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Forecasting and Hedging in the Ship Recycling Market

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FORECASTING AND HEDGING IN THE SHIP RECYCLING MARKET

Master Thesis

by

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ABSTRACT

This study examines the accuracy and hedge effectiveness of different static models to forecast and hedge ship demolition prices. Nine international forecasting variables and six futures contracts relevant in the ship demolition market are used in a Vector Error Correction Model, Error Correction Model, and Auto Regressive Moving Average model to perform this analysis. Out of sample results for the ECM using the Chinese iron ore index had the most accurate out of sample forecast accuracy. All models had low hedge effectiveness. Based on the study, regional variables and dynamic models are recommended for improved forecasting and hedging models which would address basis risk between spot and futures prices and changing correlation between variables over time.

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List of Abbreviations

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List of Symbols

Symbol	Description
v , u	Error term/Residual
λ	Parameter for Johansen test
τ	Autocorrelation coefficient
c, a	Constant (intercept)
F	Parameter for futures contracts
g	Length in a row and/or column
h	Hedge ratio
k	Number of lags in a VECM or ECM
ℓ	Slope Coefficient of Speed of Adjustment
m	Maximum number of lags
p	Number of lags in AR term
q	Number of lags in MA term
r	Number of cointegration vectors
T	Total sample size
t	Parameter for time
X	Parameter of explanatory variable
y	Parameter of dependent variable
β	Slope coefficient
γ	Cointegration coefficient
Γ	Parameter for coefficients of lagged values
Δ	Parameter for change
δ	Slope Coefficient of a time trend
θ	Slope coefficient in MA term
$\mathrm{I}(.)$	Integration of order $(.)$
Π	Parameter for a Long-run Cointegration matrix
ϕ	Slope coefficient in AR term
ψ	Unit root in an ADF test
ω	Cointegration vector

Variables	Description
B	The Baltic Tanker Index
C	ClarkSea Index
D	Demolition price
E	VLCC Earnings
IO	Iron Ore price
N	Nickel prices
O	Crude Oil prices
RD	Indian Rupee and US dollars exchange rates
S	Scrap Metal prices

Futures contracts	Description
Clc	Oil futures
CP	Iron Ore futures
HR	Hot rolled coil steel futures
M	Steel Scrap Futures contracts
NI	Nickel futures
SR	Steel rebar futures

1. Introduction & Motivation

1.1 Ship Recycling Industry Background

Although seldom in the limelight, the ship recycling industry plays an important role in the maritime sector. Nearly all ocean-going vessels are recycled once they reach the end of their useful economic life. Even though nearly every vessel is recycled, relatively little financial research covers this aspect of the maritime economy. This thesis aims to add to the body of knowledge in the field of maritime finance by considering different methodologies which can be utilized to forecast the scrap value of the vessel and assessing their accuracy. Additionally, this thesis will evaluate the effectiveness of these models in hedging demolition price volatility. Throughout this thesis the terms “demolition”, “recycling”, and “scrapping” will be used interchangeably to refer to end of life process where a vessel is dismantled. Before outlining the specific methodologies utilized in this thesis, an overview of the ship recycling industry is provided including a brief observation on the size of the industry and where ship recycling fits into the global scrap metals market.

1.2 Size of the Market

Though ship recycling produces only a small percentage of global steel scrap metal, the industry has tremendous importance in a concentrated set of developing economies. According to Merikas, Merika, and Sharma (2015), the ship recycling industry supplies nearly 1.5% of the raw material used by the global steel industry; however, most ship recycling activity occurs in only 5 developing countries: Bangladesh, India, China, Pakistan, and Turkey. These countries rely on imported steel scrap via vessel demolition to fuel their domestic steel, construction, and manufacturing industries. To gain a sense of the magnitude of steel scrap produced by vessels and the number of commercial vessels which have been recycled, between January 2000 and August 2020 nearly 15,000 vessels were recycled which produced 575 million Dead Weight Tons (DWT) worth of scrap steel according to Clarkson’s database (2020). Appendix 1 shows where these recycling activities occurred based on the percentage of total vessels recycled over time and total DWT produced.

Over the last 20 years, India recycled the greatest number of vessels and was the second largest producer of total scrap weight. Given India's importance in the ship recycling industry, this thesis selected to focus solely on ship demolition in India. Moreover, the analysis focuses on Indian demolition prices of Very Large Crude Carrier (VLCC) vessels since these types of ships held the great overall scrap value compared to other vessel types. Appendix 2 provides a table of the aggregate nominal scrap value based on ship type from 2000 to 2020 to illustrate this point.

1.3 Vessel Recycling in the Scrap Metal Market

Within the main 5 countries where vessels are demolished, most of the steel scrap is reused in industries located in the same country. Very little steel scrap from vessels is exported once the vessel is dismantled. According to Stopford (2009), the metal produced by vessels during the recycling process are prime inputs into the steel industry which can heat and re-roll the steel into rods which are used in the construction industry. According to the London Metal Exchange (LME), most scrap is purchased by Electric Arc Furnaces (EAF) operators where scrap-metal can represent up to 70% of steel production costs (2015). Stopford (2009) goes on to claim that steel scrap, including the scrap produced by ship demolition, is a critical element in the growth of the 5 developing countries where ship recycling is located.

1.4 Residual Vessel Value

For certain vessel owners, the scrap value can represent a significant percentage of the overall value of the vessel. Alizadeh and Nomikos (2009) explains this concept using a discounted cash-flow model in which the scrap value of the vessel is represented as the residual value of the asset. For older vessels which have a short useful economic life, the residual value of the vessel could reflect a substantial percentage of the overall value of the vessel. As such, methodologies which accurately forecast and hedge the scrap value of a vessel are highly relevant to these market participants. Clarkson's Research (2016) illustrates the importance of the scrap (residual) value for older vessels which tend to have shorter useful economic lives than new-build vessels by taking the ratio of the second-hand prices of vessels over the scrap value of the vessels as shown in Appendix 3.

Based on the Clarkson study, the scrap value of the vessel oscillated between nearly all to one eighth of the vessel's value depending on the age of the vessel and market forces discussed in later sections. Given the large portion of total asset wealth represented by the scrap value, the need to manage terminal value price risk is important for vessel owners and asset managers with older vessels in their fleet. Although there are many maritime stakeholders which would be interested in forecasting ship demolition values and hedging demolition price risk, the primary audience of this thesis is shipowners that have a large exposure to older vessels. For this audience, forecasting the scrap value of their vessels is a critical variable in determining whether to sell, lay-up or scrap a vessel during a down-turn in the shipping market.

1.5 Motivation

There are two primary motivations for this research: 1) assess the accuracy of different models which can be used to forecast ship demolition prices and 2) determine the hedge effectiveness of these same models. If found successful, ship owners, ship recyclers, and maritime insurance companies may be able to utilize this methodology to predict demolition price movements and reduce the price volatility associated with the end of a vessel's life. Such a methodology could be commercialized and adopted by the maritime industry, specifically the segment which focuses on the sale and purchase of vessels in the secondary vessel market.

Although important, this thesis will not investigate any of the technical matters associated with ship recycling nor discuss the different ways that a vessel can be dismantled once it has reached the end of its useful economic life. Also, this thesis will not consider the social-economic factors which are often associated with the ship demolition industry such as human rights violations, poor and unsafe working conditions, or environmental harm or degradation. These factors are certainly important and should be considered alongside the financial observations made in this thesis.

1.6 Summary of Findings and Organization

This thesis uncovers that the Error Correction Model (ECM) using iron ore spot prices as the dependent variable has the lowest out of sample Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) while the Naïve forecast has the lowest Mean Error (ME) and Tracking Signals (TS). One of the reasons this model performed better than the Vector Error Correction Model (VECM), the presumed superior model, can be attributed to high periods of volatility during the in-sample period. The hedging analysis conducted in the latter half of the thesis found that all models performed poorly and did little to reduce demolition spot price risk. These results are attributed to large basis risk stemming from location and grade differences between the spot and futures contracts as well as changing correlation between the spot and futures prices over time.

The thesis is organized as follows: Section 2 provides the literature review, Section 3 formalizes the research question, Section 4 provides an overview of the theory and methodology used, Section 5 discusses the two data sets used in the study, Section 6 contains the results of the forecasting analysis, Section 7 contains the results of the hedging analysis, and Section 8 concludes the thesis.

2. Prior Literature

A broad literature review on forecasting and hedging in the ship demolition industry indicates that most research in this field has focused on developing supply and demand models which predict whether a vessel will be demolished and econometric models which forecast ship demolition prices. Very little has been written on ship demolition price hedging methodologies. This literature review uses previous studies on the ship demolition market to inform the development of forecasting and hedging models in this thesis. Relevant topics reviewed can be broadly grouped into 3 sub-topics: i) supply and demand factors affecting the ship demolition market, ii) methods of forecasting ship demolition prices, and iii) financial hedging techniques.

2.1 Supply and Demand Factors

Most literature on the ship recycling industry is focused on supply and demand factors affecting a ship owners' decision to recycle a vessel. Often authors use an equilibrium approach to study underlying economic signals which drive a shipowner's decision. Buxton (1991) was one of the first authors to explore supply and demand factors governing the ship recycling industry by looking at the revenue and cost factors which go into the vessel demolition decision making process. Although Buxton (1991) did not extend these findings to forecast ship demolition prices, the study informed several other studies on the ship demolition industry. Many of the variables selected in the forecasting study were influenced by the underlying economic rationale presented in Buxton's work.

One such study informed by Buxton's (1991) work is Mikelis' (2008) summary of ship demolition statistics prepared for the International Maritime Organization (IMO). Within his work, Mikelis (2008) indicates that vessel size, age, weighted average earnings per day, Baltic freight indexes, and ship demolition prices are relevant to International Maritime Organization (IMO) decision makers when making global ship recycling policies. Mikelis' (2008) work influences this thesis by providing economic rationale for the variables selected to forecast ship demolition prices.

Knapp et al. (2008) built on the works of Buxton (1991) and Mikelis (2008) by developing a model which estimated the probability that a vessel would be recycled. Their work used close to 120 different signals to forecast the probability a vessel would be demolished by employing a binary logistics regression for each of the five major scrapping locations around the world (India, Bangladesh, China, Turkey, and Pakistan). The variables used in the logistics regression were grouped into 5 categories including economic data (e.g. vessel earnings, second hand prices and new-build prices), demolition data (e.g. location and demolition prices), ownership data (e.g. flag and classification society), ship safety data, and historic safety performance. Knapp et al. (2008) found that vessel earnings have a negative relationship with the decision to recycle a vessel and suggests that there may be a negative relationship between vessel earnings and ship demolition prices. Knapp et al.'s study also supports the concept that the economic life of the vessel is of greater important to the recycling decision than the physical age of the vessel. This study also uses the economic rationale from Knapp et al. (2008) to inform variable selection in the forecasting analysis of this thesis.

Alizadeh and Nomikos (2009) utilized the observations from Knapp et al. (2008) to illustrate that vessel earnings and the residual value of the vessel, either the secondhand price or demolition value, are both related to vessel pricing by applying the classic dividend discount model to vessel valuation. The observations made by Alizadeh and Nomikos (2009) further supported the decision to include ship secondhand prices in the forecasting analysis in this thesis. This decision was based on Alizadeh and Nomikos' (2009) assertion that vessel owners consider freight rates (current and expected), secondhand prices and demolition prices on whether vessel owners operate, lay-up, sell or demolish their vessels. Given that both secondhand prices and demolition prices affected the overall value of the vessel, it was reasonable to include vessel secondhand prices in the forecasting model in this thesis.

Açık and Başer (2017) looked specifically at the relationship between freight revenue and ship disposal decisions using a simple Ordinary Least Squares (OLS) regression of the log changes in the Baltic Dry Index (BDI), an indicator of freight rates by bulker vessels, and the log changes in the global tonnage of ship scrap metal. Their results confirm the negative relationship between vessel earnings and the decision to scrap vessels pointed out by Knapp et al. (2008). This thesis used Açık and Başer's compelling rationale to use the Baltic Tanker Index (BTI), a corollary to the BDI for tanker vessels, to represent tanker earnings when forecasting ship demolition prices in the tanker market.

2.2 Forecasting Ship Demolition Prices

The second body of literature is centered on studies specifically focused on forecasting ship demolition prices. Kagkarkis, Merikas and Merika's (2016) were some of the first authors to formally develop econometric models which forecast ship demolition prices. Using international steel-scrap prices, demolition prices for tanker vessels, brent crude oil prices and the exchange rate between Indian rupees and US dollars (INR/USD), the authors compared the forecasting ability of a Vector Autoregressive (VAR), Autoregressive Moving Average (ARMA), random walk, and linear trend model to forecast tanker ship demolition prices. The study found that the VAR model produced the most accurate results out of sample when comparing the Theil coefficient and RMSE to the other models. The authors also used a Granger causality test, impulse response analysis and variance decomposition to find that a one-directional causal relationship existed between international steel-scrap prices and ship-demolition prices. The work of Kagkarkis, Merikas and Merika (2016) heavily influenced the forecasting analysis in this thesis by providing economic insight into which variables could be utilizes in forecasting as well as intuition into econometric methodologies which would be appropriate in ship demolition forecasting. One factor that Kagkarkis, Merikas and Merika's (2016) work did not consider; however, is the possibility that the signals utilized in the forecasting model are cointegrated. This relationship is explicitly considered in this thesis which uses an ECM and VECM which accounts for long-run relationships between forecasting variables.

A study by Karlis, Polemis, and Georgakis (2016) supports Kagkarkis, Merikas and Merika's (2016) decision to use local exchange rates in forecasting ship demolition prices. Within their work, Karlis, Polemis, and Georgakis (2016) examine the statistical significance of coefficients produced by a simple OLS linear regression which regresses average ship demolition prices by size against currency exchange rates in China, India, Pakistan, and Bangladesh. The authors found that labor costs, proxied by the local exchange rate to the US dollar, is inversely related to ship demolition prices in most of the major ship recycling countries and influenced the decision to include local exchange rates as a forecasting variable in this study.

One of the most recent studies in the field of ship demolition forecasting was produced by Andrikopoulos et al. (2020) who built on the models established by Kagkarakis, Merikas, and Merika (2016) to further explore the relationship between macroeconomic variables and ship demolition prices. Specifically, Andrikopoulos et al. (2020) used international steel-scrap prices, nickel prices, crude oil prices, different measures of seaborn trade, and demolition prices grouped by vessel size in a VECM to test the explanatory power of the different variables in predicting ship demolition prices. These authors found that there were several long-run relationships between the explanatory variables and ship demolition prices and reasoned that these commodities are critical to the growth of developing countries where ship demolition occurs. The study conducted by Andrikopoulos et al. (2020) is novel in that it was one of the first to document nickel’s relationship with ship demolition prices through a Granger causality test as well as using the VECM to account for cointegrating relationships between variables. Andrikopoulos et al. (2020) like Kagkarakis, Merikas, and Merika (2016) point out that the VAR and VECM allow researchers to avoid the need to categorize variables as either endogenous or exogenous and is a compelling reasons why these model are used in this study.

This study compliments the work performed by Andrikopoulos et al. (2020) since it focuses on forecasting ship demolition in Indian while Andrikopoulos et al. (2020) focused on the demolition market in Bangladesh. One major different between this study and the one conducted by Andrikopoulos et al. (2020) is that this study focuses solely on VLCCs, which is a specific size of tanker vessel, while Andrikopoulos et al. (2020) focused on broader types of vessels (e.g. bulkers, tankers, and cargo carriers). Another major difference is that this study combines variables suggested by other studies described in the literature such as local exchange rates and secondhand prices. Finally, this study is one of the first published work to propose a hedging methodology for demolition price risk which was informed by the models and variables used in the first part of the thesis.

2.3 Hedging Price Risk

The body of knowledge on general risk management techniques and hedging is tremendous. To develop a foundational understanding of hedging techniques, several classical influential studies were reviewed. Keynes (1930) is perhaps one of the more well-known authors to document the use of futures contracts by hedgers to reduce price risk. The rationale behind this fundamental work is one of the underlying reasons why liquid futures contracts are used as hedging instruments in the study. Building on the works of Keynes (1930), Johnson (1960) and Stein (1961) utilized portfolio theory to calculate optimal hedge ratios which minimized the variance of a portfolio of spot and future contracts. Edrington (1979) added to the works of Johnson (1960) and Stein (1961) by applying simple univariate and multivariate regressions in minimizing the variance of a portfolio of assets. Specifically, Edrington (1979) showed that Government National Mortgage Association (GNMA) and T-bill futures were effective in hedging cash (or spot positions) in the GNMA or T-bill market. This study leverages the insight provided by Johnson (1960), Stein (1961), and Edrington (1979), by taking the same variance minimizing portfolio concept and applying this concept to more advanced regression techniques. Another specific insight offered by Edrington (1979) is the explicit definition of hedge effectiveness which is used to compare the effectiveness of the different hedging models and further specified in the methodology section.

One of the first to propose the use of the ECM in hedging was Ghosh (1993) who argued that the price-level hedge ratio proposed by Johnson (1960), Stein (1961), and Edrington (1979) were mis-specified because they do not include an error correction term and ignore lagged values which affect the short run dynamics of the hedge model. Ghosh (1993) argued that the ECM which employs the Engle and Granger (1987) two step method to detect long-run equilibrium relationships between changes in futures and changes in spot prices was a preferred static hedging model. The author illustrated his points by using Standard and Poor's 500 (S&P500) futures contracts to hedge position in the S&P500 index, Dow Jones Industrial Average (DJIA), New York Stock Exchange (NYSE) composite index. Using the adjusted R^2 value as a measure of hedge effectiveness, Ghosh (1993) found the ECM produced higher adjusted R^2 over the simple OLS regression when hedging positions in all three indices. This study finds the assertions made by Ghosh (1993) to include an error correction term in the regression to correct for long-run relationships compelling and utilize the ECM within this study as one of the comparative hedge models.

Using the foundational groundwork laid by the authors above, there is a sub-body of knowledge which focuses on hedging and risk management in the maritime industry. Alizadeh and Nomikos (2009) provide a comprehensive overview of maritime risk techniques which was referenced throughout this thesis. According to Alizadeh and Nomikos (2009), most maritime hedging studies have been focused on risk management in the freight, new-build, and secondhand vessel market. To date, no formal academic study has been conducted on hedging techniques in the ship demolition market though several industry trade magazines and white papers, like the one published by Glawion (2020), suggest such techniques are possible. For example, Alizadeh and Nomikos (2009) suggests that demolition prices published in shipping information databases like Clarksons Shipping Intelligence Network (CSIN) and the Baltic Exchange could be used to specify over the counter contracts to hedge the residual value of vessels. An additional contribution by Alizadeh and Nomikos (2009) to this work is the observation that ship demolition prices are closely linked to world steel scrap prices. This observation influenced the decision to include steel scrap futures contracts traded on the London Metal Exchange as potential hedging contracts which is further specified in the data section of this thesis.

Given a comprehensive overview of the literature published on forecasting and hedging in the ship demolition market, the next section fully specifies the research question explored in this thesis.

3. Research Question

This analysis assesses which of the following static forecasting methodologies produces the most accurate ship demolition prices in an out-of-sample test: ECM, VECM, ARMA**,** or a Naïve model. Both the theory and methodology for these models are provided in Section 4 (Methodology & Theory). The forecasting variables used to parameterize these models are fully described in Section 5 (Data). Given the similar structure of the forecasting and hedging models, this thesis also tests the hedge effectiveness of the ECM, VECM and Naïve models where tradeable futures contracts are use in lieu of the forecasting variables. The model with the best static hedge will produce the greatest hedge effectiveness. Theory suggests that an in-sample set of data should be used to parameterize the forecasting and hedging models, and an out-of-sample set of data should be used to test the accuracy / hedge effectiveness. To test the accuracy of the forecasting models, the out of sample RMSE, MAE, ME and TS will be compared amongst the different forecasting models. Similarly, the hedge effectiveness which measures the total variance reduction provided by the combined spot and hedge positions will be used to assess which model provides the best hedge. Given the concise objective of the thesis above, the next section discusses the different methodologies used to explore these questions.

4. Methodology & Theory

The methodology section outlines the procedures used to forecast and hedge demolition spot prices in the ship recycling industry. Each subsection specifies whether a technique was used in the forecasting analysis, hedging analysis or both since many of the same techniques are used in each analysis. Within the forecasting section, explanatory variables suggested by Andrikopoulos et. al (2020) and Kagkarakis, Merikas, and Merika (2016) were utilized given their economic importance in the ship recycling industry. The hedging section uses comparable futures contracts which match the variables used in the forecasting section. Since several long-run, cointegrating relationships were found in the explanatory variables in the forecasting and hedging section, the ECM and VECM were utilized to forecast and hedge ship demolition prices. Additionally, a de-trended ARMA is used in the forecasting section and a naïve hedge is used in the hedging section as comparative models to the ECM and VECM. Finally, the forecast accuracy of the different models is measured and using the RMSE, MAE, ME, and TS and the variance reduction in the hedging section is measured and compared using the hedge effectiveness.

4.1 Rationale for Model Selection

One of key characteristics underlined by recent studies in the ship demolition market is the presence of long-run cointegrating relationships between the variables considered in this study. The ECM was selected for both the forecasting and hedging analysis because the presence of a single long-run cointegrating relationship creates a straightforward economic story that can be conveyed to practitioners. One of the major drawbacks of the ECM; however, is that only one cointegrating relationship can be illustrated within the error correction term. This issue is addressed by the more computationally complex VECM which allows an econometrician to prove multiple cointegrating relationships between groups of variables. This is particularly useful when the forecasting and hedging variables are concentrated in specific industrial sectors such as shipping and metal processing. The ARMA model was selected as a basis of comparison in the forecasting section given its flexibility in modeling a wide range of financial time-series (Brooks, 2019). Finally, the naïve hedge was selected for a basis of comparison in the hedging section since it represents a default hedging approach where no specific insight is applied. Given its simplicity, it can be viewed as a minimum acceptable standard by which to measure hedge effectiveness. The next several sections provide the general forms of the forecasting and hedging models.

4.2 Model Specification for Forecasting

The subsections below describe the models used in the forecasting and hedging analysis. This section describes the models in their general form. Later sections of the methodology describe the steps used to further specify these models leading to the ones used in the forecasting and hedging analysis. The forecasting analysis uses the ECM(k), VECM(k) and a de-trended ARMA(p, q) model.

4.2.1 The Error Correction Model

The first model considered in both the forecasting and hedging analysis is the ECM. To define the ECM, one starts with a regression of the level values of the variables as shown in Equation (1).

$$D_t = a + \beta_1 X_t + u_t \tag{1}$$

In equation (1), D_t is the demolition spot price and X_t is a single explanatory variable, which is defined further in Section 5 (Data), a is a constant and u_t is the residual. If both the explained and explanatory variable contain a unit root, then Equation (1) is lagged by one time step and re-arranged as provided in Equation (2).

$$u_{t-1} = D_{t-1} - a - \gamma X_{t-1} \tag{2}$$

In equation (2), γ is the cointegrating coefficient. Finally, the lagged residual term (u_{t-1}) from Equation (2) is included in the ECM to reflect the long-run relationship between D_t and X_t as illustrated in Equation (*3*).

$$\Delta D_t = c + \beta_1 \Delta X_{t-1} + \beta_2 (u_{t-1}) + \beta_3 \Delta D_{t-1} + v_t \tag{3}$$

In Equation (*3*), c is a constant, Δ represents the change in the price and v_t is an error term. $\beta_2(u_{t-1})$ is the Error Correction Term (ECT) and represents the cointegrated, long-run relationship between the ship demolition prices and the explanatory variables. One of the limitations of the ECM is that only one cointegrating relationship can be modeled at a time. The next model, the VECM, uses similar regression concepts as the ECM but allows for multiple cointegrating relationship in the same expression.

4.2.2 The Vector Error Correction Model

The next model considered is the VECM which is a generalized form of the ECM which allows for multiple cointegrating relationships between sets of variables. Equation (4) provides the general form of the VECM (Brooks, 2019).

$$\underset{(g\times 1)}{\Delta y_t} = \underset{(g\times 1)}{c} + \underset{(g\times g)}{\Pi}\underset{(g\times 1)}{y_{t-k}} + \sum_{i=1}^{k} \underset{(g\times g)}{\Gamma_i}\underset{(g\times 1)}{\Delta y_{t-i}} + \underset{(g\times 1)}{v_t} \tag{4}$$

Using similar concepts to the ECM, the VECM represents a generalization of the ECM which uses a system of equations to describe the long-run relationship between multiple variables. In Equation (4) g represents the number of variables in the system that are integrated of order I(1), c represents a $g \times 1$ vector of intercepts and ΔY_t represents $g \times 1$ vector of variables which includes both the explained and explanatory variables, $\Delta Y_t = [\Delta D_t, \Delta X_t]^T$. Π is a $g \times g$ long-run, cointegration matrix where the rank of Π represents the number of cointegrating vectors that are present in the system. The combined term $\Pi\, y_{t-k}$ represents a $g \times 1$ vector of ECTs. $\sum_{i=1}^{k} \Gamma_i\, \Delta y_{t-i}$ represents a $g \times 1$ vector of lagged terms in the system and v_t represents a $g \times 1$ vector of error terms. It is possible to factor the cointegration matrix, Π, into two different sets of matrices shown in Equation (5).

$$\Pi = \ell\omega' \tag{5}$$

In Equation (5), ℓ is the matrix representing speed of adjustment from short term dynamics to the long-run cointegrating relationship given by the matrix ω. For a well specified VECM, the terms in the ℓ matrix are usually negative and statistically significant to reflect that the model reverts to its long-run relationship over time. The results and discussion section of this thesis will consider whether the forecasting and hedging models produce ECTs which are statistically significant.

4.2.3 The Autoregressive Moving Average (ARMA) Model

To serve as a basis of comparison, the ARMA model was tested against the ECM and VECM in the forecasting section of the analysis. Equation (6) provides the general form of the ARMA(p, q) with a time trend.

$$D_t = c + \sum_{i=1}^{p} \phi_i D_{t-i} + \sum_{i=1}^{q} \theta_i u_{t-i} + \delta t + v_t \tag{6}$$

In Equation (6), p represents the number of lags present in the Autoregressive (AR) term, $\sum_{i=1}^{p} \phi_i D_{t-i}$, and q represents the number of lags in the Moving Average (MA) term, $\sum_{i=1}^{q} \theta_i u_{t-i}$. As in previous expressions, c represents the regression constant. The term δt represents the time trend where δ representing the slope of the time trend and t represent the time since the start of the data series. Finally, v_t represents the error term. To assist in programming the regression into regression analysis software (e.g. MATLAB), it is possible to "de-trend" the expression above by subtracting the time trend term from both sides of the expression as shown in Equation (7).

$$D_t - \delta t = c + \sum_{i=1}^{p} \phi_i D_{t-i} + \sum_{i=1}^{q} \theta_i u_{t-i} + \varepsilon_t \tag{7}$$

4.2.4 The Naive Model

The VECM, ECM, and ARMA forecasting model are compared against a random walk, hereafter referred to as the "Naïve" model. Pedregal (2019), describe this technique as simply using the most recent observation at time, t, as the forecasted result for the next period. An illustration of this simplified methodology is provided in Equation (*8*).

$$E[D_{t+1}] = D_t \tag{8}$$

4.3 Unit Root Test

The first set of diagnostics tests ensures that the time-series used in the forecasting and hedging analysis are integrated of the same order to avoid spurious results generated from a mismatch in integration orders. To ensure time series are integrated of the same order, the Augmented Dickey-Fuller (ADF) test is utilized in both the forecasting and hedging section of the thesis to investigate whether a unit root is present in the time series. The null hypothesis of the ADF test, H_0, indicates a unit root is present in the time series $(\psi = 1)$ while the alternative hypothesis, H_1, indicates that the series is stationary $(\psi < 1)$. If the null hypothesis is not rejected, the first difference of the time series is taken until the test rejects the null hypothesis. To determine the number of lags included in the test, the Bayesian Information Criteria (BIC) is utilized. When testing the variables used to specify the ECM and VECM, a constant is utilized in the ADF test but not a time trend term as shown in Equation (9) below (Fuller, 1976).

$$\Delta y_t = c + \psi\, y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + v_t \tag{9}$$

In Equation (9), y_t refers to all variables, both the explanatory and explained variables, in the forecasting and hedging data sets, $\Delta y_t = \{\Delta D_t, \Delta X_t\}$. Section 5 (Data) provides a full description of the variables used. In Equation (9), c is the constant term, p are the number of lags in the AR term, ($\sum_{i=1}^{p} \phi_i y_{t-i}$), and v_t is the error term. If the ADF test indicates the presence of a unit root in the time series, then the first difference will be taken and the ADF test will be performed again to ensure that the time series is integrated of order 0.

For the ARMA model, an additional test is performed to detect the presence of a time trend in ship demolition prices. First, the ADF test is conducted on the level using the regression shown in Equation (9). If the test fails to reject the null hypothesis, then the test is repeated with a time trend term, δt, included as shown in Equation (10) below (Fuller, 1976).

$$\Delta y_t = \mathrm{c} + \psi\, y_{t-1} + \delta t + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + v_t \tag{10}$$

If the test rejects the null hypothesis after including a time trend term, then there is strong evidence that a time trend exists in the demolition price time-series. Later sections show that the demolition spot price is "detrended" by subtracting the time trend from both sides of the ARMA equation before the regression is performed.

4.4 Information Criteria

The information criteria provided by the BIC was selected to designate the number of lags in the hedging and forecasting model because, according to Brooks (2019), BIC tends to provide models that do not provide an overabundance of parameters compared to other information criteria like the Akaike Information Criteria (AIC) which provide "too large a model". It is desirable to balance the number of parameters with the accuracy provided by each parameter since too many parameters could lead to over-fitting and poor forecast accuracy and hedge effectiveness in the out of sample tests.

4.5 Heteroskedasticity

The next diagnostic test performed is the Engle Autoregressive Conditional Heteroscedasticity (ARCH) test to detect conditional heteroskedasticity in the residuals. According to Engle (1982), heteroscedasticity is a condition where the variance of the residual is not consistent over the entire test period. Brooks (2019) notes that when heteroskedasticity is present the regressors still produce unbiased coefficient estimates, but "they are no longer Best Linear Unbiased Estimators (BLUE)" and "they no longer have the minimum variance among the class of unbiased estimators". This suggests that the standard errors of the regression coefficients will be incorrect and misleading. As stated by Engle (1982), the test is performed by regressing squared residuals against lags of itself. Under this testing procedure, the null hypothesis of the Engle ARCH test is that no conditional heteroskedasticity exists against an alternative hypothesis that conditional heteroskedasticity exists. To conduct hypothesis testing, the Lagrange multiplier test statistic is utilized, TR^2, where T is the sample size and R^2 is the coefficient of determination from a regression of the squared residuals onto lags of itself (Brooks, 2019). The test statistic measured against a critical value derived from the Chi-squared distribution.

Since the forecasting part of the thesis is focused on assessing the accuracy of different forecasting models and less concerned about the standard errors of the regression coefficients, heteroskedasticity is of secondary concern for the forecasting analysis. Heteroskedasticity becomes important; however, when comparing the hedge ratios produced by the regressions of the different hedge models. Given this delineation, the Engle ARCH test is used to test for heteroskedasticity in the hedging section but not the forecasting section.

4.6 Autocorrelation

After testing for heteroskedasticity, the Ljung-Box Q-test is used to test for autocorrelation. According to Brooks (2019), autocorrelation is a condition where the current values of residuals are corelated with previous residuals. Brooks (2019) notes, "the consequences of ignoring autocorrelation when it is present are like those of ignoring heteroscedasticity. The coefficient estimates derived using OLS are still unbiased, but they are inefficient, i.e., they are not BLUE, even at large sample sizes, so that the standard error estimates could be wrong". Using a similar argument as the section above, since the standard errors of the regression coefficients are of secondary importance in assessing the accuracy of different forecasting models but primary importance in the hedging section, the Ljung-Box Q test for autocorrelation is used in the hedging section but not in the forecasting section.

To conduct the Ljung-Box Q test, a certain number of lags of the residual are selected to test for autocorrelation. According to Ljung and Box (1978), the null hypothesis is that the residuals do not exhibit autocorrelation and the alternative hypothesis is that autocorrelation exists within the residual lags. The test statistic for the diagnostic test is given in Equation (11).

$$Q^{*} = T(T+2)\sum_{k=1}^{m}\left(\frac{\hat{\tau}_k^2}{T-k}\right) \quad (11)$$

In Equation (11), $\hat{\tau}_k$ denotes the autocorrelation coefficient at lag k, T is the sample size and m are the maximum number of lags. This test statistic is measured against a critical value which is generated from the Chi-squared distribution.

4.7 Adjustments for Heteroskedasticity and Autocorrelation

If heteroskedasticity and autocorrelation is detected in the residuals, Brooks (2019) suggests reducing the measure of size of the variables by taking the first difference. Since most econometric data is transformed into first differences to adjust for the present of a unit root, this data transformation should reduce the effects of heteroskedasticity and autocorrelation. Brooks (2019) suggests that such a transformation will reduce the effects of extreme outliers.

4.8 Multicollinearity

After addressing heteroskedasticity and autocorrelation in the residuals, another consideration is multicollinearity within the explanatory variables in both the forecasting and hedging analysis. According to Brooks (2019), multicollinearity occurs when the explanatory variables are highly correlated with one another. One of the issues posed by multicollinearity is that the goodness-of-fit measure, R^2, will be high while the standard errors for the individual regression coefficients will also be high making it difficult to determine which variables contribute most to the goodness of fit.

Brooks (2019) points out that when multicollinearity is present, adding and removing variables may result in large changes in coefficient values which could affect the comparison of the accuracy of the different models. Additionally, multicollinearity could affect the statistical significance of the inferences made regarding the regression coefficients.

Since multicollinearity has a direct impact on the hedging section, it is included in Section 5.5.4 (Multicollinearity) and the steps used to address the multicollinearity are discussed. Comparatively, multicollinearity does not have a direct impact on the forecasting results if the collinearity between the variables is assumed constant over time. For consistency, the tests for multicollinearity are also performed in the forecasting section but the results are included in the appendix. To test for the presence of multicollinearity among the explanatory variables, the Variance Inflation Factor (VIF) and Belsey Collinearity Diagnostic tests are utilized. Each diagnostic test is specified in the subsections below.

4.8.1 Variance Inflation Factor

The relatively straightforward VIF test is used as a basic litmus test to determine if multicollinearity is present among the explanatory variables. According to Brooks (2019), VIF indicates how much larger the variance of a parameter estimate is because of correlation with other explanatory variables. To calculate VIF, one of the explanatory variables is regressed against the other explanatory variables in the model and the R_i^2 of the auxiliary regression is collected. VIF is then calculated for each of the explanatory variables using Equation (12).

$$VIF = \frac{1}{(1 - R_i^2)} \tag{12}$$

According to Brooks (2019), larger values for VIF indicates a stronger presence of multicollinearity. Researchers generally use a threshold between 5 and 10 to determine whether the presence of multicollinearity is high. Since a certain amount of multicollinearity is expected within the dependent variable data sets, a threshold of 10 is utilized which is the default specification in MATLAB (Mathworks, 2021). The next diagnostic test, the Belsley collinear test, will further specific which groups of explanatory variables exhibit multicollinear relationships.

4.8.2 Belsley Collinear Diagnostic test

After using the VIF as a general indicator for the presence of multicollinearity, the Belsley collinearity diagnostic test determines how strong the collinear relationships are between the different dependent variables. The diagnostic test starts by calculating "condition indices" for the group of dependent variables. Condition indices are calculated by the determining the characteristic roots from a **X'X** matrix of the dependent variable time series and taking the square roots of the ratio of successive eigenvalue pairs (IBM, 2014). According to IBM (2014), condition index values greater than 15 indicates a moderate collinear relationship between the explanatory variables. A condition index value greater than 30 indicates a strong collinear relationship among the explanatory variables. MATLAB has a default tolerance of 30 for the conditional index to indicate the presence of multicollinearity and a default tolerance of 0.5 within the variance decomposition columns to indicate the presence of collinear relationships between variables (Mathworks, 2021). These default tolerances will be used to test for the presence of collinear relationships between the explanatory variables.

4.9 Cointegrating Relationships

After searching for the presence of unit roots, heteroskedasticity, autocorrelation and multicollinearity within the time series, the next series of tests are used to determine whether cointegrating relationships exist between variables used in the ECMs and VECM. According to Brooks (2019), if two or more variables are cointegrated there is a long-run equilibrium relationship between these variables. The next two subsections describe the methods used to test for single and multiple cointegrating relationships between variables.

4.9.1 Single Cointegrating Relationships

The Engle and Granger (1987) two-step test for cointegration is utilized to test for a single cointegrating relationship between D_t and each of the other explanatory variables. This test is conducted to determine whether D_t has a single long-run relationship with one of the other signals. The Engle-Granger (EG) two-step method is performed by first regressing the demolition prices (D_t) into each of the other time series in a univariate regression (X_t), collecting the residuals from the regression (u_t), and testing the residuals for the presence of a unit root using the ADF test (Brooks, 2019). The EG test requires that D_t and X_t are integrated of order 1. As described in the ADF subsection, a constant but no time trend is included in the specification of the regression for the ADF test.

4.9.2 Multiple Cointegrating Relationships

To test for cointegration relationships between multiple variables, the Johansen (1990) test for cointegration is utilized. As discussed in earlier sections, Π is the long-run cointegration matrix within the VECM. To fully specify the VECM, it is necessary to find the rank of Π. Johansen and Juselius (1990) propose two different methodologies for finding the rank of Π. Recalling that the rank of a matrix is given by the number of characteristic roots (eigenvalues) that is not equal to zero, the test procedure includes calculating the eigenvalues, placing them in descending order and testing each eigenvalue successively using the two test statistics described below. Each eigenvalue is associated with a different cointegrating vector. As the eigenvalue becomes greater, the test statistic becomes larger indicating a stronger presence of a cointegrating relationship (Brooks, 2019). The first methodology uses the trace of the eigenvalues to determine the rank of the cointegration matrix. The trace eigenvalue is shown in Equation (13).

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_i) \tag{13}$$

The second methodology uses the maximum eigenvalue to determine the rank of the cointegration matrix. Equation (14) provides the expression for this methodology.

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \tag{14}$$

Both test procedures should produce the same rank of the cointegration matrix. In the equations above, r is the number of cointegrating vectors and $\hat{\lambda}$ is the estimated eigenvalue from the long-run cointegration matrix (Brooks, 2019). According to Brooks (2019), "λ_{trace} is a joint test where the null is that the number of cointegrating vectors is less than or equal to r, against an unspecified or general alternative that there is more than r … λ_{max} conducts separate tests on each eigenvalue, and has as its null hypothesis that the number of cointegrating vectors is r against an alternative of $r + 1$". The test is performed successively starting with the test statistic for the largest eigenvalue and moving towards the test statistic with the smallest eigenvalue. Once the hypothesis test fails to reject the null hypothesis, the test progression stops. The test progression used by Brooks (2019) to explain the hypothesis testing using the $\lambda_{\text{trace}}(r)$ and $\lambda_{\max}(r)$ are provided in Table 1.

Table 1: Johansen Trace Hypothesis (Brooks, 2019)

Null hypothesis for both tests	Trace Alternative	Max Alternative
H_0: $r = 0$	H_A: $0 < r \leq g$	H_A: $r = 1$
H_0: $r = 1$	H_A: $1 < r \leq g$	H_A: $r = 2$
$\vdots$	$\vdots$	$\vdots$
H_0: $r = g - 1$	H_A: $r = g$	H_A: $r = g$

The order of the long-run cointegration matrix, Π, is established when the test fails to reject the null hypotheses with increasing values of r. Note that Johansen and Juselius (1990) established a unique distribution of critical values in order to perform the hypothesis testing described above.

4.10 Parameter Stability

After performing the regressions specified above, the stability of the parameters will be confirmed using the Cumulative Sum (CUSUM) test first developed by Brown, Durbin, and Evans (1975). According to Brooks (2019), the CUSUM test normalizes the cumulative sum of the residuals from a sub-sample of the data starting with the beginning of the time series and then recursively adds an observation and repeats the test. The null hypothesis of the test is that the parameters are stable, and the alternative hypothesis is the parameters are unstable indicating the presence of a breakpoint. As additional observations are added, the upper and lower bounds set by the critical value grows. The CUSUM test is traditionally illustrated graphically to assist researchers in locating the approximate period in which the breakpoint occurs. If a breakpoint is present and the parameters become unstable, an assessment is made on where the data set should be truncated to omit the time before the breakpoint.

4.11 Model Evaluation for The Forecasting Analysis

After confirming parameter stability, the ECM, VECM, and ARMA are used in combination with the forecasting data set to forecast the ship demolition prices one month ahead for the in-sample period (August 1998 to December 2018) and out-of-sample period (January 2019 to December 2020) to compare the accuracy of each of the models. Model accuracy is assessed using the following metrics: RMSE, MAE, ME and TS for both the in-sample and out-of-sample periods. Additionally, the AIC and BIC information criteria will be calculated to examine the amount of parameterization of the model. As described in earlier sections, a well-defined model will balance the number of terms, which is penalized by the information criteria, against the accuracy of the model, which is given by the four measures of accuracy, to avoid out-of-sample issues related to overfitting.

In the expressions below, y_{t+1} is the actual demolition price, $\hat{y}_{t+1}$ is the forecasted demolition price, and n is the number of observations. The expression for RME and MAE are provided in Equation (15) and (16).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (y_{t+1} - \hat{y}_{t+1})^2}{T}} \tag{15}$$

$$MAE = \frac{\sum_{t=1}^{n} |y_{t+1} - \hat{y}_{t+1}|}{T} \tag{16}$$

To test whether the forecasting estimates have bias (e.g. the tendency to overestimate or underestimate a parameter), ME metric is utilized as shown in Equation (17).

$$Mean\ Error(ME) = \frac{y_{t+1} - \hat{y}_{t+1}}{T} \tag{17}$$

Finally, to determine if the average bias is acceptable in the forecasting model, TS is utilized as shown in Equation (18).

$$Tracking\ Signal\ (TS) = \frac{\sum_{t=1}^{T} (\hat{y}_t - y_t)}{MAE} \tag{18}$$

According to SCRC SME (2017), a TS between 4 and -4 suggests the forecasting model contains an acceptable level of bias. With the metric for forecast accuracy fully defined, the next sub-section will focus on the metrics used to measure hedge effectiveness.

4.12 Model Specification for The Hedging Analysis

The same general form of the ECM and VECM are used to specify the hedging models with minor adjustments. Instead of using non-tradable forecasting variables, a sperate set of data containing the weekly averages of month-ahead traded futures contracts are used to calculate static hedge ratios from an in-sample period from November 2015 to December 2018. These hedge ratios are then used to offset weekly price movements in the demolition spot price during an out of sample period from January 2019 to December 2020.

4.12.1 The Error Correction Models

To calculate the hedge ratio of the ECM, the residuals are collected from the ECMs, which estimates the changes in the spot price (ΔD_t) and change in the futures price (ΔF_t) as illustrated in Equations (19) and (20).

$$\Delta D_t \ = \ c_1 \ + \ \beta_{11}\Delta F_{t-1} \ + \ ECT_{t-1} + \ u_{D,t} \tag{19}$$

$$\Delta F_t \ = \ c_2 \ + \ \beta_{21}\Delta D_{t-1} \ + \ ECT_{t-1} \ + \ u_{F,t} \tag{20}$$

Using the residuals from Equation (19) and Equation (20), a bivariate regression is performed as shown in Equation (21).

$$u_{D,t} \ = \ c \ + \ \beta u_{F,t} \tag{21}$$

In Equation (21), the beta coefficient (β) is the minimum variance hedge ratio which is calculated as the covariance between residuals divided by the variance in the residuals for the change in futures prices (Brooks, 2019).

4.12.2 The Vector Error Correction Model

The same approach used in calculating the hedging ratio of the ECM is used to calculate the multiple hedge ratios in the VECM. Recall that in the general expression of the VECM, the residuals are presented by an $g \times 1$ vector as shown in Equation (22).

$$\Delta y_t = \Pi \, y_{t-k} + \sum_{i=1}^{k} \Gamma_i \Delta y_{t-i} + u_t, \qquad where\ u_t = \begin{bmatrix} u_{D,t} \\ u_{F1,t} \\ \vdots \\ u_{Fn,t} \end{bmatrix} \tag{22}$$

In this equation, $u_{D,t}$ refers to the residuals from changes in the spot price and residuals $u_{F1,t}$ through $u_{Fn,t}$ are from changes in the futures prices. To find the optimal hedge ratio, a multivariate regression is estimated, as illustrated in Equation (23).

$$u_{D,t} = c + h_1 u_{F_1,t} + h_2 u_{F_2,t} + \cdots + h_n u_{F_n,t} \tag{23}$$

Since multicollinearity could be an issue in a multivariate regression, the same diagnostic tools to test for multicollinearity (correlation matrix, VIF, and Belsley collinearity test) will be used to confirm whether this assumption holds.

4.12.3 The Naïve Model

A naïve hedge is employed in the hedging analysis for comparative purposes. Brooks (2019) describes the naïve approach as a one-to-one relationship in the changes of demolition spot prices to futures prices. The hedge ratio for the naïve model is simply assumed to be 1. Equation (24) illustrates this relationship where ΔF_t represents the change in the futures prices for each of the different hedging instruments.

$$\Delta D_t = \Delta F_t \tag{24}$$

4.12.4 Hedge Effectiveness

In the hedging analysis, portfolio variance and hedge effectiveness (HE) will be the two primary metrics used to compare the different models. Once the hedge ratios have been calculated for each of the different models using the in-sample data, the hedge portfolio is provided in Equation (25).

$$\Delta V_t = \Delta D_t - h\,\Delta F_t \tag{25}$$

In Equation (25), $-h\,\Delta F_t$ is a short position taken to offset changes in the spot price, ΔD_t. The entire portfolio is represented by the symbol, ΔV_t. The variance of the portfolio is given by Equation (26).

$$\mathrm{var}(\Delta V_t) = \mathrm{var}(\Delta D_t) + h^2\ \mathrm{var}(\Delta F_t) - 2 \times h \times \mathrm{cov}(\Delta D_t, \Delta F_t) \tag{26}$$

If the hedge is effective, the variance of the portfolio will be less than the variance of the changes in the spot price. To indicate "how much" variance is reduced, the hedge effectiveness metric is used. Equation (27) illustrates how HE is calculated.

$$HE = 1 - \frac{var(\Delta V_t)}{var(\Delta D_t)} \tag{27}$$

5. Data

This section provides a full description of the two separate sets of data used in the forecasting and hedging analysis. It was necessary to utilize two separate sets of data to balance the length of the data available in the forecasting section against the requirement that traded contracts are utilized in the hedging section. The 9 forecasting variables span nearly 22 years of monthly data and contain a mixture of spot and index values while the 7 hedging variables contain close to 5 years of the weekly average of daily settled futures contracts. In transitioning from the forecasting analysis to the hedging analysis, an attempt was made to utilize futures contracts that had underlying assets which closely matched the underlying assets represented by the forecasting variables. Each subsection in this section provides a description of each of the variables and which data sources were used to obtain the information.

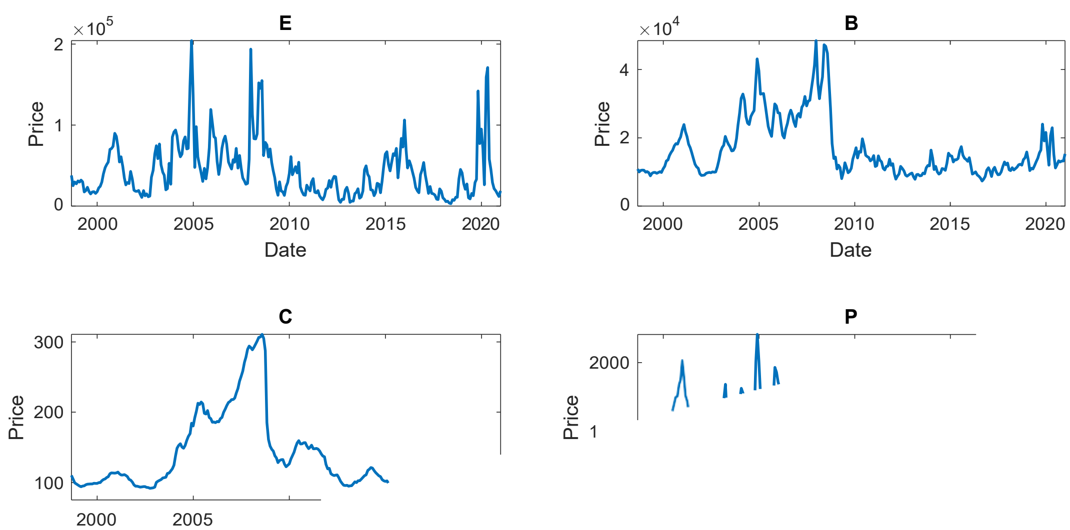
5.1 Data Description of Forecasting Variables

The data set used to forecast ship demolition prices (D_t) encompasses 9 different explanatory variables given in Table 2. For visualization, a time-series plot of the different variables is provided in Figure 1.

Table 2: Forecasting Variables

Symbol	Time Series	Data Source
D	Scrap prices VLCC for India (USD)	Clarksons
S	Producer Price Index: Metals and Metal Products: Iron and Steel Scrap (US)	US FRED
O	Brent Crude Oil Price (USD/BBL)	Clarksons
RD	Exchange rate between Indian rupee & USD (RUP/USD)	Eikon
IO	Iron Ore, Index: China Import Iron Ore Fines 62% FE spot (CFR Tianjin port), US dollars per metric ton (USD/MT)	US FRED
N	Nickel Index: melting grade, LME spot price, CIF European ports, US pr metric ton (USD/MT)	US FRED
B	Baltic Tanker Index (Average of BDTI and BCTI)	Clarksons
E	Average VLCC Long Run Historical Earnings (USD/day)	Clarksons
C	Clarksea Index	Clarksons
P	Secondhand Price Index	Clarksons

Figure 1. Forecasting Variables



As described in earlier sections, the focus of this thesis is on forecasting and hedging the demolition prices for VLCC vessels which are recycled in India. According to Karan (2019), VLCCs are a type of vessel which carry large quantities of crude oil. VLCCs exist within a larger grouping of vessels called "tankers" which are organized by the volumetric displacement measured in DWT. Within the broad category of tanker vessels, VLCCs displace around 320,000 DWT. Alizadeh and Nomikos (2009) point out that demolition prices for different size and displacements of tanker vessels tend to be highly cointegrated and move in the same direction over time. The demolition prices of VLCCs in India were specifically selected since the data series had nearly 50 years of data in the CSIN database. This relatively long period of time enabled the examination of cointegrating relationships with other meaningful economic signals to better forecast ship demolition prices.

The monthly time series for D_t was obtained from CSIN, a database utilized primarily by shipbrokers and vessel operators. Clarksons collects demolition price information by polling large shipbrokers on a weekly basis. The average demolition price for a specific region and vessel type is weighted by the Light Displacement Tons (LDT), which is a vessel's weight after removing cargo, bunkers, and fresh water (Alizadeh and Nomikos, 2009).

One explanatory variable used in the forecasting analysis is international monthly scrap metal prices (S_t) represented by the Iron and Steel Scrap Producer Price Index from the US Federal Reserve Economic Data (FRED). According to Kagkarakis, Merikas, and Merika (2016), a strong correlation relationship exists between ship demolition prices and international steel scrap prices. and Alizadeh and Nomikos (2009) point out that the volatility of ship demolition prices and steel scrap prices are linked. Based on the assertions of these authors, there was compelling evidence that international steel scrap prices would be an appropriate forecasting variable for ship demolition prices.

Another forecasting variable used to predict ship demolition prices was monthly average Brent Crude Oil Prices (O_t) represented in US dollars per barrel (USD/BBL) taken from CSIN. Andrikopoulos et. al, (2020) claim that international crude oil prices are a suitable signal to forecast ship demolition prices since both oil and steel scrap are necessary inputs in the growth of developing nations like India. It was reasoned that international oil prices would be a suitable proxy for overall economic growth in the developing nations where ship demolition occurs.

The monthly average exchange rate between Indian Rupee and US dollars (RD_t), taken from the Eikon database, was used as an additional forecasting variable. Karlis, Polemis, and Georgakis (2016) claimed that RD_t is a proxy for labor costs in the ship recycling industry. In their study, the authors established a linear relationship between exchange rates in countries where ship demolition operations prevail and regional ship demolition prices. These authors found that if the local currency depreciates against the dollar, then ship demolition prices decline. Because of this direction relationship between local exchange rates and ship demolition prices, RD_t was included as a forecasting variable.

An index of monthly Chinese Iron Ore prices (IO_t) taken from FRED was also included in the list of forecasting variables because iron ore is a direct substitute to steel scrap in several steel furnaces. Currently, there are two major types of steel furnace technology used in the production of finished steel: Basic Oxygen Furnace (BOF) and EAF. BOF is an older steel furnace technology which uses iron ore and coking coal as raw inputs. EAF uses steel scrap as its primary raw input. Chalabyan et al. (2017) point out that international scrap prices are highly correlated with iron ore. Since iron ore is a direct substitute to the steel scrap produced by ship demolition, this variable is utilized in the forecasting analysis.

The price of nickel given by the European melting grade Nickle Index in US dollars per metric ton taken from FRED is as another suitable explanatory variable in forecasting ship demolition prices. Hossain, Iqbalm and Zakaria (2010) and Rahman and Mayer (2015), show that nickel and ship demolition prices are strongly correlated and that nickel prices Granger cause ship demolition prices. These authors indicate that nickel is a raw material extracted from the ship demolition process and used in the construction industry in many developing countries. Because of nickel's strong connection with the ship demolition industry, it is included as a signal used to forecast ship demolition prices.

The next three explanatory variables, E_t, B_t, and C_t, all relate to the earnings of different groupings of commercial vessels. The smallest subset of vessels, E_t, is the average monthly VLCC fleet long run historical earnings given in US dollars per day, which provides a fleet average of revenue from VLCCs obtained from CSIN. The next larger subset of vessel earnings is the Baltic Tanker Index (B_t) which would include the earnings of VLCC vessels. This metric provides the average earnings of all vessel sizes carrying crude oil. To simplify the regression analysis, the Baltic Dirty Tanker Index (BDTI) and Baltic Clean Tanker Index (BCTI) were averaged to reflect the overall demand for crude oil transportation in one metric. The earnings metric for the largest subset of vessels is the monthly ClarkSea Index (C_t), collected from CSIN, which is a weighted average of the entire world fleet of commercial vessels. Obviously, this earnings metric includes both E_t and B_t.

These three earnings variables were included in the forecast study to reflect the tradeoff ships owners make between the decision to continue to operate their vessels versus collecting the residual value of the vessel via the ship demolition market. As mentioned in the literature review, Knapp, Kumar and Remjin (2008) found that vessel earnings are negatively correlated with the probability that a vessel is scrapped. The decision to include the three different metrics related to vessel earnings was done deliberately to determine which level of vessel groupings had the greatest impact on forecasting accuracy.

Finally, the sale of older vessels in the secondary market, an alternative to demolishing the vessel, is given by Clarksons Secondhand Price Index (P_t) downloaded from CSIN. According to Buxton (1991) and Alizadeh and Nomikos (2009), the ratio of ship demolition prices to secondhand vessel prices is a general indication of the strength of a shipping segment. When this ratio is low, the specific shipping segment is profitable. On the other hand, when the ratio of demolition prices to secondhand vessel prices is close to one then the specific vessel segment is performing poorly, and vessel owners are more likely to scrap their vessels. P_t can be thought of as a bellwether for a vessel ownership's choice between scrapping and continuing to operate the vessel.

To test the accuracy of the different forecasting methods, an in-sample period was designated from 08/31/1998 to 12/31/2018 and the out-of-sample period was taken from 01/31/2019 to 12/31/2020. According to Brooks (2019), the practice of setting aside a subset of the data is used to test the performance of regression models.

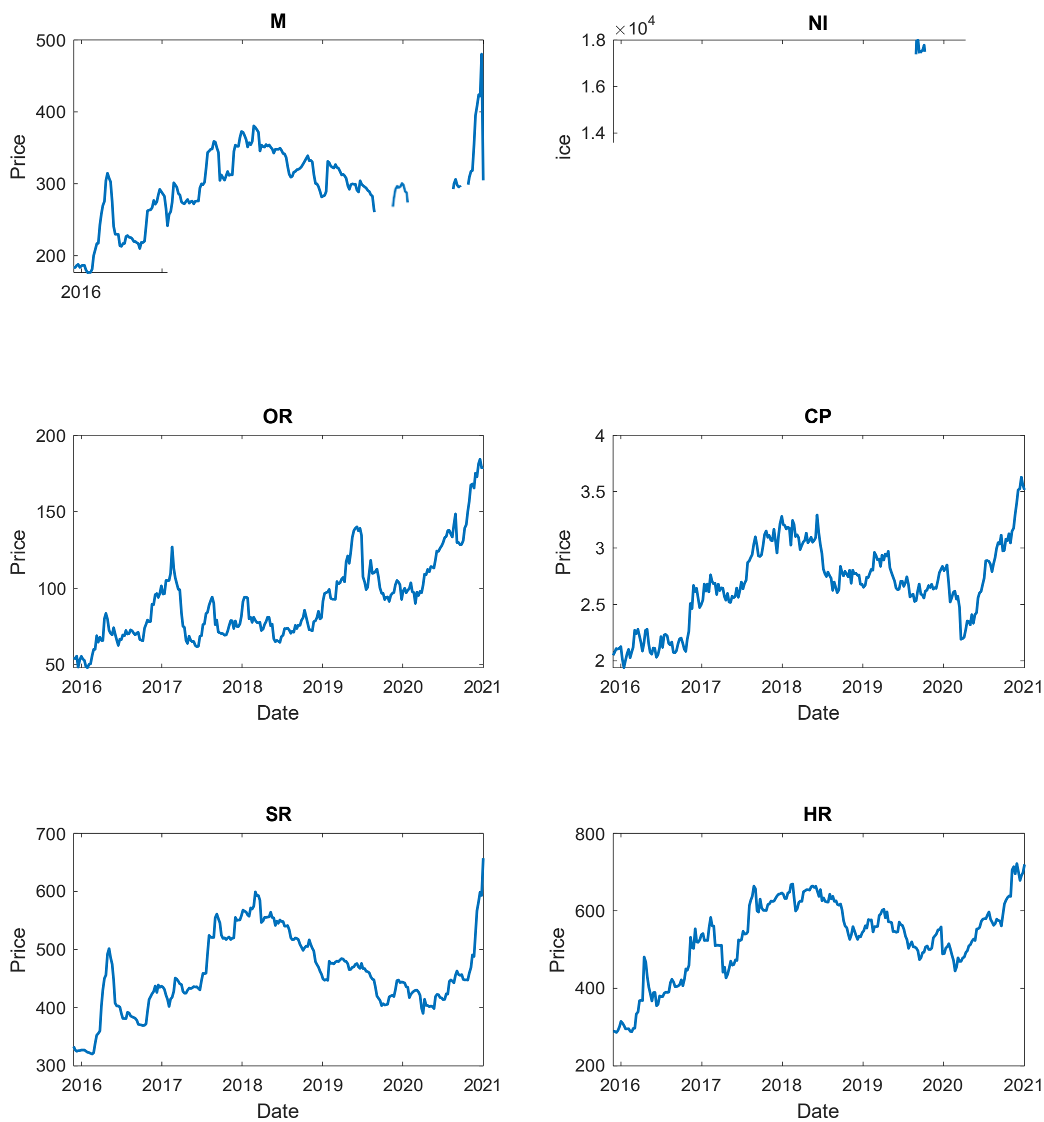
5.2 Data Description of Hedging Variables

A separate data set of the weekly averages of daily settled one-month ahead futures contract was utilized for the hedging section of the thesis. These futures contracts were selected to best match the underlying assets of the forecasting variables used in the previous section. For some forecasting variables, such as E_t, B_t, C_t, and P_t, there were no futures contracts which traded on the same underlying asset. A brief description of these futures contracts are in given in Table 3 and a time-series plot of the different variables is shown in Figure 2.

Table 3: Hedging Variables

Symbol	Time Series	Data Source
D_t	Scrap prices VLCC for India (USD)	Clarksons
M_t	Steel Scrap futures contracts	LME
Clc_t	Oil futures contracts	Eikon
NI_t	Nickel futures contracts	LME
OR_t	Iron Ore futures contracts	Eikon
CP_t	Copper futures	Eikon
SR_t	Steel Rebar futures	LME
HR_t	Hot Rolled Coil Futures	LME

Figure 2. Hedging Variables



To represent the steel-scrap index used in the forecasting section, steel scrap futures contracts traded on LME were used in the hedging analysis. LME introduced steel scrap futures contracts, M_t, in November 2015 to facilitate hedging between scrap metal producers and buyers. According to LME (2015), the futures contracts are settled according to the Turkish Import Heavy Melting Steel #1&2, 80:20 measured using the Cost and Freight Rate (CFR) Iskenderun Port Index price. LME asserts the prices recorded in Turkey are indicative of world steel scrap prices since it correlates closely with the other major hubs where scrap metal is traded. According to a primer produced by the exchange, LME Steel Scrap contracts are provided in 10 metric ton lot sizes and are quoted in US dollars per metric ton.

Month ahead crude oil futures were used in lieu of oil spot prices in the hedge analysis. The international, highly liquid month ahead New York Mercantile Exchange (NYMEX) Light Sweet Crude Oil (West Texas Intermediate) published by CME Group, Clc_t, was used as one of the cross hedging instruments.

Nickel futures contracts were utilized in the hedging analysis instead of the nickel index used in the forecasting section. Nickel futures quoted by LME, NI_t, are listed in lot sizes of 6 tons and provided in USD per ton price quotations.

Chinese iron ore futures were used in the hedging analysis instead of the iron ore index used in the forecasting section. The iron ore Chinese futures contracts, OR_t, used in the hedging analysis were quoted by CME Group in USD per dry metric ton and come in contract units of 500 dry metric tons. Although not used as a signal in the forecasting analysis, copper futures, CP_t, published by CME Group, quoted in USD per pound, and settled in 25,000-pound contract units were also used in the hedging analysis. Copper futures were included in the hedging analysis since, like steel and nickel, it is one of the main scrap commodities produced during the ship recycling process.

Unlike in the forecasting analysis, steel rebar futures (SR_t) and hot rolled coil steel futures (HR_t), both published by LME and quoted in USD per metric ton were used in the hedging analysis. The steel rebar futures are settled based on the monthly average index price of the Turkish Platts Steel Rebar price and the hot rolled coil steel futures are settled on the monthly average of the Argus HRC Tianjin China Index (LME, 2020). Although not included as variables in the forecasting analysis, it is hypothesized that these hedge instruments will reduce the volatility of demolition spot prices when an offsetting position is taken since ship recycling and steel rebar/hot rolled coil are part of the same industrial value chain.

Like the forecasting section, a portion of the futures dataset was held aside in the regression analysis to serve as an out of sample test. The in-sample period was designated from 11/27/2015 to 12/28/2018 and the out-of-sample period was designated form 01/04/2019 to 12/25/2020. Now that the different data sets used in the forecasting and hedging analysis have been fully described, the next subsection describes the data transformation used to reduce spurious regression results stemming from time-series with a unit root present.

5.3 Data Transformation

For variables with a unit root, the first difference is taken as shown in Equation (28). According to Brooks (2019), there are several benefits from taking the first difference of variables when making statistical inferences. One benefit is that it reduces the effects of autocorrelation in the residual.

$$r_t = \frac{\Delta y_t}{\Delta t} = \frac{y_t - y_{t-1}}{\Delta t}, \qquad where \;\; \Delta t = 1\, month/week \tag{28}$$

To avoid confusion, Δy_t is used throughout this thesis to refer to changes in the explained variable. The next two subsections include the summary statistics of the two different datasets and includes the diagnostic results for the detection of multicollinearity and a unit root. Separately, the hedging section includes the results of the diagnostic tests for heteroskedasticity and autocorrelation.

5.4 Descriptive Statistics of Forecasting Variables

This section includes a brief analysis of the summary statistics for the forecasting variables including the mean, standard deviation, skewness, and kurtosis as well as the tests results for a unit root.

5.4.1 Summary Statistics

Summary statistic of the variables used in forecasting demolition price movement are provided in the Table 4 and Table 5 below corresponding to the level values and the first differences.

Table 4: Summary Statistics on the Levels (Forecasting)

	Arithmetic mean	Standard deviation	Skewness	Kurtosis
D	338.240	128.910	0.031	2.706
S	371.178	167.186	0.087	2.141
O	60.531	30.944	0.433	2.169
RD	1109.192	224.955	0.688	2.264
N	153.992	81.719	1.641	6.971
IO	111.137	82.854	0.657	2.363
E	43415.021	33958.029	1.783	7.183
B	16628.206	8511.358	1.500	4.792
C	131.035	54.078	1.710	5.279
P	903.663	352.689	1.280	4.516

All the forecasting variables on the level were found to be right skewed compared to symmetric data sets which have a skewness of zero. Additionally, the level values of the forecasting variables exhibited either leptokurtic or platykurtic compared to a normally distributed data set which has a kurtosis value of 3.

Table 5: Summary Statistics on the First Difference (Forecasting)

	Arithmetic mean	Standard deviation	Skewness	Kurtosis
ΔD	1.015	30.310	-3.568	39.038
ΔS	1.394	35.635	-1.115	13.199
ΔO	0.143	5.574	-1.278	6.449
ΔRD	2.412	105.958	0.088	2.505
ΔN	0.496	17.088	-1.270	11.685
ΔIO	0.890	12.265	0.234	7.102
ΔE	-71.010	23913.559	0.880	14.588
ΔB	16.607	2549.676	-0.438	7.549
ΔC	-0.063	7.558	-9.270	125.332
ΔP	-1.348	148.570	0.500	7.395

The table of first differences indicates that the forecasting variables exhibit either left or right skewness and fat-tails, except for the first difference of the exchange rates which appear to be close to normally distributed. This summary statistic suggests that the normality assumption is likely violated for most of the level and first difference values of the forecasting variables (Brooks, 2019). Additionally, the multicollinearity between the different forecasting variables is determined and provided in Appendix 4. As discussed in the methodology section, multicollinearity is assumed to have a negligible impact on the forecasting results and no additional measures are taken to adjust for multicollinearity.

5.4.2 Unit Root Test

As discussed in the methodology section, the ADF test is used to test the presence of a unit root. The null hypothesis for the ADF test is that at least one unit root exists, and the alternative hypothesis is that a unit root does not exist. At a 5% level of significance, the critical value for the ADF test of the level values and first differences of the forecasting variables is -2.903. Figure 3 and Figure 4 provides the results of the diagnostic test for the level values of the variables and the first differences.

Figure 3. ADT Test Statistics on the Level (Forecasting)

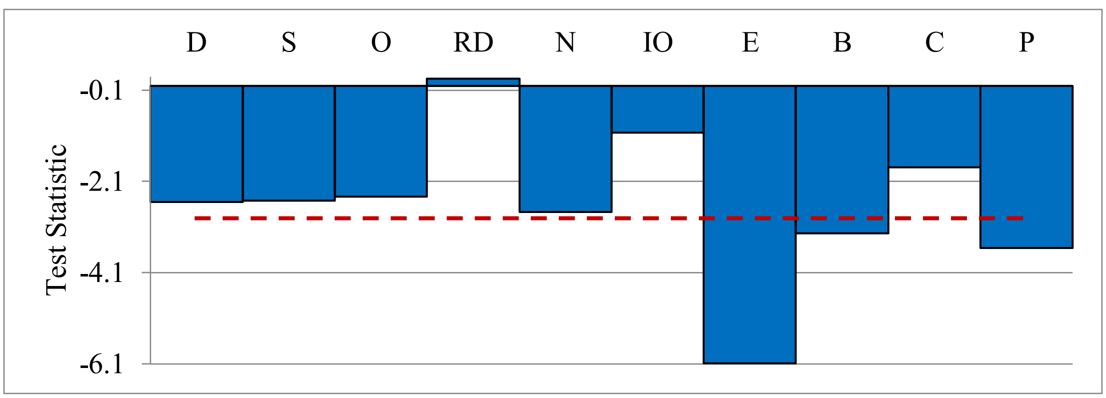


Figure 3 show the test statistic for each variable (blue bars) and the red line is the critical value for a 95% confident interval of -2.903. There do not exist one unit root if the test statistic is more negative than the critical value (i.e., the bar crosses the red line)

When testing the forecasting variables on the level, Figure 3 show that the test statistic for E_t, B_t, and C_t are more negative than the critical value. This suggests that these variables do not have a unit root (e.g. are integrated of order zero). It also implies these variables are poor forecasting variable candidates since it would be undesirable to mix variables of different integration orders. For the remaining variables (D_t, S_t, O_t, RD_t, N_t, IO_t, and C_t), the first difference is taken.

Figure 4. ADF Test Statistics on the First Difference (Forecasting)

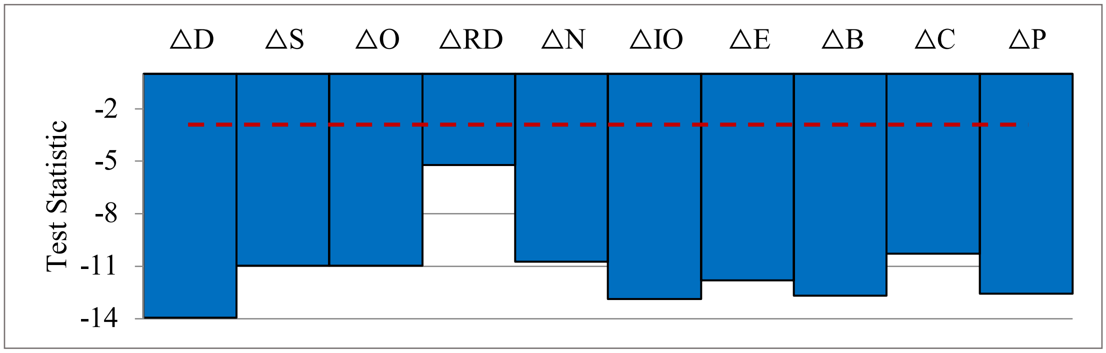


Figure 4 show the test statistic for each variable (blue bars) and the red line is the critical value for a 95% confident interval of -2.903. There do not exist two unit roots if the test statistic is more negative than the critical value (i.e., the bar crosses the red line)

In Figure 4, one can see that the test statistic for the remaining variables is more negative than the critical value, suggesting these variables all have a single unit root which is removed when the first difference is taken.

An additional ADF test was performed which indicates the presence of a time trend in the demolition price time series. As discussed in the methodology, when the level values of the demolition time series were de-trended the time series became integrated of order zero. Appendix 5 provides a graph of the demolition time series before and after the time trend was removed. The next subsection provides similar summary statistics for the variables used in the hedging analysis.

5.5 Descriptive Statistics of Hedging Variables

This section includes a brief analysis of the summary statistics for the hedging variables including the mean, standard deviation, skewness, and kurtosis as well as the diagnostic tests results for the presence of multicollinearity, a unit root, heteroskedasticity, and autocorrelation.

5.5.1 Summary Statistics

Summary statistics of the futures contracts used to hedge demolition price movement are provided in Table 6 and Table 7 for both the level values and the first differences. The level values exhibit left and right skewness and leptokurtic and platykurtic distribution; however, steel scrap (M), oil (Clc), Copper (CP), and steel rebar (SR) futures appear to have distributions which are nearly normally while the demolition spot price (D), iron ore (OR), and hot rolled coils (HR) (Brooks, 2019). This observation is supported by the Jarque Bera (JB) test for normality in which the null hypothesis is that the time series is normally distributed while the alternative hypothesis is that the time series is not normally distributed.

Table 6: Summary Statistics on the Levels (Hedging)

	Arithmetic mean	Standard dev.	Skewness	Kurtosis	JB Test Statistic
D	356.180	62.500	-0.466	1.940	<u>22.172</u>
Clc	50.940	11.252	-0.309	3.076	4.303
M	289.609	50.034	0.048	3.371	1.638
NI	12115.337	2355.527	0.347	2.519	<u>7.943</u>
OR	92.272	27.507	1.083	4.038	<u>64.221</u>
CP	2.681	0.354	-0.083	2.547	2.589
SR	458.507	65.793	0.141	2.675	2.067
HR	531.144	99.848	-0.647	2.940	<u>18.661</u>

The 95% critical value of the JB test are 5.749. The underline indicate we reject the null hypothesis of normal distribution in favor to the alternative (i.e., the test statistic is greater than the critical value).

The first differences of these variables; however, have JB test statistics which indicate that the transformed time series is not normally distributed as shown in Table 6.

Table 7: Summary Statistics on the First Difference (Hedging)

	Arithmetic mean	Standard dev.	Skewness	Kurtosis	JB Test Statistic
ΔD	0.415	7.916	1.102	8.637	404.499
ΔClc	0.032	2.539	-0.581	4.104	28.393
ΔM	0.393	15.815	-6.419	84.035	74327.256
ΔNI	33.557	389.738	0.480	5.089	58.357
ΔOR	0.472	5.067	-0.743	7.261	224.858
ΔCP	0.005	0.075	0.070	3.808	7.427
ΔSR	1.244	11.420	1.330	8.776	446.533
ΔHR	1.627	18.998	0.686	9.544	493.660

The 95% critical value of the JB test are 5.749. All of the test statistics in the JB test is higher than the critical value, meaning they are not normally distributed.

After analyzing the summary statistics for the hedging variables, a series of diagnostic tests are analyzed in the next sub-sections.

5.5.2 Heteroskedasticity

As discussed in Section 4.5 (Heteroskedasticity), Engle's ARCH test was utilized to test for the presence of conditional heteroskedasticity in lags of the residuals. In this test the null hypothesis is that there is no conditional heteroskedasticity. The test was conducted out to four lags of the residual and a critical value for each of the lags was determine at the 5% level of significance. As shown in Appendix 6, the test statistics for the different residual lags did not exceed the corresponding critical values in any of the models. This suggesting that none of the residuals exhibit conditional heteroskedasticity in any of the hedge models.

5.5.3 Autocorrelation

Like Engle's ARCH test, the Ljung-Box test was utilized to detect serial autocorrelation in the residuals of the different hedging models out to 4 lags. The results of the Ljung-Box test are provided in Appendix 7 and suggests that only the lags of the residuals for ΔClc, ΔOR, and ΔCP in the VECM do not exhibit serial autocorrelation. The remaining variables in the different forecasting models exhibit serial autocorrelation at the 5% level of significance. Unfortunately, as pointed out by Brooks (2019), the recourse for dealing with serial autocorrelation in hedging models is limited. It would be difficult to adjust for autocorrelation using popular techniques like the Cochrane-Orcutt procedure or adding additional lags in the hedging models without losing some of the model's economic intuition. Rather, the decision was made to leave the autocorrelation unadjusted in the residuals of the hedge models.

5.5.4 Multicollinearity

Like the forecasting section, the Person correlation, Variance Inflation Factor and Belsley Collinearity Diagnostic tests are used to assess whether multicollinearity is present in the explanatory variables (hedging instruments). First, the correlation of the level values and first differences in the correlation matrix in Table 8 and Table 9 were examined for high correlation. Correlations greater than 80% indicate a high degree of correlation between individual explanatory variables were placed with an underline in Table 8 and Table 9.

Table 8: Correlation Matrix on the Levels (Hedging)

	Clc	M	NI	OR	CP	SR	HR
D	0.700	0.746	0.499	0.165	0.718	0.757	0.710
Clc		0.580	0.349	-0.129	0.488	0.636	0.506
M			0.452	0.297	0.857	<u>0.931</u>	<u>0.857</u>
NI				0.605	0.641	0.448	0.635
OR					0.467	0.181	0.485
CP						<u>0.825</u>	0.903
SR							<u>0.847</u>

The underline show where there is a pair-wise correlation greater than 80%,.

The correlation matrix in Table 8 indicate month ahead steel scrap metal futures (M) and copper futures (CP) have a high degree of correlation (85.7%), which is logical given that steel scrap metal and copper are both used by developing economies in industrial applications. Additionally, steel rebar futures (SR) are highly correlated with steel scrap metal futures (M) (93.1%) and copper futures (CP) (82.5%) since all these materials are either direct or indirect components in the construction industry in developing economies. Finally, hot rolled coil futures (HR), which are coils of treated steel used as an input to make several different finished steel products, are highly correlated with steel scrap futures (M) (85.7%), copper futures (CP) (90.3%), and steel rebar futures (SR) (84.7%).

Table 9: Correlation Matrix on the First Difference (Hedging)

	ΔClc	ΔM	ΔNI	ΔOR	ΔCP	ΔSR	ΔHR
ΔD	0.019	0.067	0.088	-0.001	0.000	0.154	0.065
ΔClc		0.107	0.167	0.119	0.277	0.050	0.006
ΔM			-0.020	0.053	0.150	<u>-0.068</u>	<u>-0.035</u>
ΔNI				0.060	0.354	0.091	0.100
ΔOR					0.005	0.109	0.281
ΔCP						<u>0.089</u>	0.093
ΔSR							<u>0.107</u>

The underline show the variables that had a pair-wise correlation greater than 80% on the levels.

When the first difference of these explanatory variables is taken, the movements between the changes in these futures contracts become much less correlated with no pair of explanatory variables exhibiting a correlation greater than 80%. Although this reduces the likelihood that pair-wise collinearity would cause spurious regressions, it also increases concerns that the hedging instruments selected do co-move well with the ship demolition spot prices. The next diagnostic test used to test for the general presence of multicollinearity between three or more variables is the VIF which is presented in Figure 5.

Figure 5. Variance Inflation Factor (Hedging)

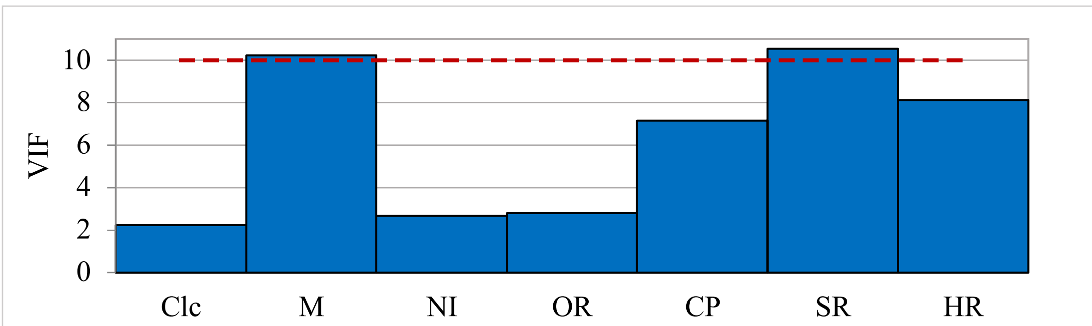


Figure 5 show the VIF for each variable (blue bars) and the red line is our threshold to indicate concern about the multicollinearity. If the bar crosses the red line (i.e., threshold of 10) multicollinearity is present.

Like the multicollinearity test in the forecasting section of the analysis, a VIF greater than 10 indicates that a multicollinear relationship is likely to exist between the explanatory variables. Based on the results in Figure 5, steel rebar futures (SR) have a VIF greater than 10 and steel scrap futures (M) have a VIF close to 10. Since these VIFs exceed the threshold value of 10, the Belsley Collinearity Diagnostics is used to determine which groups of explanatory variables exhibit a high degree of multicollinearity. The results of this diagnostic test are presented in Table 10.

Table 10: Belsley Collinearity Diagnostics (Hedging)

Conditional Index	Variance Decomposition Values						
	Clc	M	NI	OR	CP	SR	HR
1.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
9.230	0.070	0.001	0.005	0.249	0.000	0.001	0.000
18.367	0.277	0.027	0.248	0.001	0.005	0.010	0.020
25.026	0.609	0.000	0.501	0.632	0.009	0.002	0.010
39.248	0.023	0.043	0.013	0.025	0.041	0.066	0.953
49.886	0.014	0.347	0.218	0.004	0.773	0.007	0.000
64.119	0.007	0.581	0.016	0.088	0.172	0.914	0.017

The underline under the Conditional Index indicates the Conditional Index is greater than 30. The underlines in the Variance Decomposition Values show values that exhibit a high degree of multicollinearity.

As discussed in the methodology section, a Condition Index between 15 and 30 indicates a moderate degree of collinearity and a Condition Index above 30 indicates a strong degree of collinearity. Using the Condition Index for each row, the three last rows have a Condition Index above 30 but only steel scrap futures (M) and steel rebar futures (SR) in the last row have variance compositions above 0.5 in the same row. This suggests that only these pair of futures contracts exhibit a strong degree of collinearity. There are, of course, additional sub-groups of futures contracts which exhibit mild collinearity, but are not strong enough to exceed the established thresholds. Brooks (2019) suggests that multicollinearity between explanatory variables can be addressed by: 1) ignoring it depending on the type of analysis being conducted, 2) dropping one of the variables, 3) transforming highly correlated variables into a ratio, or 4) collecting more data. As presented in the next section, the test for a unit root (ADF test) indicates that there is a mismatch in integration orders between the steel scrap futures (M) and the steel rebar futures (SR). Because of this mismatch, the steel scrap futures were not included in the VECM or the ECM. Since the two variables were not included in the same model, the effects of multicollinearity in the hedging data set have been partially mitigated.

5.5.5 Unit Root Test

As in the forecasting section, the ADF test was used to determine if a unit root is present in the hedging data set time series. The results of this test are shown in Figure 6. Using a 5% level of significance, the critical value for the ADF test was -2.903 for the level values and first differences. When conducting the ADF test on the level test statistic for steel scrap futures (M) was more negative than the critical value. This suggests M does not contain a unit root and is integrated of order zero on the level.

Figure 6. ADF Test Statistics on the Levels (Hedging)

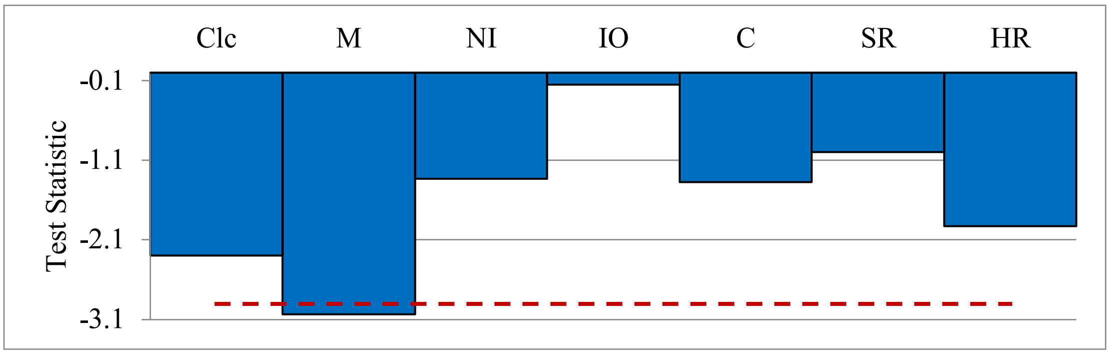


Figure 6 show the test statistic for each variable (blue bars) and the red line is the critical value for a 95% confident interval of -2.903. There do not exist one unit-root if the test statistic is more negative than the critical value (i.e., the bar crosses the red line).

The ADF test is conducted again on the first difference of the variables as shown in Figure 7. In this test, the test statistic is more negative than the critical value (e.g. the p-value is less than 5%). This suggests that the remaining variables in the hedging data set are integrated of order 1, I(1).

Figure 7. ADF Test Statistics on the First Difference (Hedging)

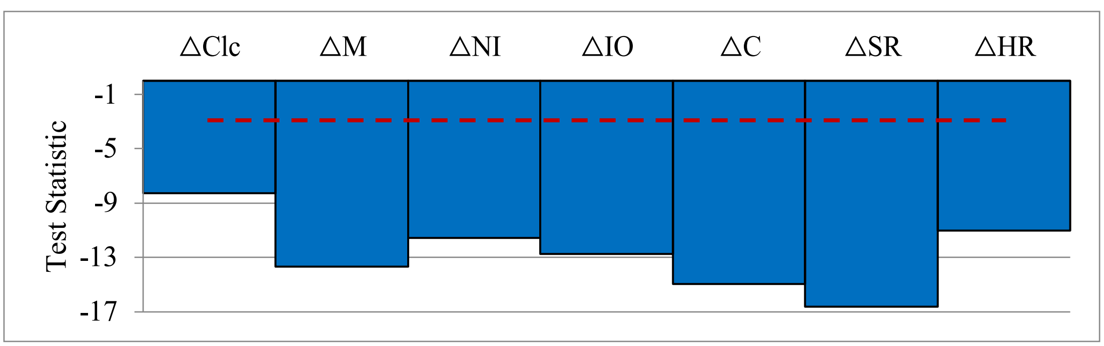


Figure 7 show the test statistic for each variable (blue bars) and the red line is the critical value for a 95% confident interval of -2.903. There do not exist two unit-root if the test statistic is more negative than the critical value (i.e., the bar crosses the red line).

6. Results & Analysis in the Forecasting Analysis

After using a series of diagnostic tests to determine the number of unit roots in the time series and detect the presence of multicollinearity, heteroskedasticity and autocorrelation in the last section, this section analyzes the regression analysis results and discusses their implications to the research question. In this section, the results and discussion for the forecasting and hedging analysis will be grouped into separate subsections.

6.1 Number of Lags

To perform the regression, the number of lags required in each of the forecasting models must be specified. As discussed in Section 4.4 (Information Criteria), the number of lags (k) which produced the lowest BIC was used to specify the number of lags in VECM and each of the ECM's. For the VECM, the BIC test suggests using 2 lags in a VAR system as shown in Appendix 8. According to Lütkepohl (2005) and Brooks (2019), the order of the VECM should be 1 less than the corresponding VAR model since at least one of the set of variables is cointegrated. A BIC result equal to 2 indicates that only 1 lag should be used in the VECM. The VECM will thus take the form given in Equation (29) where g includes D and the variables that contained single cointegrating relationships (S, O, RD, N, IO, and C).

$$\underset{(g\times 1)}{\Delta y_t} = \underset{(g\times g)}{\Pi}\,\underset{(g\times 1)}{y_{t-1}} + \underset{(g\times g)}{\Gamma_1}\,\underset{(g\times 1)}{\Delta y_{t-1}} + \underset{(g\times 1)}{u_t} \tag{29}$$

This guidance can be adapted to specify the number of lags which should be included in the ECM by taking one less lag than what is suggested by the BIC on a similar AR model. The results of the BIC diagnostic test for the ECMs indicate two lags produced the lowest value for a corresponding VAR model meaning only one lag is applied to the ECM regression. Now that the number of lags needed in the VECM and ECM are specified, the next section will analyze which forecasting variables have a cointegrating relationship with ship demolition prices (D). These cointegrating pairs will then be modeled as ECMs to account for the cointegrating relationship.

6.2 Cointegrating Relationships

As discussed in the methodology section, to determine if there exists any cointegrating relationship between two or more variables. The EG two-step method and Johansen test is utilized to determine if there exist any long-run equilibrium relationships. The results of these test will be used to further specify the ECMs and VECM.

6.2.1 Single Cointegrating Relationship

The EG test for cointegration is not performed between D and E, B, and P since it was determined in the ADF section that these variables did not contain a unit root on the level. Figure 8 provides the results of the EG two step test. The null hypothesis of the EG two step method is that a co-integrating relationship does not exist between ship demolition prices and the forecasting variables while the alterative hypothesis suggests that a co-integrating relationship does exist. The critical value for the hypothesis testing is -2.903 based on a 5% level of significance.

Figure 8. Cointegration Relationship (Forecasting)

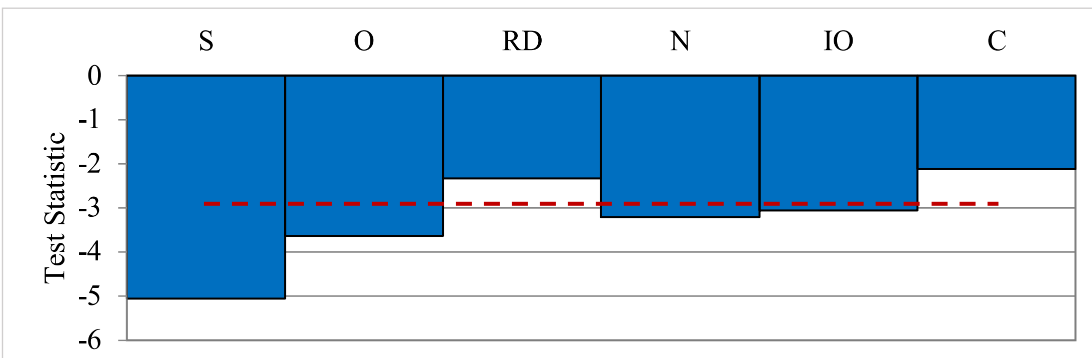


Figure 8 show the test statistic for each variable (blue bars) and the red line is the critical value for a 95% confident interval of -2.903. There exist a cointegration relationship if the test statistic is more negative than the critical value (i.e., the bar crosses the red line).

As indicated above, the EG two step method indicates that there is a single co-integrating relationship between demolition spot prices and S, O, N, and IO. Interestingly, S, O and RD are the same variables selected by Kagkarakis, Merikas, and Merika (2016) in their VAR model; however, these authors failed to account for the presence of cointegrating relationships in their analysis. Since cointegrating relationships exist, the ECM and the VECM are more appropriate than the AR and VAR models since the latter two do not account for cointegrating relationships. The next test will determine if there are multiple cointegrating relationships between D and the forecasting variables.

6.2.2 Multiple Cointegrating Relationship

To determine whether multiple cointegrating relationships existing between D and the forecasting variables, it was first necessary to determine the rank of the cointegration matrix, Π, by employing the Johansen and Juselius (1990) method which examines the eigenvalue of the cointegrating matrix. The results of the trace and maximum eigenvalue tests presented in Table 11 and Table 12 suggest that the rank of the cointegration matrix, Π, is 1 (e.g. $k = 1$).

Table 11: Johansen Trace (Forecasting)

Ranks (≤)	0	1	2	3	4	5	6
Test Statistic	<u>171.850</u>	<u>105.407</u>	64.530	39.171	17.101	7.588	171.850
Critical value	134.681	103.848	76.972	54.078	35.193	20.262	134.681

The underline show at what rank we reject the null hypothesis of cointegration rank r in favor of the alternative (i.e., test statistic is greater than the critical value)

Table 12: Johansen Maximum Eigenvalue (Forecasting)

Rank (=)	0	1	2	3	4	5	6
Test Statistic	<u>66.443</u>	40.877	25.359	22.070	9.513	5.702	1.886
Critical value	47.080	40.957	34.806	28.588	22.300	15.892	9.164

The underline show at what rank we reject the null hypothesis of cointegration rank r in favor of the alternative (i.e., test statistic is greater than the critical value)

6.3 Parameter Stability Test

After accounting for cointegration by including error correction terms in the ECM and VECM and the appropriate number of lags in all three groups of models, the stability of the regression results are tested over the entire time period of the data set. As discussed in the methodology section, both the Chow test and CUSUM test were utilized to confirm parameter stability. In the Chow test, a breakpoint corresponding to the start of the Global Financial Crisis (GFC) was used to determine if the regression parameters were statistically difference at 5% level of significance before and after the breakpoint. As shown in Table 13, the test fails to reject the null hypothesis suggesting that the parameters remain stable before and after the GFC.

Table 13: Chow Test (Forecasting)

	VECM	ARMA	ECM			
			ΔS	ΔO	ΔN	ΔIO
Test Statistic	1.855	2.201	2.016	2.199	1.416	1.558
Critical Value	1.922	2.643	2.410	2.410	2.410	2.410

Breaking point is 31/12/2007 which splits the first and second half of the data set.

The results of the CUSUM test provided in Appendix 9 support the finding in the Chow test. According to Brown, Durbin, and Evans (1975), the CUSUM test considers the stability of regression coefficients over time by recursively testing the sum of squares each period by adding an observation. Visually, the stability test statistics of the different models remains within the bounds of the critical values over time indicating that we fail to reject the null hypothesis that the parameters are stable. This suggests that although the forecasting parameters do change over time there are no dramatic shifts, including during the GFC, which causes the forecasting parameters to become unstable.

6.4 Regression Coefficients

Now that the number of lags and cointegrating relationships have been determined and the stability of the forecasting parameters have been confirmed, it is possible to present the regression results and discuss the statistical significance of the parameters.

6.4.1 Parameters of the Vector Error Correction Models

The forecasting parameters for the VECM are provided in Table 14 and the cointegrating vectors and adjustment parameters implied by the long-run coefficient matrix are provided in Appendix 10.

Table 14: Vector Error Correction Model (Forecasting)

	Equations						
	ΔD	ΔS	ΔO	ΔRD	ΔN	ΔIO	ΔC
Intercept	1.399	7.309***	0.245	-1.685	0.308	0.348	1.064**
	(1.149)	(1.055)	(0.194)	(3.208)	(0.613)	(0.442)	(0.254)
ECT_{t-1}	0.059	-0.296***	0.001	-0.001	0.004	0.005	-0.035***
	(0.048)	(0.043)	(0.001)	(0.002)	(0.008)	(0.006)	(0.008)
ΔD_{t-1}	-0.001	0.181**	-0.002	-0.092	0.043	0.023	-0.003
	(0.088)	(0.081)	(0.015)	(0.246)	(0.047)	(0.034)	(0.019)
ΔS_{t-1}	0.213***	0.372***	0.040***	-0.333*	0.142***	0.027	0.085***
	(0.070)	(0.065)	(0.012)	(0.196)	(0.038)	(0.027)	(0.016)
ΔO_{t-1}	1.311***	1.495***	0.258***	0.946	-0.383*	0.099	0.173**
	(0.387)	(0.358)	(0.066)	(1.088)	(0.208)	(0.150)	(0.086)
ΔRD_{t-1}	0.005	0.025	0.001	-0.592***	0.003	0.004	-0.001
	(0.018)	(0.017)	(0.003)	(0.052)	(0.010)	(0.007)	(0.004)
ΔN_{t-1}	0.184	-0.028	-0.002	0.017	0.413***	0.018	-0.009
	(0.114)	(0.106)	(0.019)	(0.322)	(0.062)	(0.044)	(0.025)
ΔIO_{t-1}	-0.099	0.227	-0.018	-0.209	-0.217	0.171***	-0.025
	(0.171)	(0.158)	(0.029)	(0.482)	(0.092)	(0.066)	(0.038)
ΔC_{t-1}	-0.797**	-0.941***	0.033	1.180	-0.493***	-0.265**	0.149**
	(0.327)	(0.303)	(0.056)	(0.920)	(0.176)	(0.127)	(0.073)

Figures in (.) are the corresponding Standard Errors. *** denotes the rejection of null hypothesis at the 1% level. ** denotes the rejection of null hypothesis at the 5% level. * denotes the rejection of null hypothesis at the 1% level.

One interesting observation from the VECM regression results is that the coefficient for the ECT, as known as the ‘speed of adjustment’, for the demolition spot price (D) equation in the first column is close to zero and not even statistically significant at the 10% level of significance. This suggests that the long-run relationship between the change in demolition spot prices and the other variables used in the VECM is weak and is not a good measure to forecast movements in changes in the demolition spot price. In fact, since the size of D’s ECT is small and not significant similar results are likely achieved by simply utilizing a Vector Autoregressive model which does not include an error correction term.

Another interesting observation from the short-term VECM regression coefficients is that only lagged changes in scrap metal prices, ΔS_{t-1}, lagged changes in oil prices, ΔO_{t-1}, and lagged changes in the ClarkSea Index ΔC_{t-1} are statistically significant at the 5% level of significance. Although it is anticipated that the VECM will provide more accurate predictions of the changes in the demolition spot price, ΔS_t, in the in-sample, the inclusion of 5 insignificance slope coefficients in the VECM forecasting model may cause overfitting which will result in poor predictions out of sample.

6.4.2 The Error Correction Model

The results of the ECM regression is provided in Table 15 as well as a reproduction of the general ECM(1) model in Equation (1) for ease of association.

$$\Delta D_t = c + ECT_{t-1} + \beta_1 \Delta X_{t-1} + \phi_1 \Delta D_{t-1} + v_t$$

Table 15: Error Correction Models (Forecasting)

Regressor	Intercept	ECT_{t-1}	β_1	ϕ_1
ΔS_t	2.694	-0.057	0.176^{***}	0.057
	(1.889)	(0.040)	(0.064)	(0.076)
ΔO_t	8.645^{*}	-0.079^{*}	1.372^{***}	0.067
	(3.363)	(0.031)	(0.382)	(0.069)
ΔN_t	6.868^{***}	-0.066^{***}	0.158	0.109^{*}
	(1.947)	(0.019)	(0.116)	(0.063)
ΔIO_t	13.688^{***}	-0.058^{***}	0.106	0.152^{**}
	(4.637)	(0.020)	(0.170)	(0.064)

Figures in (.) are the corresponding standard errors. *** denotes the rejection of null hypothesis at the 1% level. ** denotes the rejection of null hypothesis at the 5% level. * denotes the rejection of null hypothesis at the 1% level.

When analyzing the ECM regression parameters, one notices that the slope coefficient for the ECT term is negative for all the individual models and the regression coefficients for the ECT are statistically significant at a 10% level of significance and better except for the ECM which uses ΔS_t as the explanatory variables. Unlike the regression results from the VECM, this suggests that any deviations from the long-run relationship between the change in the demolition spot prices, ΔD_t, and the explanatory variable, ΔX_t, are corrected over time; however, the size of these coefficients are relatively small suggesting that short term mechanics dominate the changes in demolition spot price movements. The next sub-section analyzes the regression results of the ARMA(1,1) model which is used for comparative purposes to the VECM and ECMs.

6.4.3 The Autoregressive Moving Average (ARMA) Model

The regression results for the ARMA(1,1) is provided in Equation (30). Notice that the term $\mathrm{D_t} - \delta\mathrm{t}$ is given in the left-hand side of the equation to represent that the demolition spot price time series was "de-trended" before running the regression to avoid spurious regressions.

$$D_t - \delta t = \underset{(3.159)}{-0.040} + \underset{(0.020)}{0.946^{***}} D_{t-1} + \underset{(0.036)}{0.139^{***}} u_{t-1} + v_t \tag{30}$$

Figures in (.) are the corresponding Standard Errors (SE); *** denotes the rejection of null hypothesis at the 1% level.

The regression results indicate that both the AR and MA terms are statistically significant at the 1% level and that the large majority of detrended prices movements at time, t, are explained by the autoregressive term based on the size of the coefficient.

6.5 Forecasting Results

Using the regression results from the previous section, this section will test the in-sample and out-of-sample forecast accuracy of the estimated models. Each model will be compared using the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Error (ME), and Tracking Signal (TS) measures of forecast accuracy.

6.5.1 The in-Sample Results

The results from the in-sample accuracy is provided in Table 16. The most striking observation from the in-sample results is that the VECM has the lowest RMSE as anticipated given the VECM contains over twice as many terms as the ARMA and ECM. Comparatively, the Naïve has the lowest MAE and the ARMA(1,1) has the lowest ME and TS.

Table 16: Model Accuracy (In-Sample)

	RMSE	MAE	ME	TS
VECM	<u>29.015</u>	17.319	0.658	0.006
ARMA	30.431	16.893	<u>0.093</u>	<u>0.001</u>
ECM (ΔS)	30.141	16.991	0.882	0.008
ECM (ΔO)	29.510	16.719	0.446	0.004
ECM (ΔN)	29.755	16.892	0.142	<u>0.001</u>
ECM (ΔIO)	30.250	17.038	0.180	0.002
NÄIVE	31.120	<u>16.691</u>	1.202	0.011

The underline show the lowest value for each measurement.

When analyzing the AIC and BIC of the models, one notices that the VECM has a much greater information criteria compared to the other models. This is as anticipated given that the AIC and BIC penalize models for including additional terms. Since the VECM has the greatest number of terms out of all the models analyzed, it should also have the largest AIC/BIC values as shown in Table 17. According to Brooks (2019) one of the disadvantages of having many terms in a model is that it could lead to overfitting and may result in worse out of sample forecasts even though the accuracy of this model was higher in-sample compared to simpler models. To test for overfitting, the same forecasting models will be used with the out-of-sample data and the RMSE, MAE, ME, and TS will be compared.

Table 17: Model Measurement

	VECM	ARMA	ECM			
			ΔS	ΔO	ΔN	ΔIO
AIC	14231.119	2374.982	4642.204	3795.018	4391.337	4230.918
BIC	14454.675	2388.987	4673.642	3826.455	4422.774	4262.355

Plots of the error between the fitted model and the actual demolition spot prices during the in-sample period and the level values of the forecasts compared to the actual demolition prices values are provided in Appendix 11 and Appendix 12.

6.5.2 The Out-of-Sample Results

Using the regression parameters produced from the in-sample data, the out of sample data which spans a two-year period from January 2019 to December 2020 is used to calculate the accuracy of the different models. The results of the out-of-sample test are shown in Table 18. As hypothesized, the VECM which had the lowest RMSE in-sample no longer has the lowest RMSE out-of-sample. Rather, the ECM using iron ore spot prices as the dependent variable has both the lowest RMSE and MAE while the Naïve forecast holds the lowest ME and TS.

Table 18: Model Accuracy (Out-of-Sample)

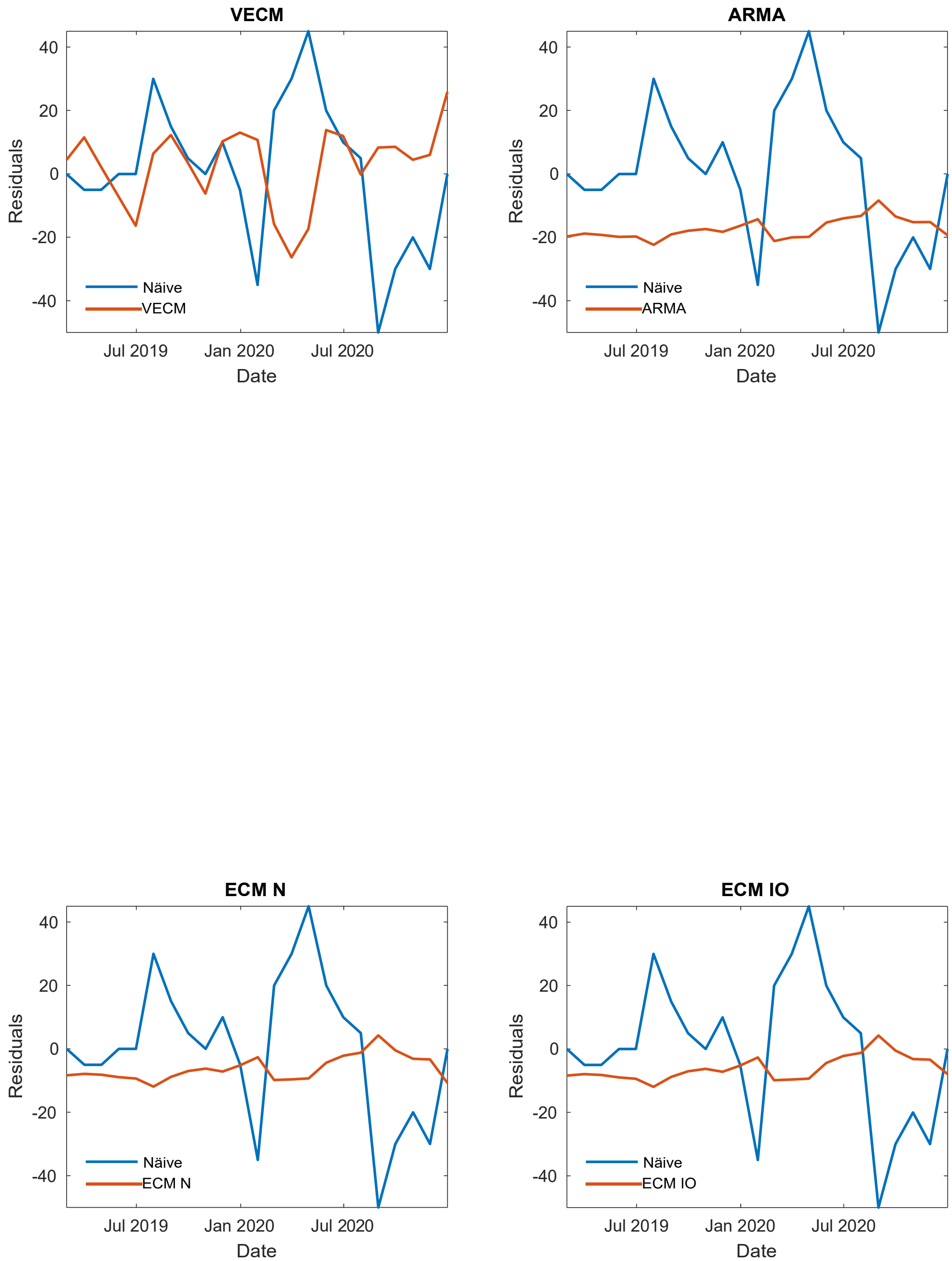
	RMSE	MAE	ME	TS
VECM	12.427	10.552	-2.790	-0.264
ARMA	17.601	17.312	17.312	1.000
ECM (ΔS)	7.521	6.686	6.317	0.945
ECM (ΔO)	7.630	6.742	6.373	0.945
ECM (ΔN)	7.286	6.546	6.177	0.944
ECM (ΔIO)	<u>7.121</u>	<u>6.419</u>	6.050	0.943
NÄIVE	21.968	16.087	<u>-0.435</u>	<u>-0.027</u>

The underline show the lowest value for each measurement.

The RMSE results for the VECM suggests that many of the forecasting variables have little predictive power in the model. Rather, the VECM may be improved by removing the forecasting signals which were shown not to have a single cointegrating relationship with the demolition spot price. Future studies may consider re-running the VECM after removing the RD and C forecasting variables from the model.

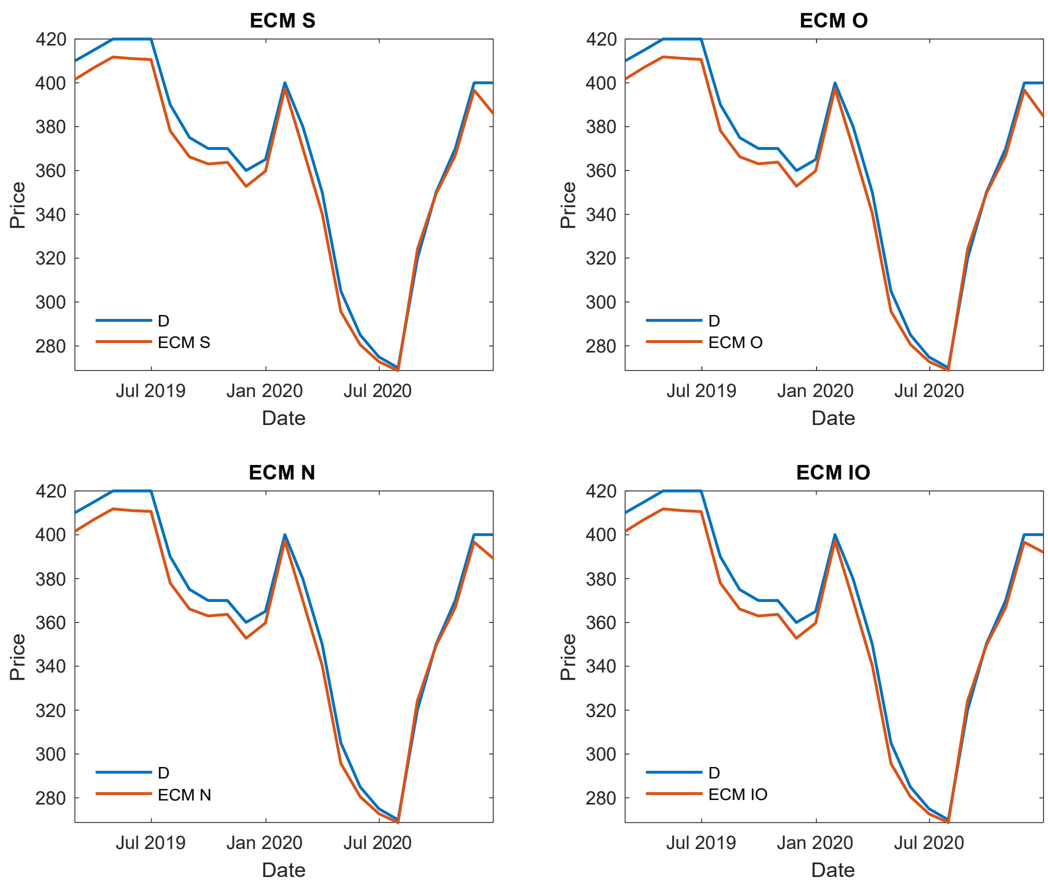
To visually confirm the results presented in Table 18, Figure 9 provides the calculated error over time for the VECM, ARMA, and ECMs against the Naïve forecasting model which is used for comparison and Figure 10 provides the level values of the forecasting results.

Figure 9: Residuals (Out-of-Sample)



Visually, one observes in Figure 9 that the ECMs produce errors which fluctuates around zero compared to the ARMA errors which has negative bias and the VECM errors which fluctuates rapidly between over-estimating and underestimating the true demolition spot prices.

Figure 10: Forecasted Values on the Levels (Out-of-Sample)



Visually, one observes in Figure 10 that the ECMs appear to have the best fit compared to the VECM and ARMA models. The next subsection will discuss how the model could be improved and puts the results in greater context for the maritime industry.

6.6 Discussion of the Forecasting Analysis

In addition to discussing how the forecasting models analyzed can be improved, the practical implications of the forecasting results for the ship recycling industry are considered. To place the in-sample and out-of-sample results in context, the RMSE from each test is normalized by dividing by the average in-sample and out-of-sample demolition prices. Normalizing these results allows for the comparison of disparate sample sizes since the in-sample period contains nearly 20-year of data against the 2-year out of sample period. The normalized RMSE results are presented in Table 19.

Table 19: Normalized RMSE Results

	VECM	ARMA	ECM				NAIVE
			ΔS	ΔO	ΔN	ΔIO	
In-Sample	8.7%	9.1%	9.0%	8.8%	8.9%	9.0%	9.3%
Out-of-Sample	3.4%	4.8%	2.0%	2.1%	2.0%	1.9%	6.0%

The most striking observation is that the normalized RMSE in-sample is nearly two to four times larger than the out-of-sample normalized RMSE results. The underlying cause of this difference is the tremendous demolition price fluctuations found in the in-sample period. For example, during the height of the GFC demolition, prices fell from an all-time high of 780 USD/LDT to nearly one third the price during 2008. Similar, albeit less dramatic fluctuations are observed during different sub-periods within the timeseries.

Given that prices in the ship demolition market are prone to dramatic fluctuations, a logical question would be whether static forecasting models like the VECM and ECM are really the most appropriate tools for practitioners. Although a normalized RMSE below 10% for the models may seem like an acceptable amount of forecasting error, if practitioners are purchasing second-hand vessels with considerable leverage and the residual value represents a large portion of the overall value of the vessel then even a margin of error below 10% may be the difference between executing a profitable or unprofitable secondary market transaction.

To address these periods of high instability, a dynamic forecasting model may provide more accurate forecasting results. One class of models which warrants further consideration is the Generalized Autoregressive Conditionally Heteroscedastic (GARCH) model which are better at modeling volatility clustering (Brooks, 2019). Within a GARCH model, a conditional variance term is specified which includes information about the volatility in past periods which allows the model to adjust forecasts more rapidly during periods of high volatility.

These characteristics are especially important for the ship demolition market based on the herding effect observed by several prominent authors in the ship demolition field. According to Papapostolou, Pouliasis, and Kyriakou (2017), herding behavior exists in the dry bulk market where a sudden depression in this shipping segment may cause many ship owners to recycle their vessels during a short time. This type of behavior causes ship demolition prices to drop rapidly. The opposite effect is observed during sudden spikes in freight earnings when vessel owners decide to forego to continue to operate older vessels. This generally causes ship demolition prices rise rapidly. Based on these recorded trends, it appears that the GARCH model may perform better than the static models tested in this thesis in forecasting demolition prices.

It is also interesting to compare the findings of this analysis with the ship demolition forecasting study conducted by Kagkarakis, Merikas, and Merika (2016). Although these authors also focused on forecasting ship demolition prices in India, they choose to forecast the broader tanker category in India compared to just VLCCs as in this study. These authors found that the VAR had the best out of sample performance which they measured using the RMSE statistic compared to an ARMA(1,1), random walk and linear trend model. Unlike this study, the authors chose not to compare simpler models like the ECM or AR models. If these simpler models were included in Kagkarakis, Merikas, and Merika (2016), the authors may have found that the VAR was over-parameterized and that a better out-of-sample model may have been achieved by using less parameters.

Finally, it is interesting to consider whether the forecasting variables utilized in this analysis are the most appropriate for forecasting ship demolition prices. One notices that many of the explanatory variables, like the scrap metal index (S_t) and crude oil prices (O_t) may be too broad and not representative of local demolition price dynamics for VLCCs in India. Central to this discussion is the idea of basis risk which is discussed in much more detail in the next section. Because the explanatory variables and explained variables are not similar in terms of basis, it is unlikely that the explanatory variable would forecast the explained variable well. One major difference in basis between the explained and the explanatory variables is the difference in locational basis. The explanatory variables represent broader, international movements of commodities relevant to the shipping industry while the explained variable, ship demolition prices of VLCCs in India, represent more specific, regional price movements within this commodity class.

Future ship demolition forecasting studies may be improved by substituting more specific regional indicators for the international explanatory variables. For example, Platts S&P which records several regional commodity indicators records recently started reporting Indian scrap metal prices at the Indian port of Nhava Sheva which is one of India’s largest and busiest container ports. Using this time series instead of the Steel Scrap Producer Price Index from the US FRED may improve forecasting results in future studies.

7. Results & Analysis in the Hedging Analysis

The second half of the results section focus on the findings of the hedging analysis. Since forecasting and hedging often use the same models with different objectives, this section considers which of the three hedging models, VECM, ECM or Naïve, has the highest hedge effectiveness. Many of the same diagnostic tests used in the forecasting section were used to characterize these models; however, an entirely different data set composed of traded futures contracts were used in parameterization.

7.1 Number of Lags

As in the forecasting analysis, the next parameter specified is the number of lags. The BIC test suggests using 1 lag in a VAR system as shown in Appendix 13. Recalling that Lütkepohl (2005) and Brooks (2019) suggest using one less lag than the VAR in an ECM and VECM, no lags are used to specify the ECM and VECM. To illustrate how this affects the specification of the hedging models, the VECM takes the form shown in Equation (31) where $\mathrm{y_t}$ is a $\mathrm{g} \times 1$ vector representing both the spot and futures contracts.

$$\underset{(g\times 1)}{\Delta y_t} = \underset{(g\times g)}{\Pi}\,\underset{(g\times 1)}{y_{t-1}} + \underset{(g\times 1)}{u_t} \tag{31}$$

7.2 Cointegrating Relationships

Like the forecasting section, the EG two-step method and Johansen test is utilized to determine whether long-run equilibrium relationships exist between hedging variables. The results of these tests will be used to further specify the ECMs and VECM in the next section.

7.2.1 Single Cointegrating Relationship

To determine if a single cointegrating relationship exists between the demolition spot rates and the futures contracts, the Engle-Granger (EG) two step method was utilized like in the forecasting section. Figure 11 provides the cointegration test results. Note that this test was not performed between demolition spot prices (D) and steel scrap futures (M) since the ADF test in Section 5.5.5 (Unit Root Test) determined that these variables were integrated of different orders.

Figure 11. Cointegration relationship (Hedging)

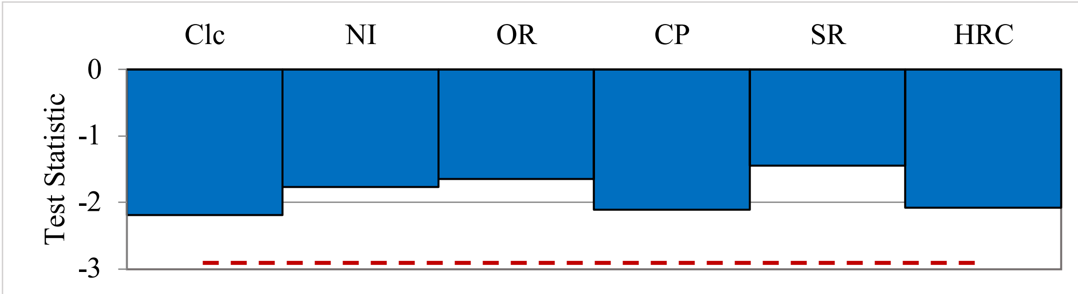


Figure 11 show the test statistic for each variable (blue bars) and the red line is the critical value for a 95% confident interval of -2.903. There exist a cointegration relationship if the test statistic is more negative than the critical value (i.e., the bar crosses the red line).

Since the test statistic is more negative than the critical value, the null hypothesis that a cointegrating relationship does not exist is not rejected. These results appear to be at odds with the outcome of the EG test in the forecasting section which found several single cointegrating relationships between the demolition spot price and the explanatory variables. One reason for this disparity is that many of the explanatory variables used in the forecasting section have slightly different underlying assets than the hedge instruments. Another reason is that the hedging variables have a relatively short in-sample period of approximately 3 years, compared to nearly 20 years for the forecasting variables. A final reason why cointegrating relationships are not present in the results is the sampling frequency. In the forecasting analysis, the forecasting variables were sampled monthly while the hedging variables were taken on a weekly basis. Higher frequency sampling likely resulted in greater volatility which distorts the true long run cointegrating relationships between the spot and futures contracts. If a longer sample period were available permitting less frequent sampling of the data, it is likely the diagnostic test would detect cointegrating relationships. Given this likelihood, the ECM is still utilized to assess hedge efficiency rather the simple univariate OLS model which would not include the error correction term. An exception is made for the OLS regression between the change in demolition spot prices and the change in scrap metal futures since these time series are integrated of different orders on the level.

7.2.2 Multiple Cointegrating Relationships

Using the Johansen and Juselius (1990) method, it was determined that the rank of the cointegration matrix, Π, is 2 at a 5% level of significance. This suggests that there are two cointegrating vectors within the VECM used in the hedging analysis. Table 20 and Table 21 presents the results of the trace and max eigenvalues tests used to determine the rank of the cointegration matrix.

Table 20: Johansen Trace (Hedging)

Ranks (≤)	0	1	2	3	4	5	6
Test Statistic	<u>181.345</u>	<u>106.151</u>	58.356	33.402	18.525	6.495	1.646
Critical Value	134.681	103.848	76.972	54.078	35.193	20.262	9.164

The underline show at what rank we reject the null hypothesis of cointegration rank r in favor of the alternative (i.e., test statistic is greater than the critical value)

Table 21: Johansen Maximum Eigenvalue (Hedging)

Ranks (=)	0	1	2	3	4	5	6
Test Statistic	<u>75.194</u>	<u>47.795</u>	24.953	14.877	12.030	4.849	1.646
Critical Value	47.080	40.957	34.806	28.588	22.300	15.892	9.164

The underline show at what rank we reject the null hypothesis of cointegration rank r in favor of the alternative (i.e., test statistic is greater than the critical value)

7.3 Parameters Stability

After running the regression for the different hedging models, parameters stability was tested using the Chow test and the CUSUM test. Since a visual examination of the time series do not indicate a clear break or jump corresponding to a period of high instability or regime shift, an arbitrary breakpoint was placed in the middle of the time series for the Chow test. The results of the Chow test are provided in Table 22.

Table 22: Chow Test (Hedging)

	VECM	ECM						OLS
		ΔClc	ΔNI	ΔOR	ΔCP	ΔSR	ΔHR	ΔM
Test statistic	1.447	1.664	1.161	1.673	1.676	1.633	1.591	0.081
Critical value	2.663	3.054	3.054	3.054	3.054	3.054	3.054	3.054

Breaking point is 13/01/2017 which splits the first and second half of the data set.

These results of the Chow test indicate that the parameters for the different models appear to be stable over the sample period. A visual inspection of the CUSUM test, presented in Appendix 14, indicate that the test statistics generated using the recursive sum of squares for the ECMs exceeds the critical value bounds at a 5% level of significance. On the other hand, the test statistic plots for the VECM and OLS models remain within the critical value bounds at the 5% level of significance. This suggests that the regression parameters for the ECMs are slightly unstable over time. One can attribute this moderate instability to the more frequent sampling; however, given the relatively small sample size available in the hedging section it would be inappropriate to reduce the sample size or decrease the sample frequency to address this instability. The decision to not decrease the sampling frequency or reduce the sampling size for the ECM may be one of the reasons, as discussed in later sections, why the ECM produced hedge ratios with low hedge effectiveness.

Now that the three models used in the hedging analysis have been fully specified, the next section will analyze the regression results. Using these results, one will be able to make inferences about how well the hedging models will perform in reducing the demolition spot price variance in the out-of-sample test.

7.4 Regression Coefficients and Hedge Ratio

This section presents and discusses the regression coefficients for the VECM, ECM, and OLS hedging model. Each subsection is dedicated to one of these models. Additionally, each subsection provides the optimal hedge ratio and its significance for each model.

7.4.1 The Error Correction Models

The regression results of the ECM are analyzed in the first subsection. Table 23 provides the regression parameters and Table 24 presents the optimal hedging ratio obtained from the simple regression of the residuals for this model.

Table 23: Error Correction Models (Hedging)

	ΔClc	ΔNI	ΔOR	ΔCP	ΔSR	ΔHR
c	-0.437**	-2.068**	-9.927***	-9.626***	-4.022**	0.331***
	(0.175)	(1.049)	(2.624)	(2.578)	(1.849)	(0.079)
ECT	-0.029**	-0.020**	-0.008***	-0.055***	-0.030**	-0.057***
	(0.012)	(0.010)	(0.002)	(0.015)	(0.014)	(0.014)

Figures in (.) are the corresponding standard errors. *** denotes the rejection of null hypothesis at the 1% level. ** denotes the rejection of null hypothesis at the 5% level. * denotes the rejection of null hypothesis at the 1% level.

When analyzing the ECM regression parameters, one notices that the slope coefficient for the ECT term is negative and statistically significant at the 5% level of significance and better. Like the VECM used in the hedge analysis, the magnitude of these coefficients is relatively small meaning that the system is slow to correct any deviations from the long run relationship between the explanatory and explained variables. This suggests that the hedge ratios inferred from the ECM will likely perform poorly in the out of sample analysis.

Table 24. The Optimal Hedge Ratio for the Error Correction Models

	u_{Clc}	u_{NI}	u_{OR}	u_{CP}	u_{SR}	u_{HR}
Intercept	0.105	0.145	0.297	0.202	0.162	0.122
	(0.622)	(0.624)	(0.608)	(0.609)	(0.608)	(0.603)
Hedge Ratio	0.069	0.002	0.058	0.546	0.168***	0.025
	(0.275)	(0.002)	(0.133)	(7.978)	(0.054)	(0.029)

Figures in (.) are the corresponding standard errors. *** denotes the rejection of null hypothesis at the 1% level. ** denotes the rejection of null hypothesis at the 5% level. * denotes the rejection of null hypothesis at the 1% level.

The results of the bivariate regressions of the different residuals from Table 24 indicate that only the hedge ratio estimated from the Steel Rebar futures (u_{SR}) are significant at a 1% significant level. This indicates that only Steel Rebar futures should be used to hedge the demolition price.

7.4.2 The Vector Error Correction Model

The next subsection analyzes the regression results from the VECM which is presented in Table 25. The optimal hedge ratio from the multivariate regression of the residuals from this model is presented in Table 26.

Table 25: Coefficients of the Error Correction Model (Hedging)

	Equations						
	ΔD	ΔClc	ΔNI	ΔOR	ΔCP	ΔSR	ΔHR
c	-4.000	1.714	652.802**	4.320	0.306***	3.858	-24.787
	(6.395)	(1.828)	(273.400)	(3.813)	(0.059)	(9.052)	(17.132)
ECT	-0.054***	-0.011***	-0.410	-0.009	0.000*	-0.068***	-0.038
	(0.015)	(0.004)	(0.625)	(0.009)	(0.000)	(0.021)	(0.039)

Figures in (.) are the corresponding standard errors. *** denotes the rejection of null hypothesis at the 1% level. ** denotes the rejection of null hypothesis at the 5% level. * denotes the rejection of null hypothesis at the 1% level.

Appendix 15 provides the cointegrating vectors and adjustment parameters implied by the long-run coefficient matrix. Like the VECM parameters for the forecasting analysis, the slope coefficient for the ECT term is close to zero for all equations in the VECM except for nickel futures (ΔNI), iron ore futures (ΔOR) and hot rolled coil steel futures (ΔHRC) whose slope coefficient is not statistically significant. This suggests that the long-run relationship between the change in demolition spot prices and the futures contracts used in the VECM is weak and many not result in a highly effective hedge.

Before running the multivariate regression of the residuals, the Pearson correlation matrix, VIF and Belsley Collinearity diagnostic for residuals was calculated to confirm that VECM residuals are uncorrelated. The results, provided in Appendix 16, indicate that there is low correlation between the residuals. Each residuals time series maintained a VIF much less than the threshold of 10 and the Conditional Index of the Belsley Collinearity diagnostic did not rise above 2 while the test threshold was set at 30. These diagnostic test results support the assumption that the VECM residuals are uncorrelated and the method for deriving the hedge ratios leading to the hedge ratio in Table 26 was accurate.

Table 26. The Optimal Hedge Ratio for the Vector Error Correction Model

Intercept	u_{Clc}	u_{NI}	u_{OR}	u_{CP}	u_{SR}	u_{HR}
0.330	-0.167	0.002	-0.102	-6.756	0.111**	0.012
(0.606)	(0.281)	(0.002)	(0.140)	(9.670)	(0.056)	(0.032)

Figures in (.) are the corresponding standard errors. *** denotes the rejection of null hypothesis at the 1% level. ** denotes the rejection of null hypothesis at the 5% level. * denotes the rejection of null hypothesis at the 1% level.

The result in Table 26 show that only the hedge ratio for the Steel Rebar futures (u_{SR}) are significant at a 5% significant level. More important, this is consistent with the result from the hedge ratio in the ECM, which suggest that only the Steel Rebar futures should be used to hedge the demolition price.

7.4.3 The Ordinary Least Square Model

Finally, the results of the OLS regression between the changes in demolition spot prices and changes in steel scrap futures prices is provided in Equation (32).

$$\Delta D_t = \underset{(0.626)}{0.714} + \underset{(0.06)}{0.102} \Delta M_t + u_t \tag{32}$$

Figures in (.) are the corresponding standard errors.

From Equation (32), the slope coefficient of 0.102 is the optimal hedge ratio. The results show that neither the slope coefficient nor the intercept coefficient is significant at the 10% level of significance.

7.5 Hedge Effectiveness

Using the methodology discussed in Section 4.12.4 (Hedge Effectiveness), the calculated variance and hedge effectiveness is presented in Table 27.

Table 27: Hedging Results

		IN-SAMPLE		*OUT-OF-SAMPLE*	
		Variance	Hedging efficiency	Variance	Hedging efficiency
UNHEDGED		63.612	-	62.245	-
VECM		<u>60.090</u>	<u>0.055</u>	62.538	-0.005
OLS (ΔM)		62.581	0.016	62.382	-0.002
ECMs	ΔClc	63.622	0.000	62.155	0.001
	ΔNI	63.566	0.001	<u>61.563</u>	<u>0.011</u>
	ΔOR	420.943	-5.617	62.155	0.001
	ΔCP	70.653	-0.111	62.219	0.000
	ΔSR	63.618	0.000	63.654	-0.023
	ΔHR	62.654	0.015	61.659	0.009
NAÏVE	ΔClc	68.557	-0.078	68.946	-0.108
	ΔM	142.444	-1.239	180.331	-1.897
	ΔNI	113326.037	-1780.514	205387.159	-3298.637
	ΔOR	86.233	-0.356	90.590	-0.455
	ΔCP	63.650	-0.001	62.199	0.001
	ΔSR	151.231	-1.377	152.017	-1.442
	ΔHR	475.553	-6.476	298.689	-3.799

The underline indicate which model has the lowest variance and highest hedging efficiency in the in-sample and out-of-sample.

The result in Table 27 show that the overall hedge performance of the naïve hedge strategies were the worst in both in-sample and out-of-sample period. In fact, the hedge positions taken both in-sample and out-of-sample do not substantially reduce the portfolio variance in any of the static models. The hedged portfolio from the VECM in the in-sample period had the best hedge efficiency of 5.5% and the ECM hedge strategy using Nickle produced the best out-of-sample hedge efficiency of 1.1%. One interesting observation in the ECMs is that Steel Rebar futures are the only hedged portfolio which had a negative hedge efficiency out-of-sample, even though only the hedge ratio for the Steel Rebar futures were significant.

To cross-reference the hedging results presented in Table 27, changes in the demolition spot price were regressed against changes in the futures contracts using the multi-variate OLS and univariate OLS techniques. Additionally, the hedge effectiveness produced from the implied hedge ratios from these regressions were calculated. The hedge ratio and hedge effectiveness results, presented in Appendix 17 and Appendix 18, indicate that out-of-sample hedge effectiveness results for the multivariate and univariate OLS are very close to the out-of-sample hedge results for the VECM and ECM provided in Table 27.

7.6 Discussion of the Hedging Analysis

Given the relatively poor hedge effectiveness of the strategies tested, this section discusses the underlying reasons for this poor performance. Specifically, it was determined that basis risk, changing correlation between the spot and futures prices, and limitations of the static hedging model all contributed to relatively low hedge effectiveness.

The first explanation for the poor hedging effectiveness is attributed to basis risk which McDonald (2014) describes as the risk when the price of the hedge instrument and spot do not move in the same direction. This risk becomes more pronounced when risk managers use the cross-hedging technique which Hall (2018) describes as "hedging an exposure to the price of one asset with a contract on another asset". This technique is used when the underlying asset for the hedge contract does not exactly match the underlying asset for the spot price as is found in this study since a hedging instrument with the exact same underlying as the spot price does not exist.

A brief examination of the underlying assets behind ship demolition contracts and the best hedging candidate, steel scrap futures, illustrate why considerable basis risk exists. According to Jain (2018), approximately 60% of a vessel recycled in South Asia is made of re-rollable steel scrap metal. The re-rollable steel comes from only a portion of the vessel made of steel plates, beams girders and angle bars. The remaining 40% of the vessel is made of irregular pieces of metal which is used for melting scrap. It is important to note that these proportions are rough approximations of all the types of vessels being recycled in South Asia. To date, no studies have been conducted which explicitly specify the proportions of scrap metal grades coming from a VLCC vessel in India.

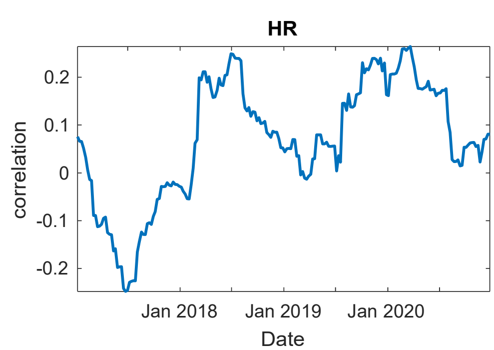
Contrast this with the most logical hedge instrument, steel scrap metal futures. Based on the name of the hedge contract and the results of the Pearson correlation matrix given in Table 8, steel scrap metal futures would appear to be an appropriate hedge instrument. However, a comparison of the settlement location and steel grade reveal that the underlying assets for the spot and futures contracts are vastly different. According to LME (2018), settlements for LME's steel scrap futures are settled based on the Monthly Index Price of the "Platts and The Steel Index (TSI) Heavy Melting Steel HMS 1&2 80:20 Cost and Freight (CFR) Turkey assessment". As the full description implies, there are clear differences in location, grade, and quality between the spot and futures contracts. The demolition spot prices for the VLCCs in India reflection regional prices for a specific type of vessel while the Turkish TSI HMS 1&2 80:20 reflect international steel scrap originating from multiple locations. S&P Platts (2020) describes the TSI HMS 1&2 80:20 as the "price assessment [that] reflects the tradeable value of bulk ferrous scrap imports into Turkey from all supply regions. These supply regions are predominantly the US, UK, Benelux, Baltics". Given these locational differences, basis risk is likely to exist. This is especially true when broad, international steel scrap futures contracts are used to hedge regionally specific exposures to steel scrap produced from a vessel.

In addition to locational differences, there are differences in grade between the spot and futures contracts. S&P Platts (2020) describes the Turkish TSI HMS 1&2 80:20 as a blended mix of shredded, plat and structural steel scrap where 80% is composed of shredded steel used in the melting process while the remaining 20% is the grade of steel scrap which is used for re-rolling. On the other hand, VLCCs contain 40% meltable steel scrap, comparable to shredded steel, and 60% re-rollable steel. The differing portions of meltable to re-rollable steel scrap is another source of basis risk when using steel scrap futures to hedge demolition spot prices.

Taken together, the differences in settlement location and grade are some of the reasons why the hedge models performed poorly. To address these issues, an alternative futures contract may be considered in future studies. In October 2020, LME announced plans to launch a new steel scrap futures contract with settlement based on the Indian steel scrap market (S&P Global Platts, 2020). This new futures contract may reduce the basis risk caused by locational differences between the spot and futures contract. Specifically, these new futures contract will be underwritten on the Platts' containerized shredded scrap CFR Nhava Sheva index, which is more aligned with the ship demolition operations in India. S&P Platts claims that these new Indian steel scrap contracts are being issued to "address basis risk between geographical and regional differences among India, Turkey, and eastern Asian markets" (2020). Once these contracts have been established, an additional study may be conducted to test the hedge effectiveness of these new futures contracts.

An additional reason why the hedge models performed poorly is the changing correlation between the spot and futures prices. Ghosh (1993) pointed out that the stability of the Pearson's correlation between changes in the spot and futures prices was critical in establishing an effective hedge. To test whether the correlation between the changes in the spot, ΔD_t, and the changes in the futures contracts, ΔX_t, is stable over time, the 52-week rolling correlation was graphed for the different hedge instruments and presented in Figure 12. From the graph, one observes that the correlation sign changes multiple times. This is a strong indication that a static hedge would perform poorly over time.

Figure 12. Correlation Between ΔD against ΔX



To confirm that the dramatic shifts in correlation were not related to serial autocorrelation associated with overlapping observations, a separate analysis was conducted which shows the correlations between the changes in spot and futures prices for each of the whole year periods shown in Table 28.

Table 28: Static Correlation with changes in Demolition Prices

	ΔClc	ΔM	ΔNI	ΔOR	ΔCP	ΔSR	ΔHR
2016	0.039	0.244	0.094	0.132	-0.104	0.317	0.094
2017	0.083	0.134	-0.072	0.054	0.029	0.260	-0.036
2018	-0.130	-0.008	0.236	-0.274	-0.063	0.046	0.058
2019	0.067	0.138	0.095	0.021	0.080	0.075	0.170
2020	0.049	0.032	0.150	0.032	0.029	0.029	0.090

Like the graph of the 52-week rolling correlation, the correlations in Table 28 shift dramatically during each subperiod. Given that stable correlation is one of basis prerequisites for establishing an effective static hedge, the instability of the correlation between the spot and futures prices indicates that the static hedge methodology is not the most appropriate hedge methodology. Given the large basis risk and fluctuating correlation between the spot and futures prices, it is not recommended that the hedging techniques tested in this thesis be used by ship demolition market participants for risk management purposes.

A more effective hedge strategy which may be explored in future studies is dynamic hedging. According to Hall (2017) dynamic hedging occurs when the hedge position is adjusted on a regular basis. One specific dynamic hedging approach which has been recently used in the field of maritime hedging is the GARCH. For example, Kavussanos and Nomikos (2000) used this type of model when hedging vessel purchase prices using freight futures contracts. One clear advantage of this model is that the hedge ratio will adjust during periods of high volatility. Another popular dynamic hedging technique used in many industries is delta hedging which is the practice of making a portfolio of the spot and futures prices delta neutral by adjust the hedge position. According to Hall (2017), a delta natural position would be achieved when the partial derivative of the portfolio with respect to the spot price is zero. One potential disadvantage is the transaction costs which would be generated by frequently adjusting the hedge position and the potential for liquidity shortfalls.

To summarize, it is not recommended that ship demolition market participants use the techniques studied in this thesis to hedge ship demolition price risk because of poor hedging performance. The low hedge effectiveness can be attributed to two factors. One factor is the basis risk between the spot and futures contracts. Another factor is the changing correlation between spot and futures contracts. Future studies may improve upon the models tested by considering hedging instruments which better match the underlying of the spot contract and employing dynamic models which better adjust to periods of high volatility.

8. Summary & Conclusion

This thesis set about with two concrete objectives. The first objective was to determine whether the Vector Error Correction Model (VECM), Error Correction Model (ECM), or Autoregressive Moving-Average (ARMA) model provided the most accurate out of sample forecast using 9 different explanatory variables relevant to the ship recycling industry. The second objective was to determine which one of these models also provided the greatest hedge effectiveness when using several comparable futures contracts.

The analysis in the forecasting section, found that the VECM had the lowest (most accurate) Root Mean Squared Error (RMSE) in the in-sample test but failed to be the most accurate model for the out of sample test. Rather, the ECM using iron ore spot prices as the dependent variable had the lowest RMSE and Mean Absolute Error (MAE) while the Naïve forecast had the lowest Mean Error (ME) and Tracking Signals (TS). These results negated the presumed hypothesis that the VECM would be the most accurate forecasting model since it contained the greatest number of parameters. This thesis posits that the underlying cause of this difference is the tremendous fluctuations in demolition spot prices in the in-sample period. The volatility in the in-sample period caused the long-run coefficients for most of the error corrected models to be relatively small and not statistically significant producing sub-optimal forecasts.

The hedging analysis conducted in the second section of the thesis used the same regression model but utilized comparable hedge instruments to assess which model yielded the highest hedge effectiveness. The analysis found that all models tested, the VECM, ECM, Ordinary Least Squares (OLS) and Naïve hedge, produced poor hedge results. These results are attributed to a large basis risk stemming from locational and grade differences between the spot and futures contracts as well as changing correlation between the spot and futures prices over time.

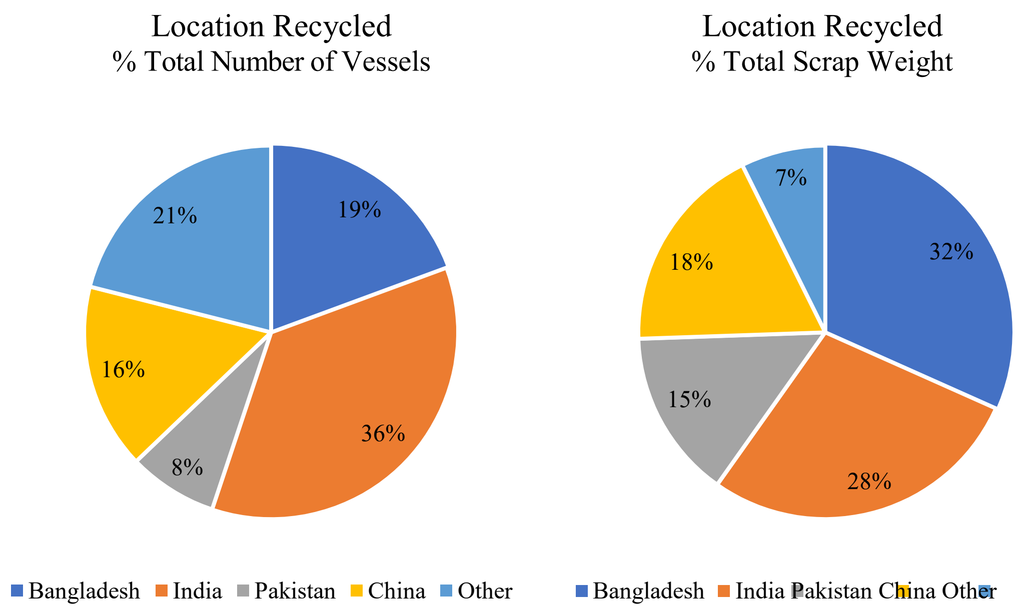
These finding have tremendous impact on market participants who maintain large exposure to older vessels where the vessel's scrap value represents a large portion of the overall value of the vessel. Depending on the amount of leverage taken against the vessel, the forecasting errors produced by the models have too great a margin of error for decision making purposes. Furthermore, based on the poor performance of the hedging models it is not recommended that the hedge models be used for ship demolition risk management purposes.

This thesis adds to body of knowledge in two important ways. First, this study was the first piece of academic literature to attempt to develop a hedging model which could be utilized in the ship demolition market. Although the hedge instruments and models ultimately proved ineffective, this study lays the groundwork for future hedging studies on the ship recycling market. Second, this work is the first piece of literature to focus specifically on forecasting VLCC demolition prices in India while other pieces of work focused on different regional markets and vessel types.

To improve both the forecasting accuracy and hedge effectiveness, several recommendations were made throughout this thesis. One suggestion is to select a dynamic forecasting model which can better adjust to periods of high volatility such as the GARCH. Another suggestion is to utilize more regionally specific forecasting variables and hedging instruments.

Appendix 1

Figure 13. Location of Vessel Recycling in Percentage (2000-2020)

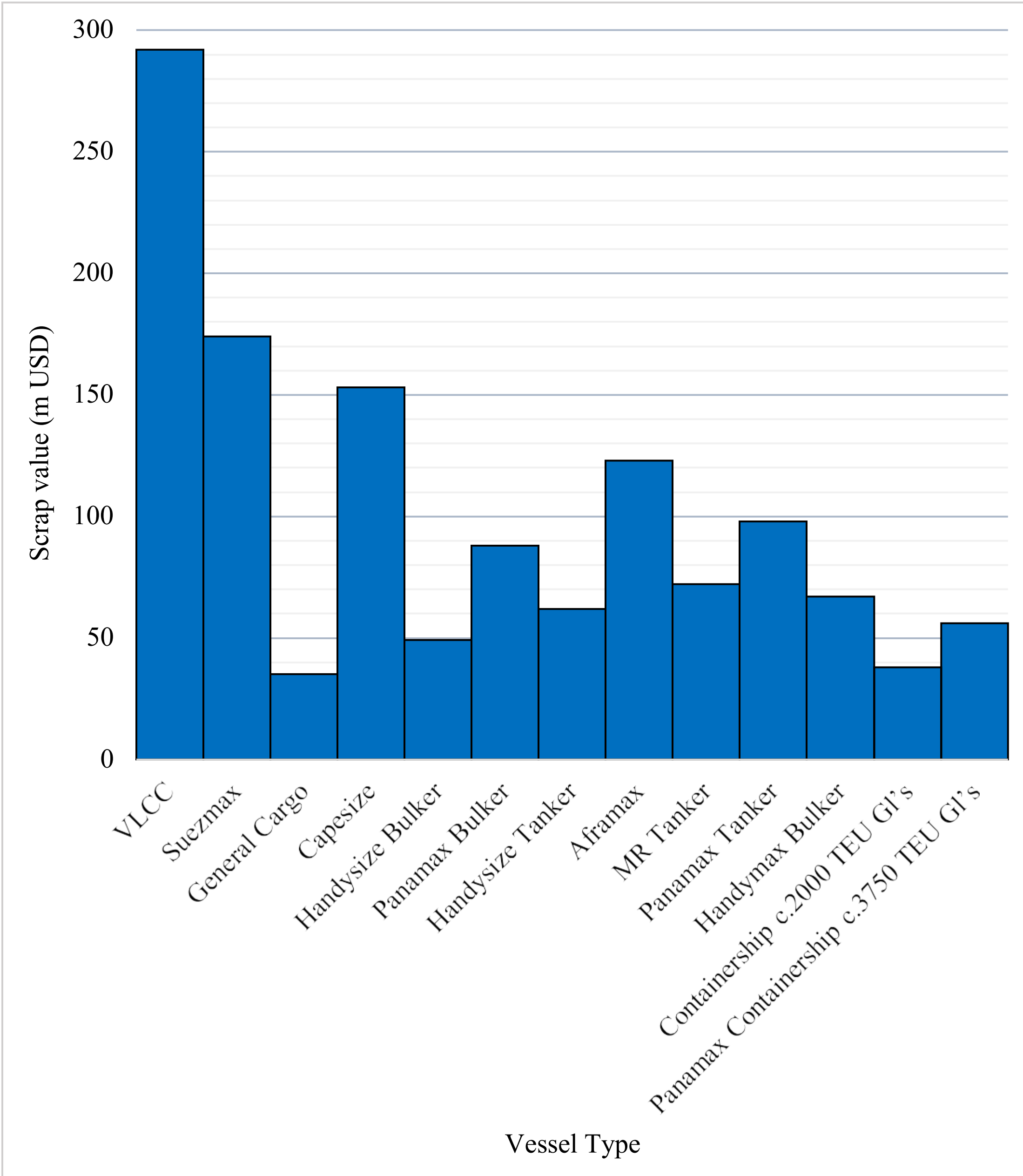


Source: Clarkson's database (2020)

The pie charts in Figure 13 indicates where the recycling activities occurred based on the percentage of total vessels and total scrap weight. The result show that Bangladesh and India recycled above 50% of total number of vessels and total scrap weight in the period of 2000 to 2020.

Appendix 2

Figure 14. Aggregate Nominal Scrap Value Based on Vessel (2000 - 2020)

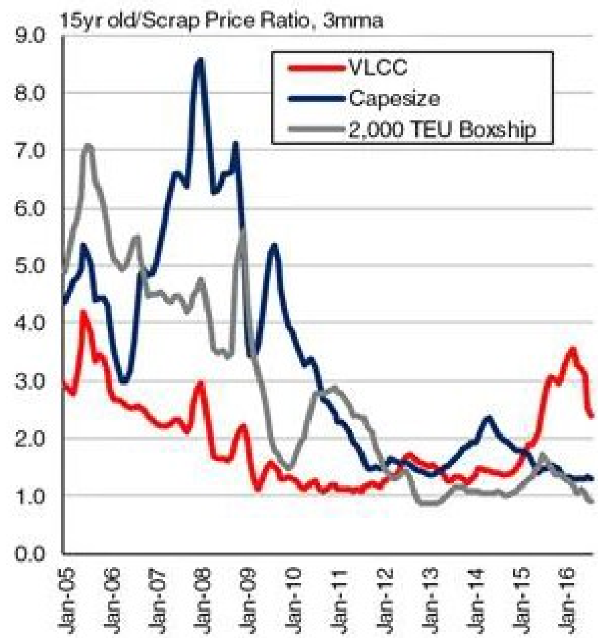


Source: Clarkson's database. Total scrap value is 1,308 m USD

In Figure 14 Very Large Crude Carrier (VLCC) has the highest scrap value of 292 million USD and represent 22.3% of the aggregate nominal scrap value from the year 2000 to 2020. The total scrap value in this period is 1,308 million USD.

Appendix 3

Figure 15. Volatility in the Ratio of Scrap Value to Second-Hand Prices (2005-2016)



Reprinted from Clarkson's Research (2016)

This graph illustrates the volatility of this metric for three different classes of vessel over a 12-year period. Clarkson's Research (2016) posited that this indicator was a rough measure of the health of the global shipping market. When freight rates are high, this indicator tends to be much greater than 1; however, during downturns in the global shipping market this ratio drops closer to one. For vessel owners, the scrap value of a vessel serves as a "floor" in the secondary vessel market.

Appendix 4

Multicollinearity in the Forecasting Variables

The correlation matrix for the variables on the level and the first difference is the first basic test for multicollinearity and is a straightforward indication of pairwise collinearity. The results are provided in Table 29 and Table 30.

Table 29: Correlation Matrix on the Level (Forecasting)

	S	O	RD	N	IO	E	B	C	P
D	0.928	0.870	0.138	0.685	0.658	0.101	0.326	0.487	-0.044
S		0.904	0.258	0.567	0.812	-0.065	0.065	0.263	-0.225
O			0.087	0.586	0.767	-0.091	0.070	0.330	-0.176
RD				-0.219	0.331	-0.177	-0.418	-0.546	-0.487
N					0.357	0.137	0.475	0.688	0.086
IO						-0.304	-0.321	-0.103	-0.480
E							0.750	0.460	0.754
B								0.840	0.775
C									0.506

The underline indicates there is a correlation greater than 80%,.

The correlation matrix of the variables on the levels in Table 29 indicate that the scrap metal index (S) and oil prices (O) have a high correlation between each other and a high a correlation with demolition prices on the level above 80%. This high degree of correlation suggests that there may be a long-run cointegrating relationship between these variables. The correlation matrix also suggests there is high correlation between the scrap metal index (S) and oil prices (O), scrap metal index (S) and iron ore (IO), and ClarkSea Index (C) and the Baltic Tanker Index (B). The correlated relationship between C and B makes economic sense since the ClarkSea Index (C) is a weighted average of the earnings of all the commercial vessels in the world fleet and the Baltic Tanker Index is an indicator of the earnings of all the tankers in the world, a large subset of the world fleet.

Table 30: Correlation Matrix on the First Difference (Forecasting)

	ΔS	ΔO	ΔRD	ΔN	ΔIO	ΔE	ΔB	ΔC	ΔP
ΔD	0.490	0.405	-0.081	0.242	0.148	-0.002	0.264	0.625	0.066
ΔS		0.356	0.061	0.217	0.251	0.047	0.261	0.506	0.148
ΔO			-0.039	0.260	0.182	-0.076	0.118	0.348	0.037
ΔRD				-0.048	0.000	0.141	0.123	-0.042	0.057
ΔN					0.235	-0.067	0.047	0.235	0.003
ΔIO						-0.080	-0.090	0.067	-0.077
ΔE							0.698	0.050	0.662
ΔB								0.382	0.764
ΔC									0.506

The underline indicates the variables had a correlation greater than 80% on the levels.

After taking the first difference of these variables, the correlation between the change in demolition prices and the change in scrap metal price and oil prices decreases by nearly half as shown in Table 30. This indicates that taking the first difference of these variables assists in reducing the collinearity between variables.

After examining the collinear relationships between variables using the correlation matrices, the VIF and Belsley Collinearity Diagnostics are used to determine if multicollinear relationships exist between multiple sets of variables. The results of the VIF and Belsley Collinearity Diagnostics tests are presented in Figure 16 and Table 31.

Figure 16. Variance Inflation Factor (Forecasting)

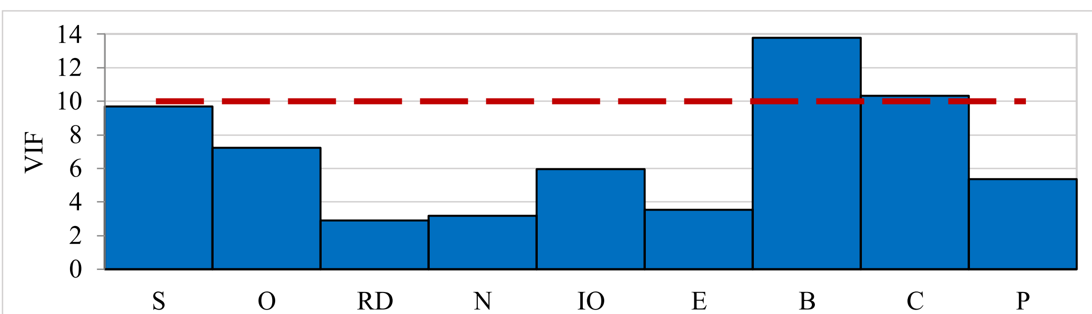


Figure 16 show the VIF for each variable (blue bars) and the red line is our threshold to indicate concern about the multicollinearity. If the bar crosses the red line (i.e., threshold of 10) multicollinearity is present.

According to Brooks (2019), VIF measures the amount of increase in the variance of the parameter estimates when multicollinearity is present. Figure 16 show B and C has a VIF larger than the threshold of 10, suggest that there is a serious collinearity between one or more explanatory variables. To determine which of the explanatory variables have multicollinear relationships, the Belsley Collinearity diagnostic test was employed.

Table 31: Belsley Collinearity Diagnostics (Forecasting)

Condition Index	Variance Decomposition Values								
	S	O	RD	N	IO	E	B	C	P
1.000	0.000	0.000	0.001	0.001	0.001	0.001	0.000	0.000	0.001
3.080	0.002	0.003	0.001	0.001	0.025	0.036	0.003	0.001	0.006
6.080	0.000	0.001	0.119	0.108	0.015	0.067	0.004	0.016	0.009
7.729	0.001	0.005	0.247	0.000	0.051	0.366	0.000	0.006	0.026
11.279	0.008	0.109	0.197	0.428	0.009	0.110	0.003	0.011	0.104
13.887	0.056	0.067	0.174	0.042	0.426	0.078	0.001	0.004	0.450
<u>17.252</u>	0.001	0.222	0.000	0.400	0.357	0.035	0.120	0.186	0.219
<u>21.465</u>	0.395	0.160	0.092	0.020	0.036	0.190	0.200	0.405	0.037
<u>28.379</u>	<u>0.537</u>	<u>0.432</u>	0.168	0.001	0.080	0.116	<u>0.670</u>	0.370	0.148

The underline under the Conditional Index indicates the Conditional Index is greater than 15. The underline in the Variance Decomposition Values indicates the values appear to be multicollinear.

As shown in Table 31, three of the rows have a Condition Index which is greater than 15 but lower than the threshold value of 30, indicating that there is a moderate multicollinear relationship among the explanatory variables. Furthermore, when applying the threshold value of 0.5 to the variance decomposition value provided to the right of the condition index only S, B, and possibly C appear to have a possible multicollinear relationship.

Since the presence of multicollinearity is moderate and this study is more focused on the forecasting ability of different regression models rather than the statistical significance of the parameters, the explanatory variables will not be adjusted to account for the presence of multicollinear relationships.

Appendix 5

Figure 17. Detrending Demolition Prices

In Figure 17, the demolition price time series is “de-trended” so that it becomes integrated of order 0. The linear time trend removed from this data set was fitted using an OLS regression with the demolition price as the dependent variable and a time trend from 1 to the length of the time-series (245 time steps) as the explanatory variable. After calculating the time trend, the series was detrended by removing fitted values from the actual values.

Appendix 6

Table 32. Engle's ARCH Test Statistics (Hedging)

lags	VECM	ECM						OLS
	ΔD	ΔClc	ΔNI	ΔOR	ΔCP	ΔSR	ΔHR	ΔM
1	1.278	0.977	1.058	0.793	1.143	0.953	1.145	1.162
2	1.502	1.095	1.103	1.334	1.335	1.009	1.531	1.182
3	2.037	1.569	1.618	1.407	1.911	1.424	1.869	1.714
4	2.710	2.357	2.467	1.864	2.510	2.241	2.587	2.449

The critical value for a 95% confidence interval for ARCH(1) to ARCH(4) are 3.841, 5.991, 7.815 and 9.488.

In Table 32, none of the models rejects the null hypothesis of no conditional heteroscedasticity (i.e., test statistics is lower than the critical value) for up to 4 lags.

Appendix 7

Table 33. Ljung-Box Test Statistics (Hedging)

lags	VECM	ECM						OLS
	ΔD	ΔClc	ΔNI	ΔOR	ΔCP	ΔSR	ΔHR	ΔM
1	1.827	2.507	2.413	0.498	2.072	2.861	1.410	1.265
2	<u>9.643</u>	<u>12.002</u>	<u>11.723</u>	<u>6.497</u>	<u>10.666</u>	<u>13.120</u>	<u>8.465</u>	<u>7.957</u>
3	<u>10.424</u>	<u>13.698</u>	<u>13.431</u>	6.798	<u>11.895</u>	<u>15.203</u>	<u>8.881</u>	<u>8.847</u>
4	<u>10.968</u>	<u>15.062</u>	<u>14.869</u>	6.998	<u>12.690</u>	<u>16.618</u>	9.203	<u>9.449</u>

The critical value for a 95% confidence interval for LBQ(1) to LBQ(4) are 3.841, 5.991, 7.815 and 9.488.

The underlines given in Table 33 show which model that reject the null hypothesis of zero autocorrelation (i.e., the test statistic is larger than the critical value) in favor of an ARCH(k) model, with k lags.

Appendix 8

Table 34. Information Criteria (Forecasting)

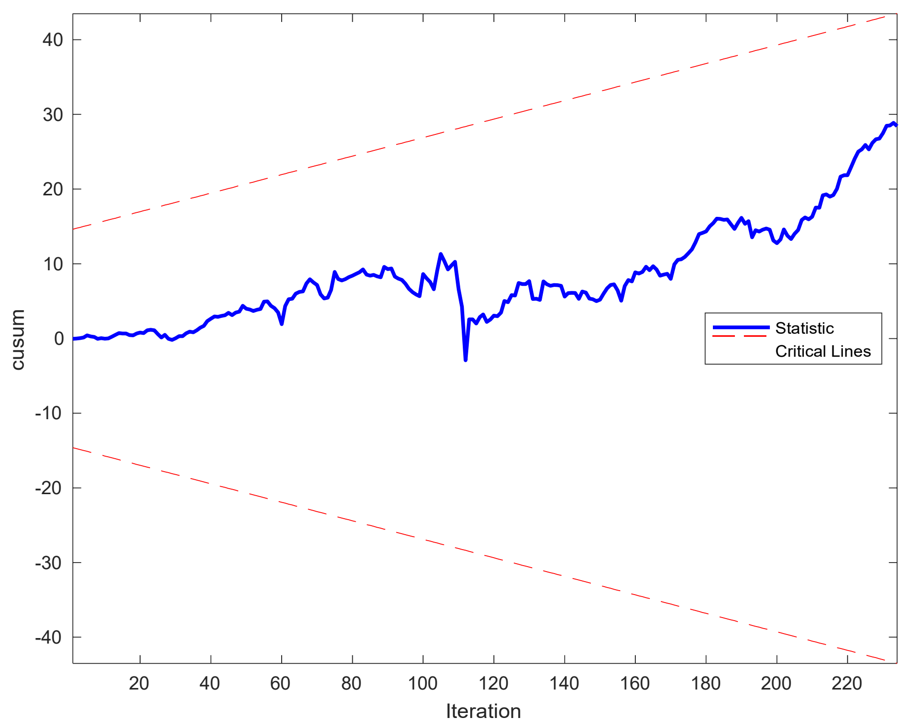
k	AIC(k)	BIC(k)	HQ(k)
0	55.381	55.381	55.381
1	39.971	40.626	40.234
2	38.903	40.213	39.429
3	38.595	40.559	39.383
4	38.617	41.236	39.669
5	38.676	41.950	39.991
6	38.746	42.675	40.324
7	38.804	43.387	40.644
8	38.833	44.071	40.937
9	38.557	44.451	40.924
10	38.511	45.059	41.140
11	38.422	45.625	41.315
12	38.088	45.946	41.244

The information criteria of a VAR model in the forecasting section for up to 12 lag is provided in Table 34 and show that the selected order for BIC is two. The lowest values for the AIC, BIC and HQ are shown with an underline in the table.

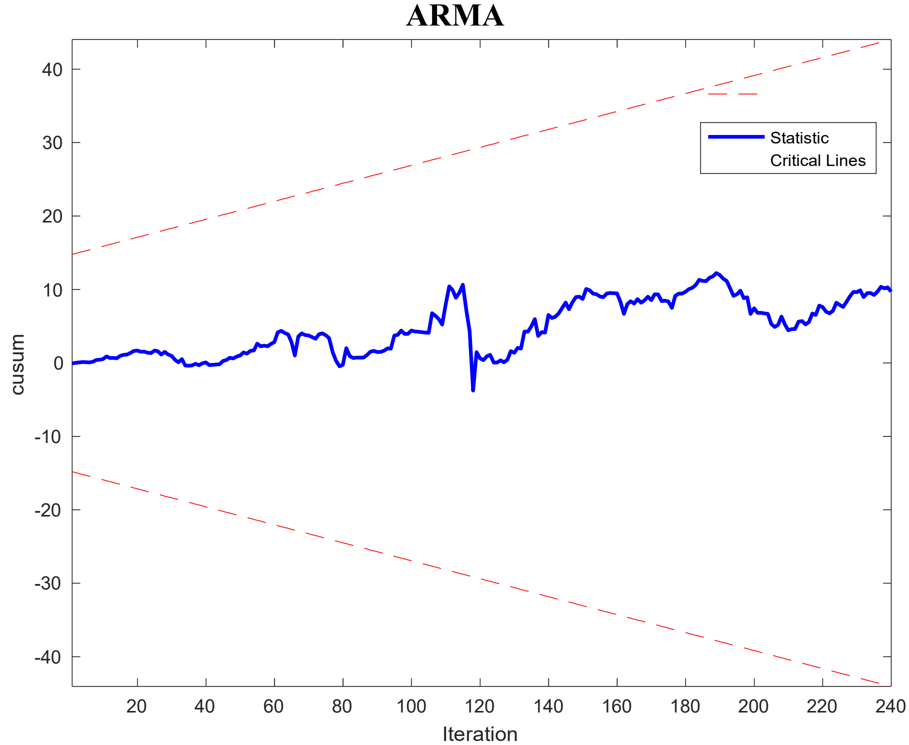
Appendix 9

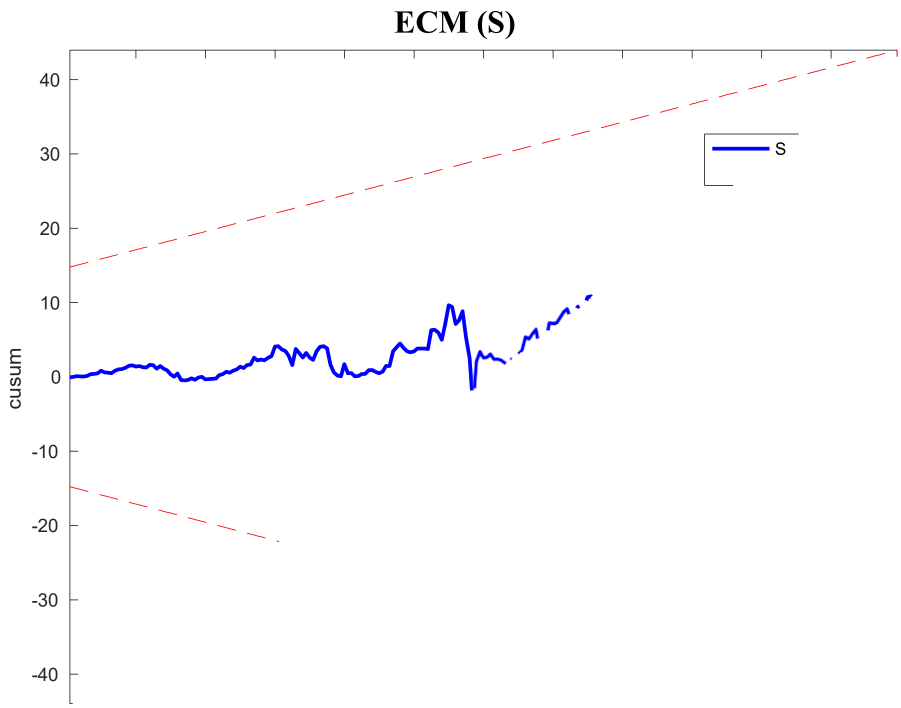
Figure 18. Results of CUSUM Tests (Forecasting)

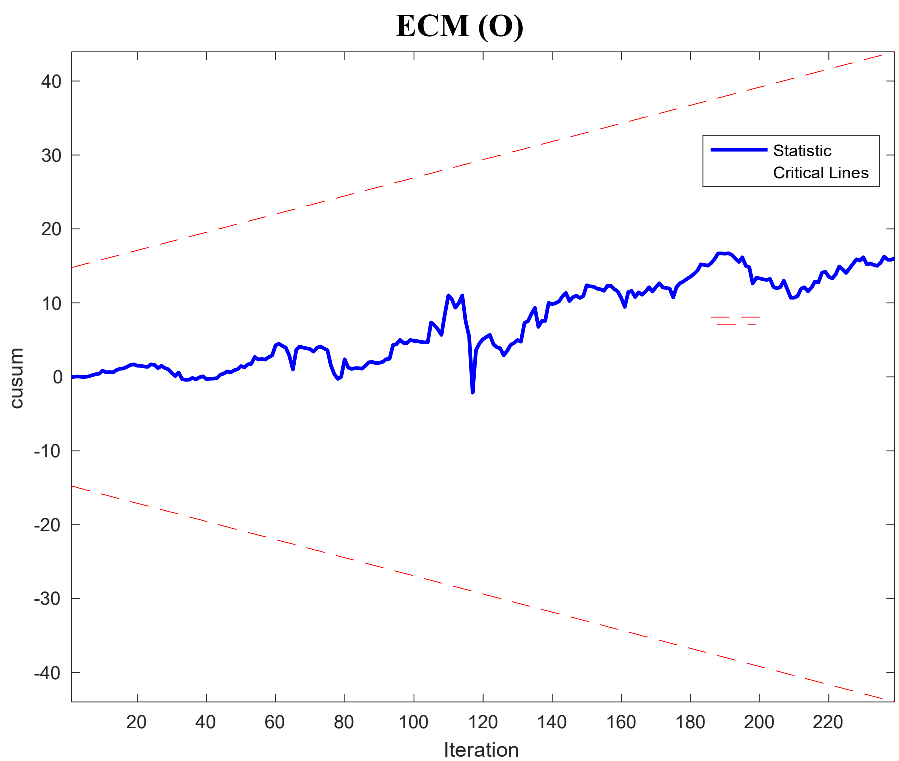
VECM

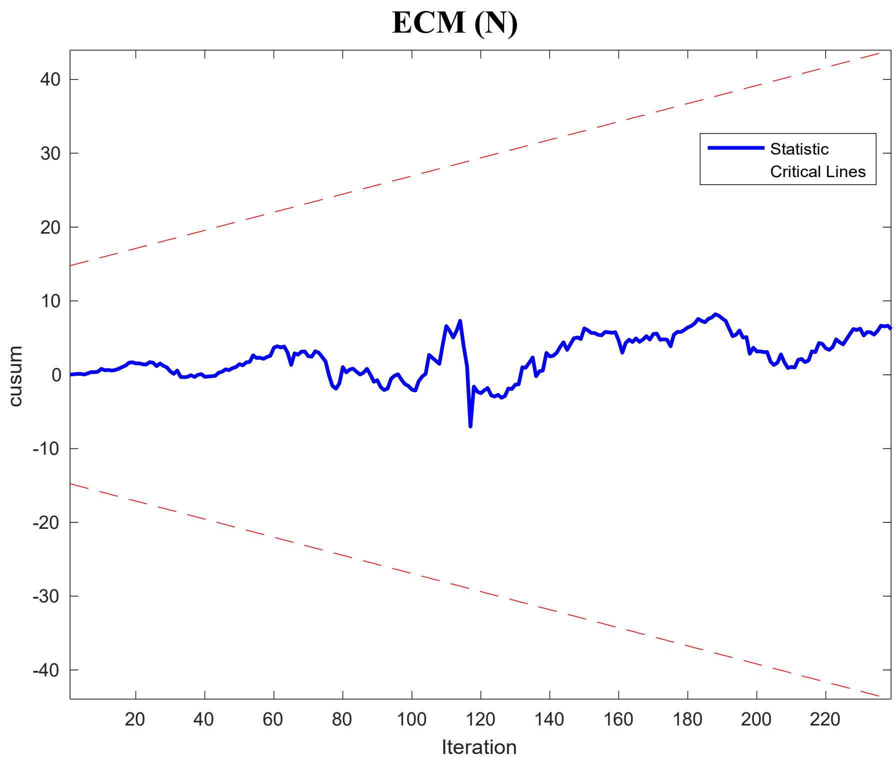


ARMA




ECM (S)
40
30
20
10
0
-10
-20
-30
-40
cusum
S


ECM (O)
40
30
20
10
0
-10
-20
-30
-40
cusum
20
40
60
80
100
120
140
160
180
200
220
Iteration
Statistic
Critical Lines



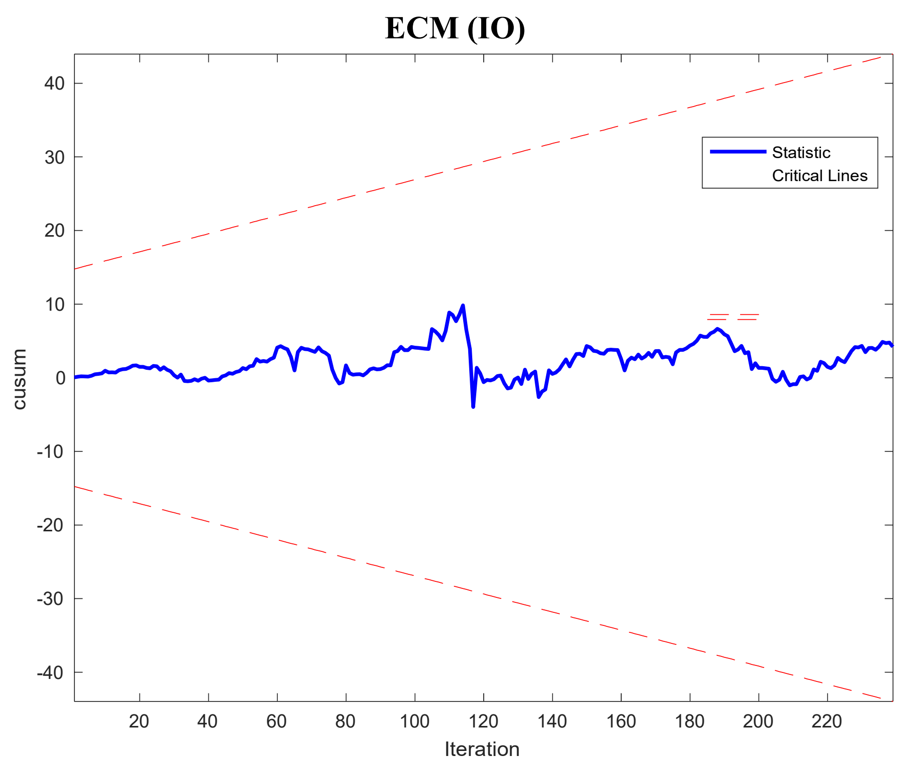


Figure 18 show the statistic (blue line) and the critical lines (red lines) for the CUSUM test for all of the models. If the statistic crosses the critical lines, the null hypothesis of constant coefficients, α and β, is rejected in favor to the alternative of existence of a structural change.

Appendix 10

Table 35. Vector Error Correction Parameters (Forecasting)

	D	S	O	RD	N	IO	C
Adjustment (ℓ)	-2.282	-11.920	-0.400	2.749	-0.502	-0.567	-1.735
Cointegration (ω)	-0.026	0.025	-0.003	0.000	-0.008	-0.008	0.020

Cointegration constant = - 0.613

Recall from the methodology section that the impact matrix is derived from the following expression using the adjustment matrix (ℓ) and the Cointegration matrix (ω).

$$\Pi \; = \ell\omega'$$

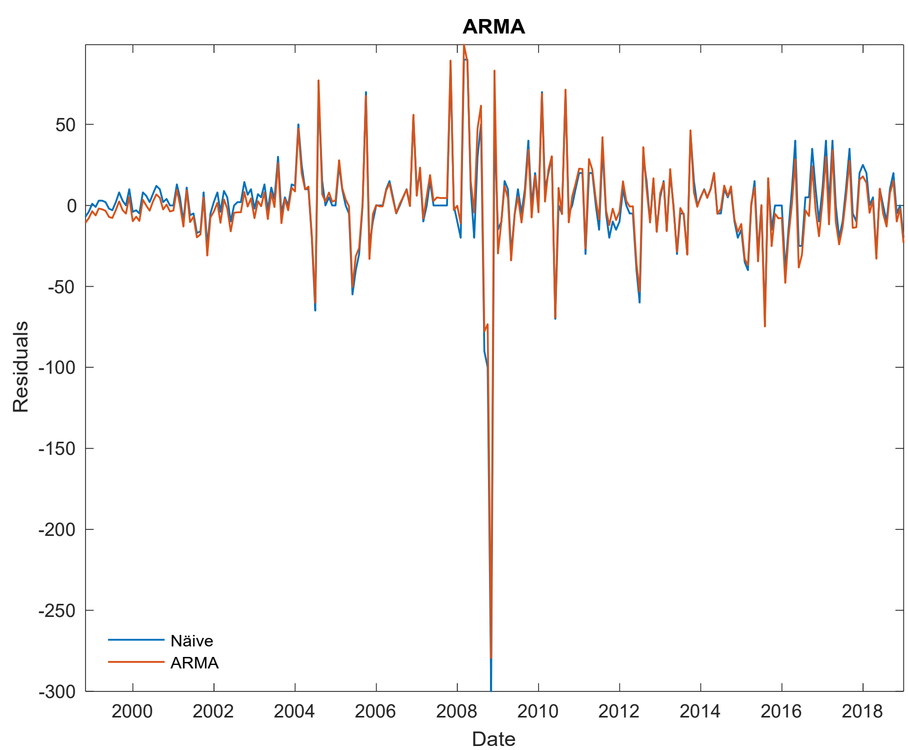
Table 36. Impact Matrix (Forecasting)

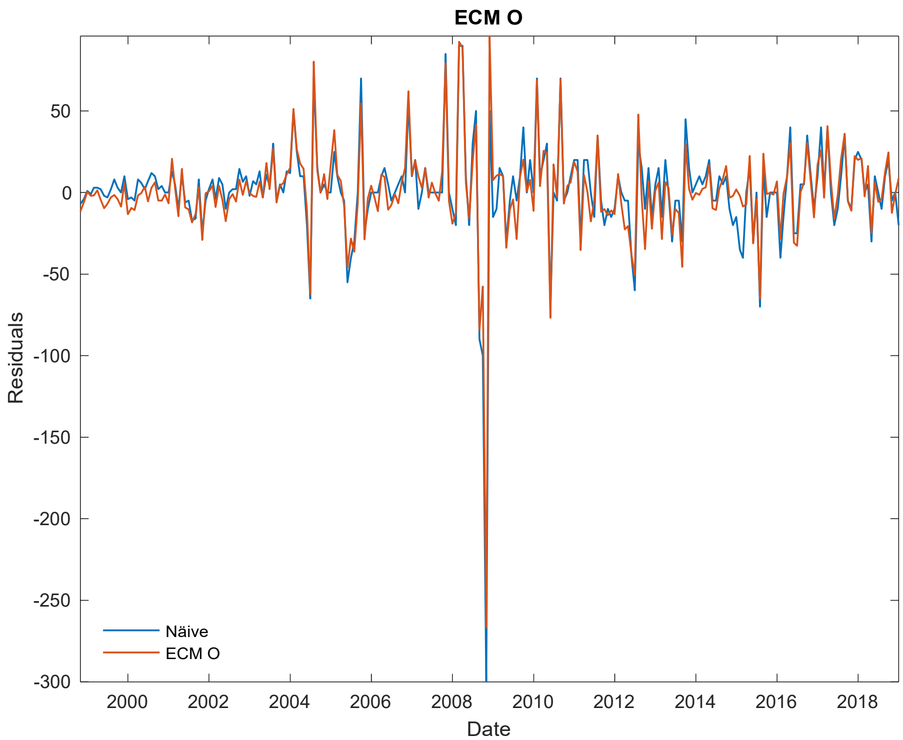
	D	S	O	RD	N	IO	C
Equation ΔD:	0.059	-0.057	0.007	0.001	0.018	0.019	-0.047
Equation ΔS:	0.307	-0.296	0.035	0.003	0.092	0.100	-0.243
Equation ΔO:	0.010	-0.010	0.001	0.000	0.003	0.003	-0.008
Equation ΔRD:	-0.071	0.068	-0.008	-0.001	-0.021	-0.023	0.056
Equation ΔN:	0.013	-0.012	0.001	0.000	0.004	0.004	-0.010
Equation ΔIO:	0.015	-0.014	0.002	0.000	0.004	0.005	-0.012
Equation ΔC:	0.045	-0.043	0.005	0.001	0.013	0.015	-0.035

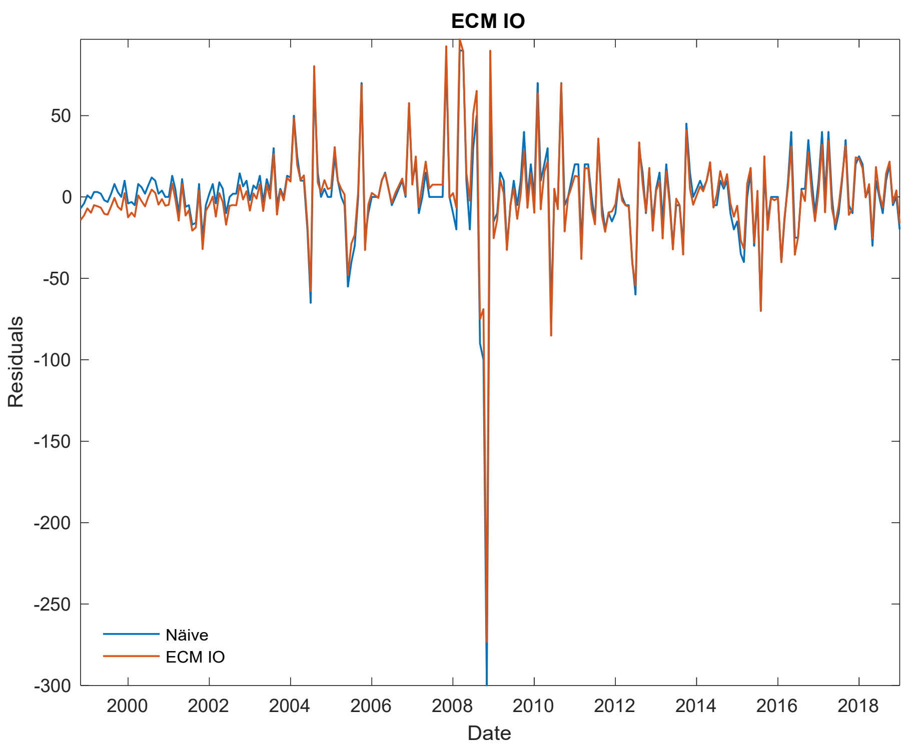
The Impact Matrix given in Table 36 measures the long-run level for each equation in the VECM and its explanatory variables.

Appendix 11

Figure 19. Estimated Residuals (Forecasting)

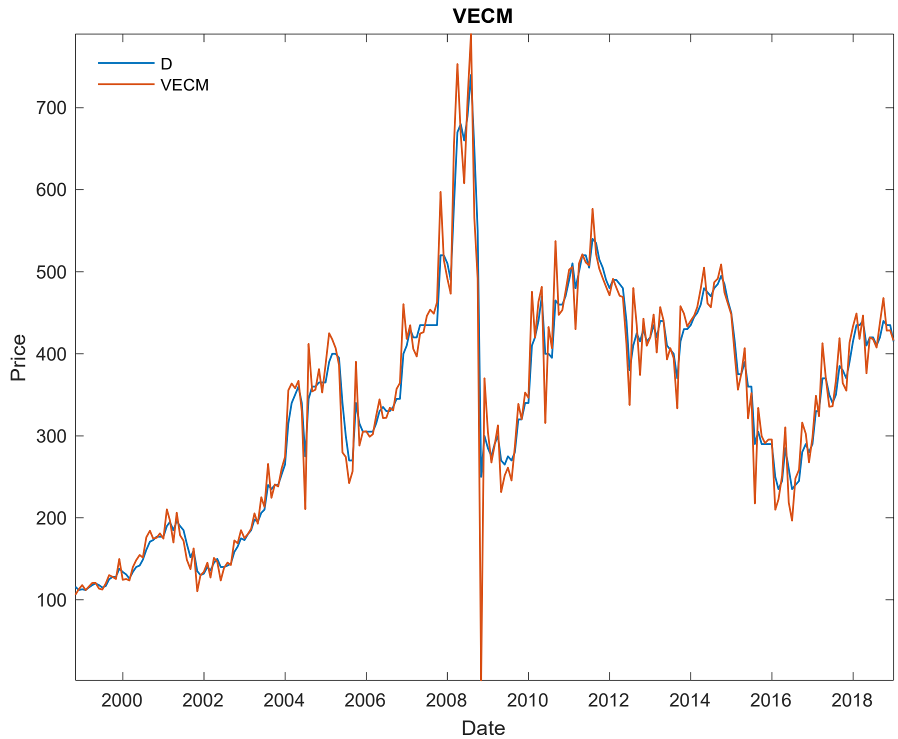


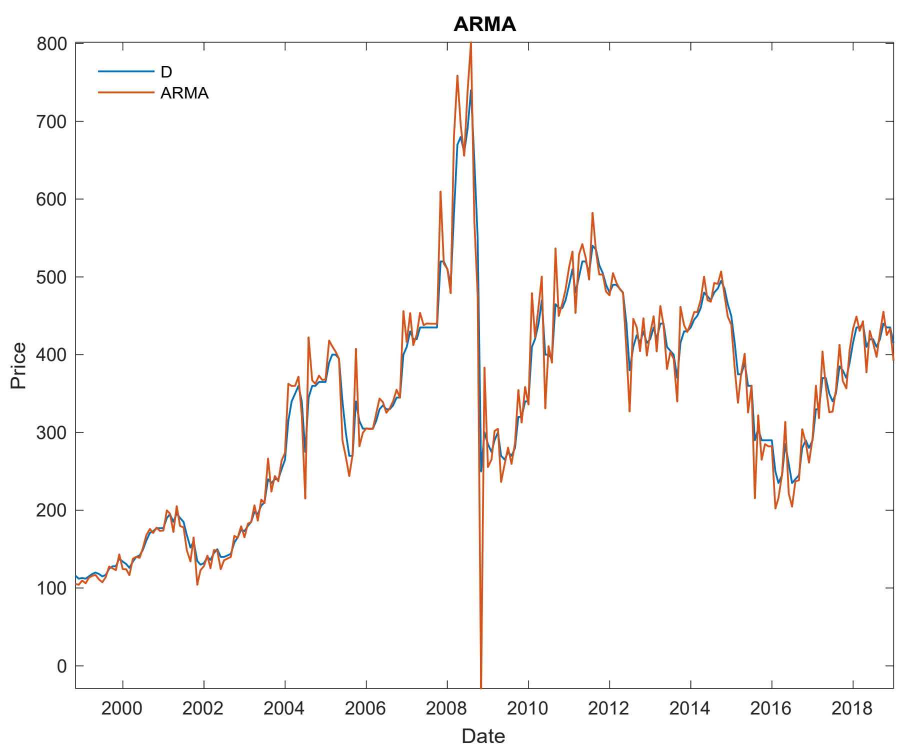

ECM O
Residuals
Date
Näive
ECM O
50
0
-50
-100
-150
-200
-250
-300
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018

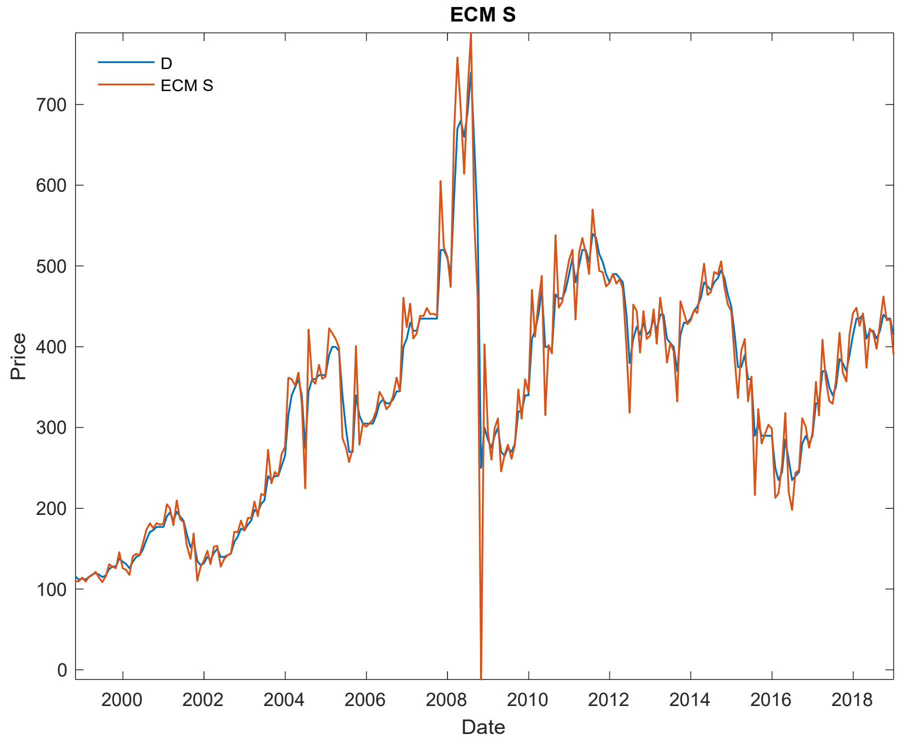

ECM IO
Residuals
Date
Näive
ECM IO
50
0
-50
-100
-150
-200
-250
-300
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018

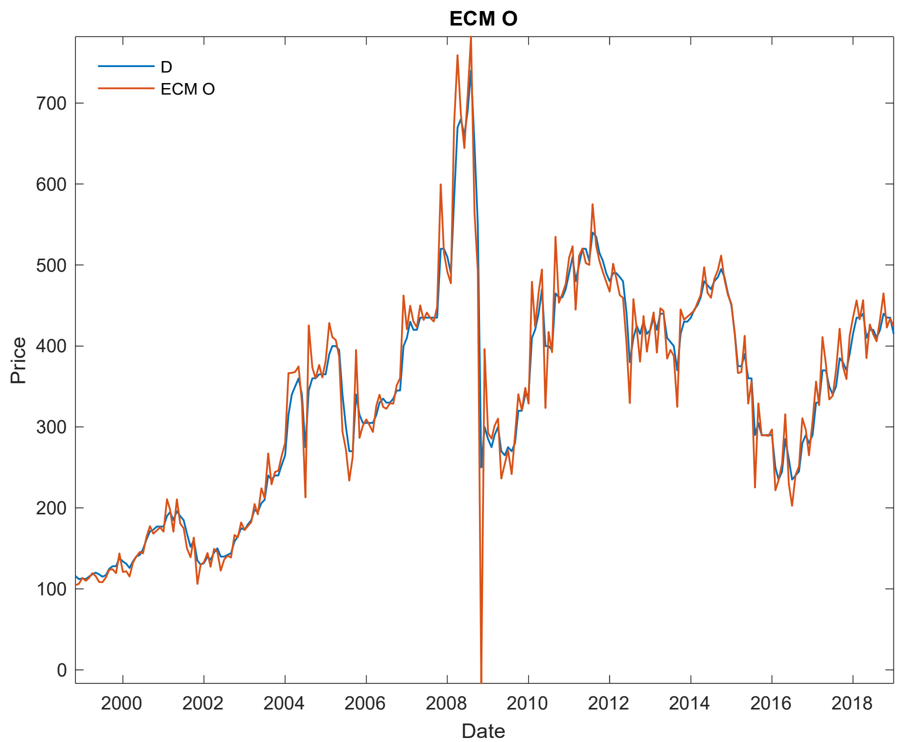
Appendix 12

Figure 20. Fitted Values (Forecasting)






ECM S
D
ECM S
Price
0
100
200
300
400
500
600
700
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
Date


ECM O
D
ECM O
Price
0
100
200
300
400
500
600
700
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
Date


ECM IO
D
ECM IO
Price
Date
0
100
200
300
400
500
600
700
800
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018

Appendix 13

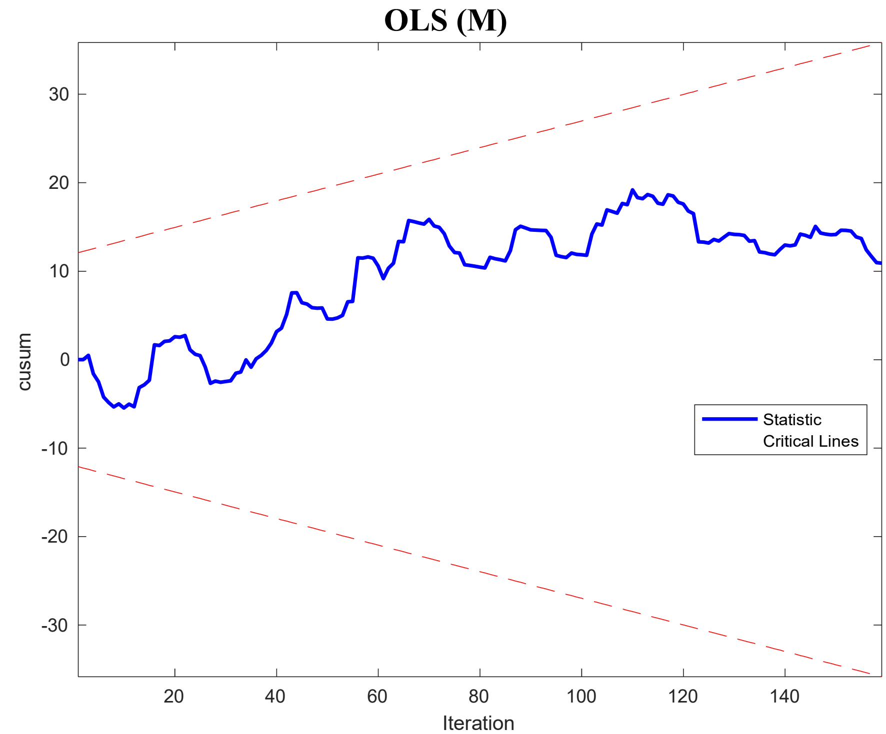
Table 37. Information Criteria (Hedging)

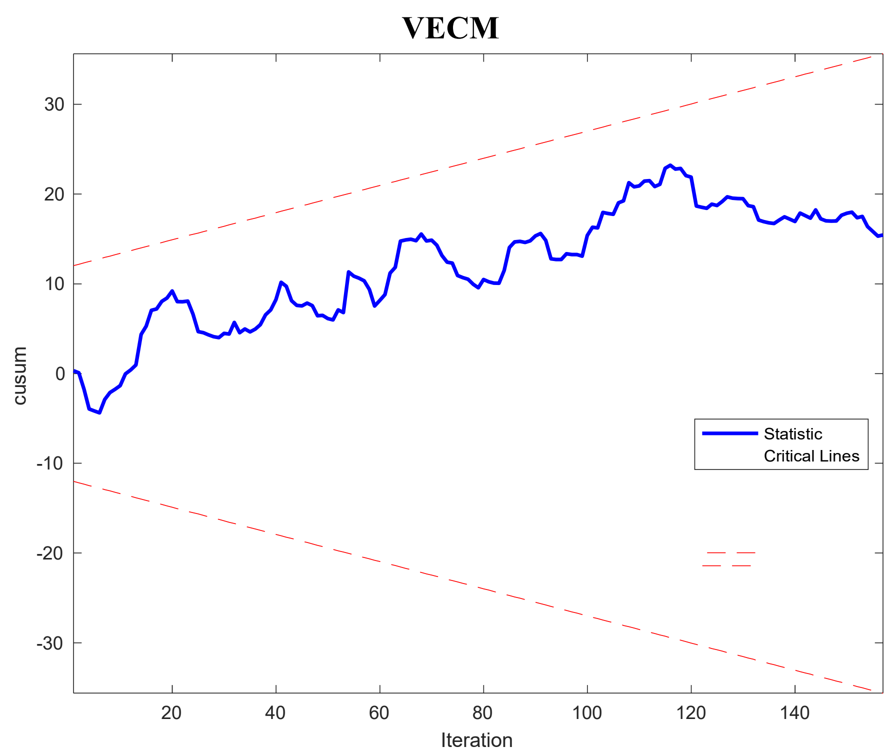
p	AIC(p)	BIC(p)	HQ(p)
0	44.247	44.247	44.247
1	26.153	<u>26.811</u>	<u>26.417</u>
2	<u>26.124</u>	27.440	26.652
3	26.157	28.132	26.950
4	26.238	28.871	27.296
5	26.323	29.615	27.646
6	26.416	30.366	28.003
7	26.498	31.106	28.349
8	26.573	31.839	28.688
9	26.711	32.636	29.092
10	26.758	33.341	29.403
11	26.880	34.122	29.789
12	26.995	34.895	30.169

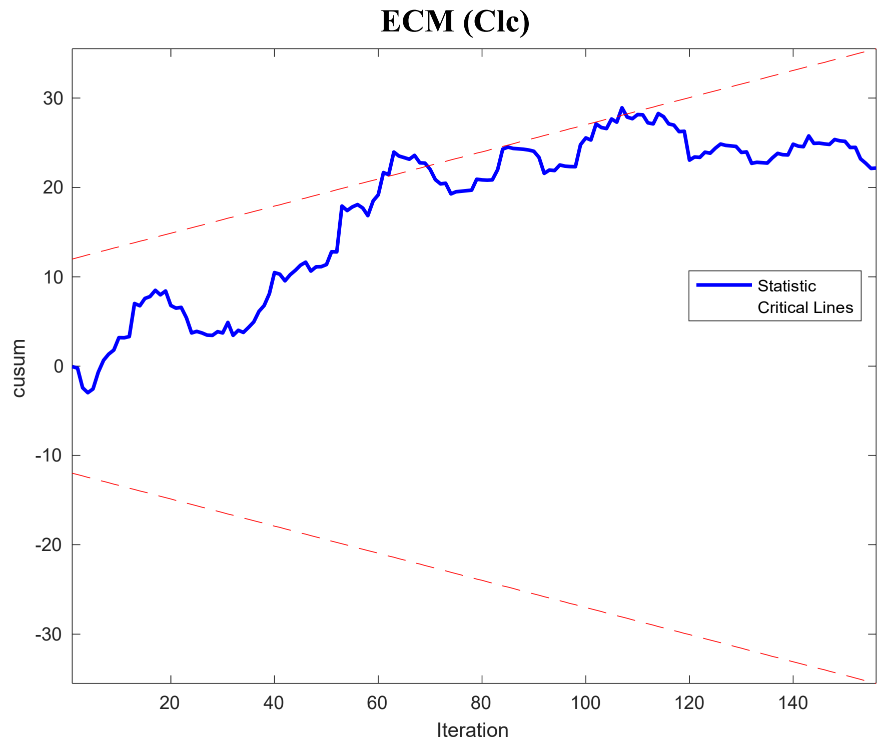
The information criteria of a VAR model in the hedging section for up to 12 lag is provided in Table 37 and suggest that the selected order for BIC is one. The lowest values for the AIC, BIC and HQ are indicated with an underline in the table.

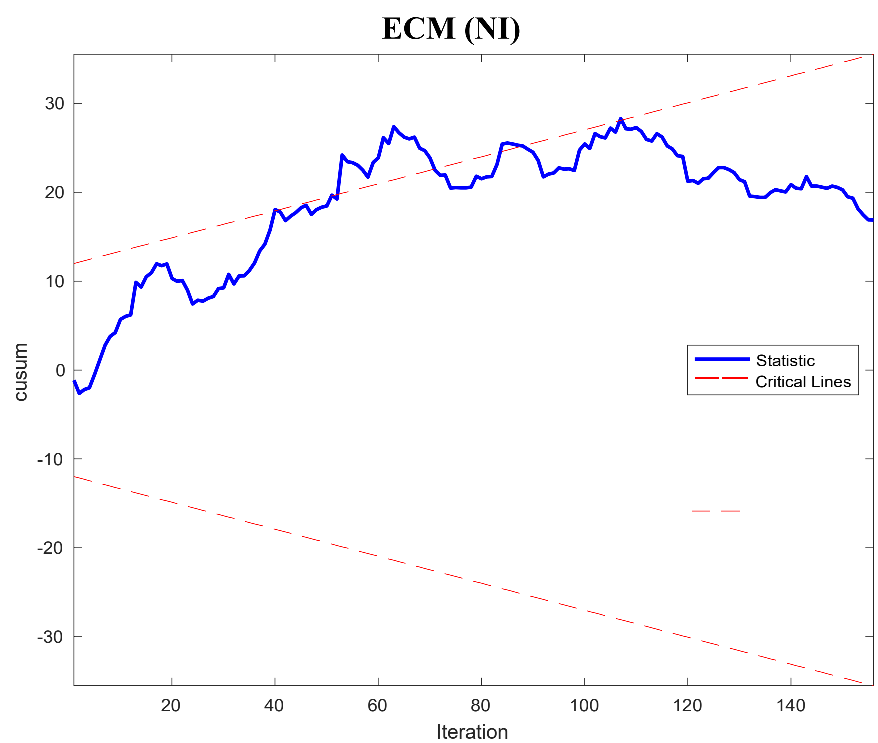
Appendix 14

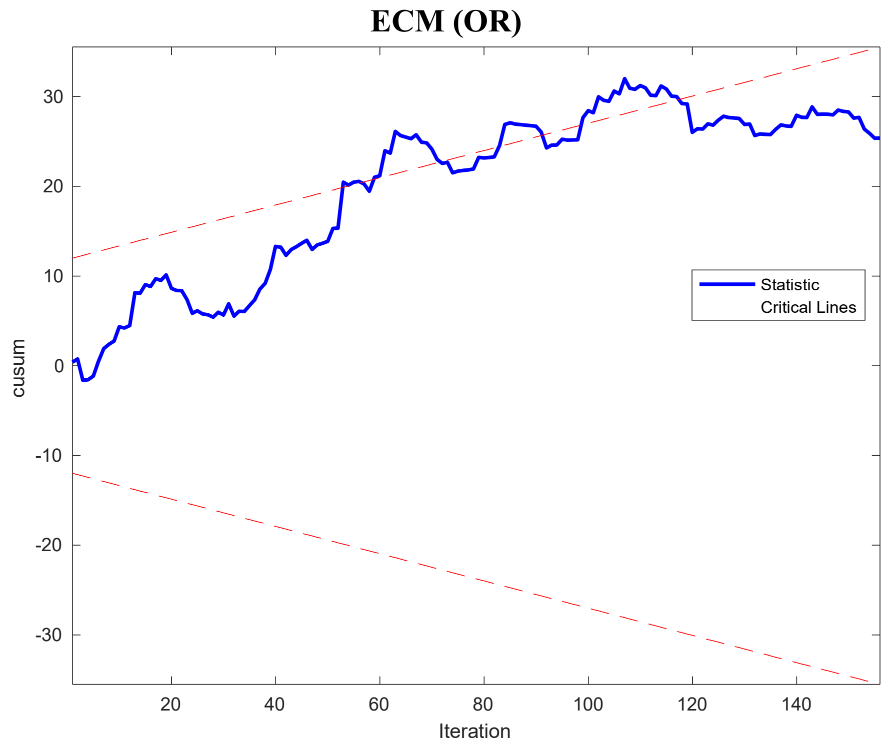
Figure 21. Results of CUSUM Test (Hedging)

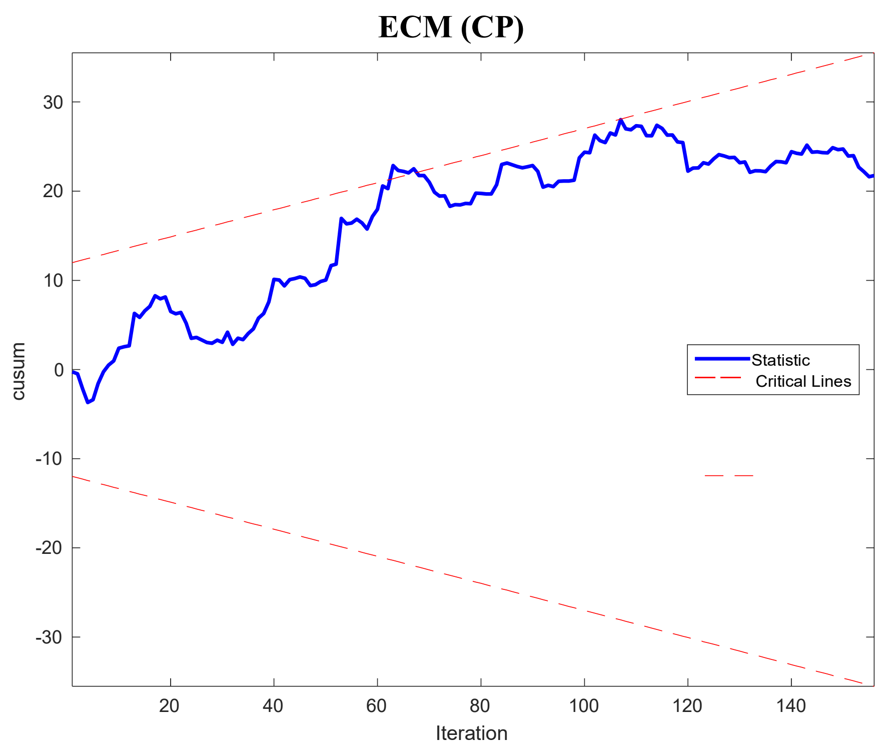




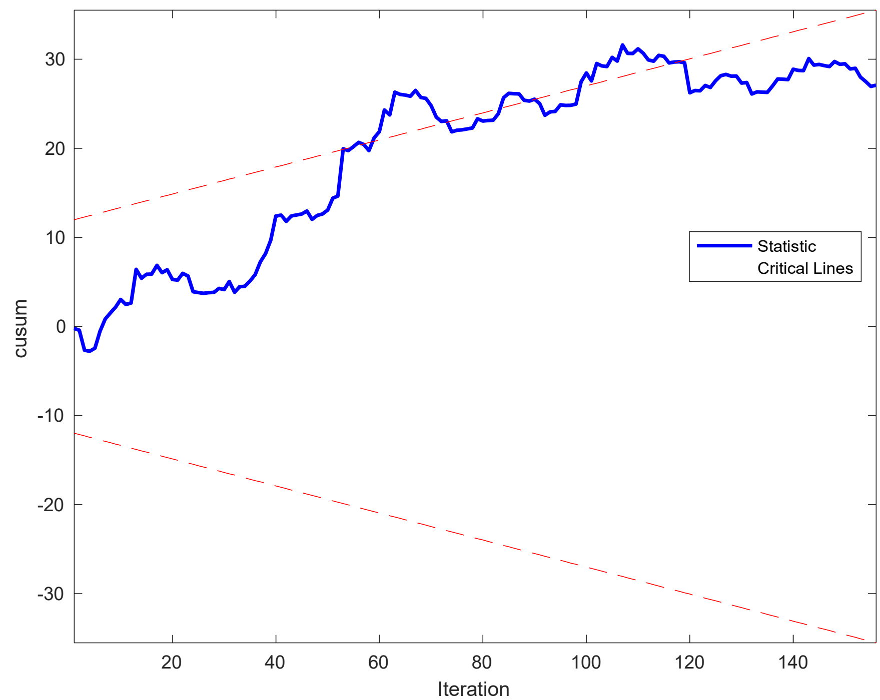

ECM (Clc)
cusum
Iteration
Statistic
Critical Lines
30
20
10
0
-10
-20
-30
20
40
60
80
100
120
140


ECM (NI)
cusum
Iteration
Statistic
Critical Lines
30
20
10
0
-10
-20
-30
20
40
60
80
100
120
140


ECM (OR)
cusum
Iteration
Statistic
Critical Lines
30
20
10
0
-10
-20
-30
20
40
60
80
100
120
140


ECM (CP)
cusum
Iteration
Statistic
Critical Lines
30
20
10
0
-10
-20
-30
20
40
60
80
100
120
140

ECM (SR)



ECM (HR)

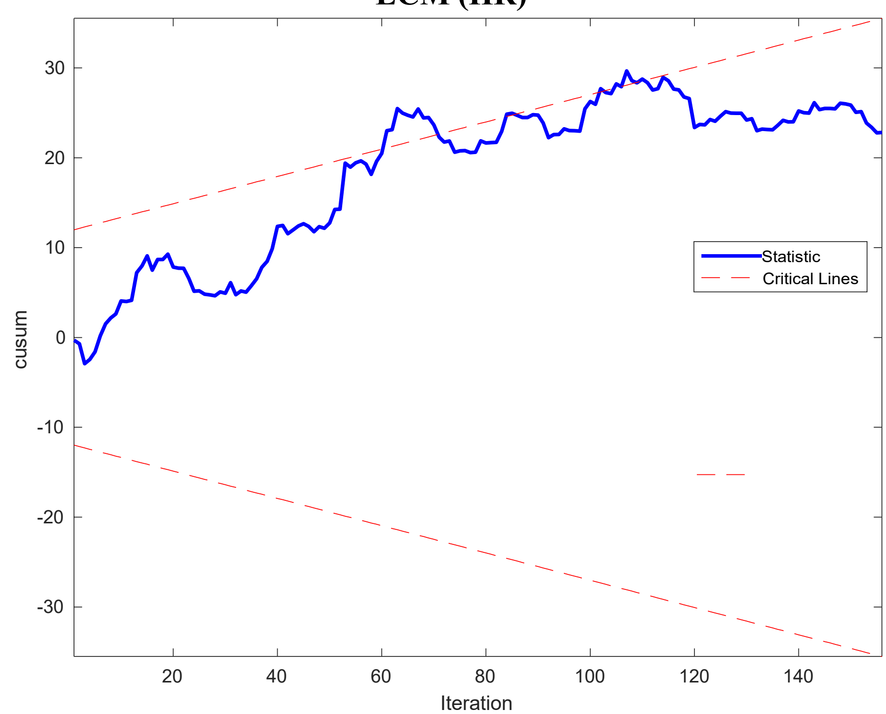


Figure 21 show the statistic (blue line) and the critical lines (red lines) for the CUSUM test for all of the models. If the statistic crosses the critical lines, the null hypothesis of constant coefficients, α and β, is rejected in favor to the alternative of existence of a structural change.

Appendix 15

Table 38. Impact Matrix (Hedging)

	D	Clc	NI	IO	C	SR	HR
Equation ΔD:	-0.054	-0.054	0.000	-0.003	9.224	-0.015	0.014
Equation ΔClc:	-0.011	-0.034	0.000	-0.009	0.694	-0.007	0.011
Equation ΔNI:	-0.410	-6.749	-0.008	-2.335	-242.572	-1.090	2.445
Equation ΔOR:	-0.009	-0.056	0.000	-0.017	-0.705	-0.010	0.020
Equation ΔCP:	0.000	-0.002	0.000	-0.001	-0.174	0.000	0.001
Equation ΔSR:	-0.068	-0.152	0.000	-0.034	7.668	-0.032	0.048
Equation ΔHR:	-0.038	0.164	0.000	0.072	16.633	0.020	-0.065

The Impact Matrix in Table 38 measures the long-run level for each equation in VECM and its explanatory variables. The Impact Matrix is derived from the adjustment matrix and the Cointegration matrix.

Appendix 16

Multicollinearity in the residuals of VECM

The correlation matrix for the variables on the level is the first basic test for multicollinearity and is a straightforward indication of pairwise collinearity. The results are provided in Table 39.

Table 39: Correlation with residuals from VECM (Hedging)

	u_{Clc}	u_{NI}	u_{OR}	u_{CP}	u_{SR}	u_{HR}
u_D	-0.066	0.060	-0.050	-0.020	0.163	0.034
u_{Clc}		0.068	0.076	0.144	-0.068	0.028
u_{NI}			-0.058	0.432	0.008	0.173
u_{OR}				-0.094	0.022	0.281
u_{CP}					0.019	0.192
u_{HR}						0.108

The correlation matrix show that all the pair-wise correlation are lower than 80%, there is no evidence of a high-degree of correlation.

VIF and Belsley Collinearity Diagnostics are applied to determine if multicollinear relationships exist between multiple sets of variables. The results of the VIF and Belsley Collinearity Diagnostics tests are presented in Table 40 and Table 41.

Table 40: Variance Inflation Factor for residuals from VECM (Hedging)

u_D	u_{Clc}	u_{NI}	u_{OR}	u_{CP}	u_{SR}	u_{HR}
1.041	1.038	1.253	1.131	1.299	1.043	1.175

A VIF below the threshold of 10 indicates there is no existence of a multicollinear relationship between the variables. The Belsley Collinearity diagnostic test was employed to confirm that there are no multicollinear relationships.

Table 41: Belsley Collinearity Diagnostics for residuals from VECM (Hedging)

Conditional Index	Variance Decomposition Values						
	u_D	u_{Clc}	u_{NI}	u_{OR}	u_{CP}	u_{SR}	u_{HR}
1.000	0.003	0.030	0.178	0.004	0.182	0.006	0.103
1.124	0.020	0.008	0.034	0.306	0.045	0.100	0.178
1.144	0.294	0.154	0.008	0.108	0.000	0.204	0.005
1.321	0.163	0.739	0.021	0.000	0.004	0.062	0.048
1.386	0.482	0.004	0.016	0.027	0.015	0.592	0.006
1.594	0.002	0.017	0.327	0.420	0.010	0.030	0.544
1.727	0.036	0.047	0.416	0.135	0.744	0.004	0.115

A Condition Index between 15 and 30 indicates a moderate degree of collinearity and a Condition Index above 30 indicates a strong degree of collinearity. Since the Condition Index is below 15, there is no evidence of any serious collinearity between the residuals.

Appendix 17

Table 42. Hedging Ratios with OLS models

	Explanatory variables for single regressions						
	ΔClc	ΔM	ΔNI	ΔOR	ΔCP	ΔSR	ΔHR
Alpha	0.776	0.714	0.753	0.781	0.787	0.653	0.751
	(0.631)	(0.627)	(0.628)	(0.631)	(0.631)	(0.616)	(0.632)
Beta	0.021	0.102	0.002	-0.027	-2.727	0.159***	0.016
	(0.278)	(0.063)	(0.002)	(0.137)	(8.222)	(0.054)	(0.031)

Figures in (.) are the corresponding standard errors. *** denotes the rejection of null hypothesis at the 1% level. ** denotes the rejection of null hypothesis at the 5% level. * denotes the rejection of null hypothesis at the 1% level.

Table 43. Hedging Ratios with multivariate OLS

Explanatory variables for a multivariate regression							
Alpha	ΔClc	ΔM	ΔNI	ΔOR	ΔCP	ΔSR	ΔHR
0.644	0.025	0.044	0.003	-0.074	-10.267	0.144**	0.011
(0.625)	(0.281)	(0.068)	(0.002)	(0.142)	(9.303)	(0.059)	0.032)

Figures in (.) are the corresponding standard errors. *** denotes the rejection of null hypothesis at the 1% level. ** denotes the rejection of null hypothesis at the 5% level. * denotes the rejection of null hypothesis at the 1% level.

Appendix 18

Table 44. Hedging effectiveness with OLS models

	In-Sample		*Out-of-Sample*	
	Variance	Hedging Effectiveness	Variance	Hedging Effectiveness
Multivariate OLS	59.330	0.067	62.480	-0.004
OLS (ΔClc)	63.610	0.000	62.209	0.001
OLS (ΔM)	62.581	0.016	62.382	-0.002
OLS (ΔNI)	63.126	0.008	61.531	0.011
OLS (ΔOR)	63.596	0.000	62.361	-0.002
OLS (ΔCP)	63.568	0.001	62.424	-0.003
OLS (ΔSR)	60.342	0.051	63.445	-0.019
OLS (ΔHR)	63.504	0.002	61.836	0.007

The underline in Table 44 show the lowest variance and highest hedging efficiency in the in-sample and out-of-sample in the hedging section.

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