Scaled GVIF Values