Erasmus University Rotterdam

MSc in Maritime Economics and Logistics

2019/2020

"An empirical study on Forecasting Crude Oil Tanker Freight Rates and the impact of exogenous variables"

By

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Acknowledgements

As this postgraduate international MSc programme comes to an end I would like to express my gratitude to some individuals that contributed for the completion of that study as well as for their support throughout this year. First of all, I would like to thank my supervisor Professor Albert Veenstra. His guidance during the process of making this study was a very important contributor for the completion of it. Moreover, I would like to thank the MEL office that even if they had to manage unprecedented conditions they were always there to help us throughout this "strange" year with Covid-19. I would also like to thank my classmates for this unforgettable experience and my friends from Greece for their emotional support. Finally, and most important, I would like to thank my family for their unconditional support through multiple ways over the years.

Abstract

The importance of vessels transportation of oil for the global economy was recognized very early, even before the globalization of the economy. Subsequently, this initiated a huge scientific research around the determination and forecast of freight rates. Continuing in the tradition of empirical studies that try to analyze the future behavior of freight rates based on their past performance with the use of ARIMA econometric model, in this thesis we examined the main question of how the incorporation of one or a group of exogenous variables in an ARIMA model will influence the forecast of freight rates. A characteristic of this kind of studies is that there are sensitive to many stochastic parameters, time period of the analysis, market segments etc. For the purpose of this study twelve exogenous variables from three different categories, Financial, Oil and Commodities will be used analyzing their impact on the freight rates of four different sizes of vessels namely, VLCC, Suezmax, Aframax, Panamax. Based on the results we concluded that there are exogenous variables that improve the forecasting performance of the ARIMA models regarding freight rates. From the twelve exogenous variables examined, only four of them enhanced the predictability of the model. Specifically, Oil price, Oil production, LIBOR and Aluminum. From them only Oil price improves the forecasting fit in all categories of vessels. The best performing model among the different size of vessels is the ARIMAX for the Panamax with the Oil price as exogenous variable. The identification of the relatively low impact of the exogenous variables in the forecast of freight rates could be attributed to the highly dynamic nature of the shipping industry and the freight rate mechanism, revealed by the high level of variability and coefficient of variation in many of the time series used. Further research is proposed in terms of the choice of the econometric models, shipping routes and the selection of exogenous variables.

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List of Abbreviations

ACF	Auto Correlation Function
ADF	Augmented Dickey Fuller
ANN	Artificial Neural Networks
AR	Auto Regression
ARCH	Auto Regressive Conditional Heteroscedasticity
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
BDI	Baltic Dry Index
DF	Augmented Dickey Fuller
FOREX	Foreign Exchange
GARCH	Generalized Auto Regressive Conditional Heteroscedasticity
KPSS	Kwiatkowski– Philips–Schmidt–Shin
LIBOR	London Inter-bank Offered Rate
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
OECD	Organization for Economic Co-operation & Development
PACF	Partial Auto Correlation Function
PP	Philips Peron
RMSE	Root Mean Squared Error
T/C	Time Charter Rate
ULCC	Ultra Large Crude Carrier
VAR	Vector Auto Regression
VECM	Vector Error Correction Model
VIX	Volatility Index
VLCC	Very Large Crude Carrier
WNN	Wavelet Neural Networks
WTI	West Texas Intermediate

1. Introduction

1.1 Background

The commercial production of crude oil started in the 1850s, where it was transported worldwide by sea. In the early period, the oil was stocked in wooden barrels and then it was loaded on ships. Soon these wooden barrels were replaced by different size of tanker vessels. As demand for oil increased the crude oil tanker ships grew considerably larger in order to meet this increased demand, a trend that continues until these days. Thus, there was a constant development on the size of the vessels and their capacity (Furset and Hordnes, 2013).

The worldwide and dynamic nature of the Oil and Shipping industry has created a lot of interest in understanding the behavior and performance of freight rates over time. The mechanism by which the freight rates are defined is the backbone of the shipping industry and it is natural that attracted the attention of many empirical studies trying to identify its determinants. The formation of the freight rate depends among other things on a number of different endogenous variables such as the freight market, the total fleet capacity, the order book of new buildings, the secondhand and newbuilding prices, and exogenous variables, such as the world GDP, the oil price, and the seaborne trade. The stochastic nature of these variables makes the study of the freight rates difficult.

Until today, a significant number of empirical studies have been conducted regarding the determination and forecasting of freight rates. Most of these studies rely on the use of econometric methods and models which due to volatility and uncertainty of the freight rates has led to a systematic application of more efficient and sophisticated stochastic econometric modeling techniques (ARIMA, VAR, VECM, ANN etc.). In many studies the use of regression models with different independent variables was extensive, seeking to identify the variables that influence the level and the behavior of freight rates. Other empirical studies moved in the direction of accurately forecasting the short-term and long-term freight rates, by using of econometric models either univariate time series (ARIMA, ARCH type) or multivariate time series (VAR, VECM, Neural Networks). Most of these studies, especially the ones of ARIMA type, try to predict the future short-term and long-term level of freight rates based on their historical performance. A difficult, almost impossible task in terms of complete accuracy in the long run, due to the stochastic nature of the freight rates and volatile economic environment of the shipping market.

All the aforementioned studies conducted over various time periods, different vessel sizes as well as routes in different geographical locations. Diakodimitris (2019) comparing the forecasting performance of different of the above econometric models and explaining their relatively low performance, one of the further research recommendation that proposed was that "…the inclusion of exogenous economic variables might affect the formation of the values of the freight rates." (Diakodimitris 2019). Following this recommendation and continuing in the tradition of empirical studies that try to analyze the future behavior of freight rates based on their past performance with the use of ARIMA econometric model, in this thesis we will try to address the following research question and sub-questions:

Research Questions

- *How will the incorporation of one or more exogenous variables in an ARIMAX model influence the forecasting performance of tanker freight rates versus the ARIMA model.*

Sub-Research Questions

- *To what extend the different exogenous or group of exogenous variables affect the tanker freight rates?*
- *How will the inclusion of exogenous variable(s) in a model affect its prediction power regarding the forecasting performance of freight rates for different size of vessels.*

The above research questions will be analyzed for one year Timecharter (T/C) freight rates of four vessels types namely, VLCC, Suezmax, Aframax and Panamax. Twelve exogenous variables will be used over the period 1990 – 2019 trying to forecast their values for a period of one month ahead.

1.2 Thesis Structure

The structure of this study is the following:

In Chapter 2, a short overview of the Oil Market and the Tanker Market will be presented. Also, the factors that directly or indirectly affect freight rates will be addressed. Then, a literature review of the for econometric studies about the tanker freight rates including their methodology and their empirical results will follow.

In chapter 3, the methodology applied in this study will be explained in details. A short description of the time-series characteristics will be presented. Followed by a general description of

Econometric Time Series. Emphasis will be given to ARIMA and ARIMAX models and how these will be applied in this study. Lastly the data sources, definition of variables, criteria of choosing the exogenous variables, type of category of exogenous variables will be discussed.

In chapter 4, the results of the analysis will be presented and discussed. First, in terms of the descriptive statistics and levels of correlation of the variables. Then, the results of each forecasting model with each exogenous variable or group of variables for each size of vessel will be analyzed in terms of their forecasting significance vs those of the ARIMA model. The impact of each exogenous variable and group of variables will be evaluated and the best performing model in each category of vessel will be compared to each other. Finally, the results of this study will be compared to the results of other similar studies.

In Chapter 5, the conclusions of this research, the answers to the Research & Sub-Research questions as well as its limitations and the recommendation for further research will be stated.

2. Literature Review

2.1 Oil Market

Of all industries, the oil industry is a global business which affects almost all countries in the world as it plays a vital role in our daily lives, impacts the economy and contributes to social and economic development. "The price of crude oil is determined by the type and quality of the crude oil itself. Once distilled, heavy and light crude oil yield several refined products e.g. gasoline and diesel to serve demands at different quantities." (Hunt et al, 2002). The location where the oil is extracted determines the quality of the product and that creates some differentiation in the prices but in general terms, they follow the same trend with very few spreads as it is presented in figure 1 and 2 below. "Global crude oil prices thus change overtime and cannot be attributed to one single market. It is a highly complicated market system dependent on several variables." (Gyagri et al, 2017).

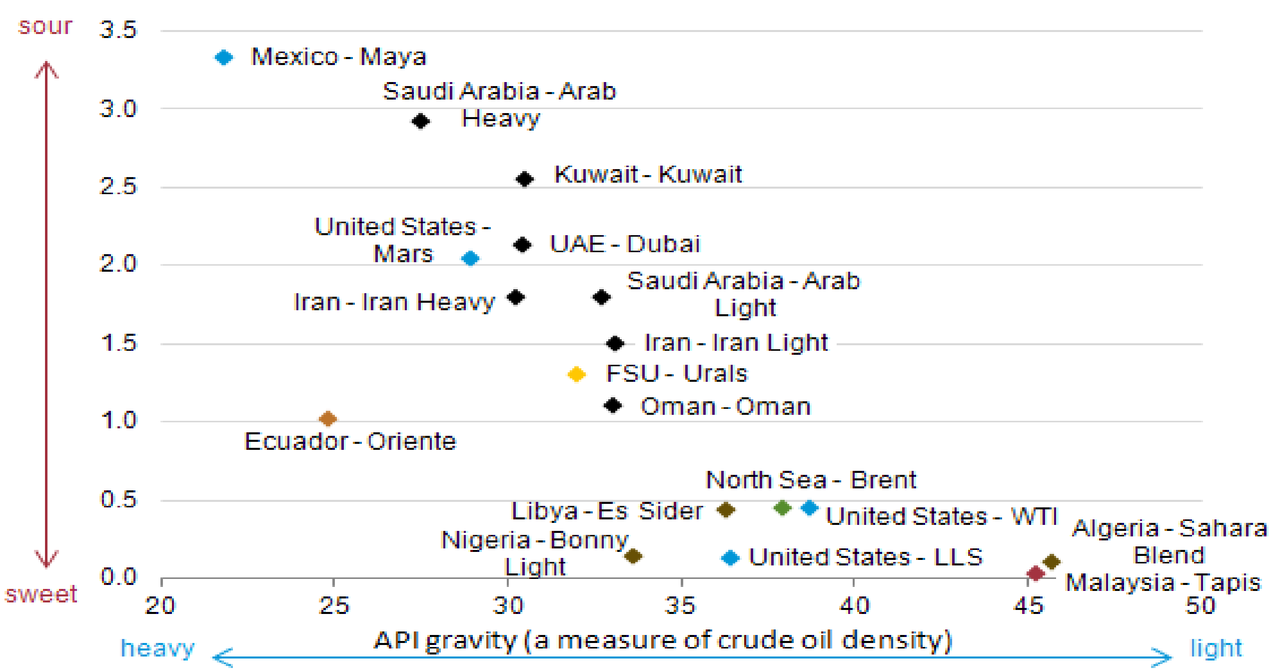

Figure 1: Grades of Crude Oil. ***Source: (U.S. Energy Information Administration.)***

A benchmark or "marker crude" is a crude oil that serves as a reference price for buyers and sellers. There are three primary benchmarks, (1) West Texas Intermediate (WTI), (2) Brent Blend, and (3) Dubai Crude with the first two to be considered oil benchmarks that influence to a large extent the international oil market. “Their prices are used as an indicator and define decisions and strategies in the refining business, financial trading and government policies.” (Chen, Huang, & Yi, 2015). During the last years, “the oil market has experienced fluctuations in the spread between the two oil benchmarks that were not prevalent before. More specifically, WTI price started decreasing in level without Brent price corresponding to the same trend. As of now we observe a narrower gap between the two oil benchmarks but WTI is still traded at a discount compared to Brent.” (Kontaxis, 2016).

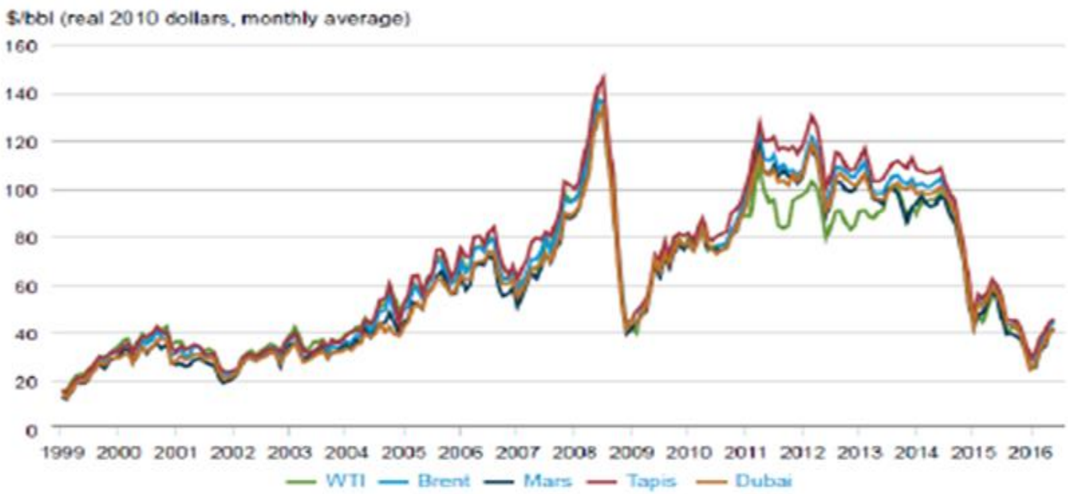

Figure 2: Price Movement of some Crude Oils-Source: (EIA, 2016)

2.2 Tanker Market

Below are presented the tanker vessel sizes as described by Stopford (2009).

VLCC: Tankers over 200,000 dwt are grouped into this category. It carries about two million barrels of oil.

Suezmax: Tankers of 120,000–200,000 dwt. Tanker able to transit Suez Canal fully loaded which carries around one million barrels of oil.

Aframax. Tanker carrying around half million barrels of oil, but usually applied to any tanker of 80,000–120,000 dwt.

Panamax. Vessels of 60,000–75,000 tonnes deadweight fall into this category. Bulk carrier which can transit Panama Canal where the lock width of 32.5 m is the limiting factor.

Demand for crude oil is global but oil production in particular is mainly concentrated in geographic areas such as the Middle East, the Americas and Africa. Compared to demand for consumption, Asia's and Europe's production is significantly lower and that creates the need for an increase in imported quantities of crude oil products. Growth in demand is primarily driven by non-OECD regions, and especially Asian countries. The highest demand levels were reached by OECD countries in the mid-2000s. After that point, demand declined as a result of the global financial crisis that begun in 2008 and a number of environmental climate change initiatives.
Larger vessels, such as, VLCC and Suezmax are being used in the intercontinental trade routes. VLCCs are mainly used from the Middle East in high volumes and over long distances (Europe and Pacific Asia). The lower vessel classes like Aframax, Panamax and Handysize are preferred for medium-short routes such as from Latin America to USA and for carrying oil products. Tankers that contact Japan are using the Malacca Strait while tankers trading in Europe and USA will either use the Suez Canal or the Cape of Good Hope, depending on the tanker's size and the destination. As it is states in McQuilling Services Report of 2019 "VLCC cover the 41% of the world tanker fleet. In 2018, global ton-mile demand to transport crude as well as residual fuels increased by 1.9%, supported by a 1.4% increase in VLCCs which accounted for 63% of the total demand for dirty tankers." (McQuilling Services, 2019). Furthermore, Suezmax fleet constitutes the 15% of the tanker fleet while Aframax for 13% and Panamax for only 1% The top 20 ownership distribution of oil tankers portrays that these companies only own 34.5% of the tanker fleet capacity. No single owner owns more than 2.5% of the total capacity (Sin.clarksons.net, 2019).

2.3 Factors Affecting the Tanker Freight Rates

Demand for Oil

The demand for oil is an obvious driver of crude tanker demand. As more oil is needed around the world the higher the demand becomes for moving this oil from production to refinery.

Supply of Oil

It is obvious that for any oil transportation business oil supply is critical to the status of its markets. Oil supply dynamics have undergone a transformation in the past decade with a shift away from being very Middle East focused to having a more diverse supply base. The development of U.S. shale oil, in particular, has played a key role to this.

Vessel Supply

Perhaps the key driver of tanker markets is vessel supply. This is the ultimate driver of market fluctuation. When the market is in short supply of ships freight rates increase. On the other hand, when we have oversupply of ships in the market, freight rates decrease.

Trade Routes & Dynamic Market

The size of ships determines the trade routes that will be followed. The size of a VLCC makes them more cost efficient for longer international trade routes between large ports that can physically accommodate their larger size. However, there is cross elasticity between vessel sizes when the price of utilizing a VLCC becomes too expensive and it may become more price efficient for a customer to use two Suezmax vessels to transport the same quantity of oil instead. It is important to keep in mind that trade routes are not static, these routes are highly dependent on oil flows and geopolitical conditions.

Seasonality and Cyclicality

Historically, there has been a visible degree of seasonality in the tanker market as freight rates have tended to perform better during the first and the fourth quarter of a calendar year. "With 90% of the global population living in the northern hemisphere, more oil is required during the northern hemisphere winter hence more oil is consumed during these quarters. Tanker shipping is a highly cyclical business with freight rates driven by numerous factors, but in the medium to long-term vessel supply and demand are the main drivers." (Euronav 2017).

Unexpected Political Events

In the shipping market, geopolitical factors play a key role in the freight rate mechanism. Governments may adopt tactics such as intervention in trade and shipping matters by implementing policies to protect their own products against foreign goods. Politics is also influenced by considerations such as whether the body is democratically elected and has predefined fiscal policies. Membership of economic trade blocs and the government's attitude towards maintaining membership conventions could also impact the freight rate mechanism.

2.4 Previous Studies on Shipping Industry

There are different empirical studies that try to identify the variables that influence the determination of freight rates and their future level. In the following sections first, it will be presented a short review of studies that analyze the relation between oil prices and tanker freight rates. Then, we will review empirical studies that try to predict the future level of seaborne freight rates using different econometric models. In this section three kind of studies will be reviewed. First, studies that try to forecast future freight rates using non-ARIMA approach. Second, studies that rely on ARIMA/Box Jenkins approach. Lastly, studies that are using Exogenous variables.

2.4.1 The relation between Oil Prices and Tanker Freight Rates

The demand for tanker services is heavily dependent upon international trade in crude oil and oil products. Like any commodity, the impact of oil price on tankers freight rates, follows the rule "the greater the demand for a product, the higher the demand for its transportation". This implies that an increase in demand causes instant rise in freight levels (Stopford, 2009).

Poulakidas and Joutz in 2009 contacted a multivariate econometric study that used five independent variables (BDI, Crude Oil Future Contracts, WTI Spot Prices, US Weekly Ending Crude Oil Stocks and Spread between WTI Spot Price and Future Contracts). The analysis that they used was cointegration and Granger causality analysis from 1997 through 2007. They concluded that "Our findings show a relationship between spot and future crude oil prices, crude oil inventories and tanker rates" and the existence of a negative relationship between supply of crude oil and spot rates of tankers (Poulakidas and Joutz,2009).

Acik and Baser in 2018 made a research on the effects of fast decline in crude oil prices on the tanker market in the short-run. They used Pearson's and Spearman's correlation analysis and they concluded that "time charter earnings in the tanker market reflected significant very strong negative correlation with oil price …" (Acik and Baser 2018).

Shi et al.in 2013 made a study for the impact of crude oil price on the tanker market through the use of a structural vector autoregressive (SVAR) model. In this model three independent variables were used, The Baltic Dirty Tanker Index, Oil production and Oil price. This study showed that "crude oil production has an insignificant effect on crude oil price and supply shocks have significant effect on the tanker market". Furthermore, he commented that "there is no evidence about a relationship between tanker freight rates and crude oil prices." (Shi et al 2013). This opinion was aligned also with the conclusions expressed by Alizadeh and Nomikos in 2004 where they showed that "there is no evidence that the tanker freight rates are related to crude and WTI future price differentials" (Alizadeh and Nomikos 2004) and that there is a correlation between future oil contracts and the freight rates in the tanker market in the US. Another research that agreed with the negligible effect of the Oil prices to VLCC Earnings is that of Merikas and Polemis in 2013.

2.4.2 Empirical studies on Forecasts using non-ARIMA models

Forecasting freight rates and indexes in the shipping industry has always been a field of research. Some of the first attempts that tried to understand the market characteristic and the freight rate formation was by Koopmans in 1939 where he made the assumption that supply and demand can create the market equilibrium (Koopmans 1939). Since that research there has been a great progress on forecasting in the shipping industry. Another early research commenced by Zeon Zannetos expressed the belief that tanker market contains itself most of the information needed to predict future prices. In order to forecast long-term charter rates, he used as a basis short-term charter rates. Before using short-term rates, he removes them from any short run fluctuations that do not reflect basic structural relationships that are not valid over time and may reflect market imperfections. Then he used correcting parameters to express long-term freight rates as a function of short-term rate (Zeon Zannetos,1966).

Beenstock & Vergotis in1993 built a model for the market equilibrium by the assumption that the demand side of the market there is a perfect competition while on the supply side there is profit optimization (Beenstrock and Vergotis,1993).

The initial studies in this area have opened the field for further research on the forecasting of the shipping freight rates with more elaborated models. Veenstra and Franses in 1997 in their paper "A co-integration approach to forecasting freight rates in the Dry Bulk shipping sector" managed to produce forecasts for Panamax vessels by using the spot rates of six different shipping routes. The model that they used for the specific paper was a VEC model which does not include any endogenous or exogenous variable. Their model was a result of the assumption that "…the series of freight rates are themselves found to be non-stationary" (Veenstrta and Franses,1997) which was an evidence on the existence of long standing cointegration relationship in the specific Panamax trade routes. Their results showed that there is a stochastic trend to all six different routes analyzed, which could have extrapolated to the market as a whole. Namely, the existence of a stable long-standing relationships in the freight rate mechanism." (Veenstrta and Franses,1997). Kavussanos in 1996 used ARCH model for comparing time varying risks between tanker vessels of different sizes. He concluded that the monthly price returns of larger vessels are more volatile than this of smaller tanker vessels. Furthermore, he came to the conclusion that the size of the vessel affects directly the volatilities (Kavussanos,1996). In 2004 Kavussanos and Visvikis managed to examine the relationship between the spot rates and compare them with the future rates on the basis of the response time. The model that they selected to use for that purpose was a hybrid multivariate model that was combining a VECM with a GARCH model. They concluded that the specific hybrid model was capable of providing better forecasts and improve the market analysis. (Kavussanos et al,2004). Scarsi in 2007 conducted a research regarding "The bulk shipping business: market cycles and ship owners' biases" In that research comes to the conclusion that the production of reliable forecast in freight rates is very difficult. He attributes that difficulty on the dynamics of the shipping industry together with the volatility that exists and the existence of a lot of exogenous factors that can directly affect them (Scarsi,2007).

2.4.3 Empirical studies using ARIMA models/Box-Jenkins Methodology

In 1992, Kevin Cullinane constructed a model based on the Box—Jenkins approach in order to forecast the Baltic International Freight Future Exchange (BIFFE). His conclusions were that the ARIMA models are capable of providing better results when they are examining short-term forecasts (Cullinane,1992).

Kavussanos and Nomikos in 1999 used four different forecasting models namely Exponential Smoothing, ARIMA, VECM, and Random Walk in the freight futures market. They also focused on the examination of the short-run spot and futures prices because they wanted to understand the response speed occurring through their long-standing relationships. They proposed that the VECM model is the best forecasting model which was something different than Cullinane who proposed the ARIMA models. The final conclusion was that the future prices are more sensitive in changes occurring in the market linked with the spot prices (Kavussanos and Nomikos,1999). Batchelor et al in 2007 commenced another research on forecasting spot and forward prices in the international freight market. Their results showed that the models which are capable of predicting future prices with the smaller error were the ARIMA &VAR Models compared to the VECM model. There was a small differentiation to the results compared to the research commenced by Kavussanos and Visvikis in 2004 that was examining the same aspect, but this difference can be attributed to the different samples of data (Batchelor et al,2007).

R. Adland and K. Cullinane in 2006 created a research for forecasting the Baltic Exchange Dirty Tanker Index (BDTI) by analyzing probabilities through the use of Wavelet neural networks (WNN). They concluded that a WNN model is better for long-term forecasts compared to an ARIMA model (Adland and Cullinane 2006). In 2013, S. Fan et al. examined non-linear and non-stationary characteristics of BDTI by the use of a WNN model. They concluded that for the short-term forecasting on BDTI there was no major difference between WNN and ARIMA models. Although for long-term forecasts their results aligned with the conclusions of Adland et al (2006) where the WNN model is better (Fan et al., 2013).

Manzannero and Krupp in 2018 conducted a research that analyzed the behavior of the freight rate in container vessels for six different trade routes over time using an ARIMA model. Their findings showed that even though it is very difficult to accurately forecast freight rates, the nature of the trade route is an important factor for the forecast and can provide important insights to the forecast

(Manzannero and Krupp, 2018). On the other hand, Geomelos and Xideas tried to forecast the spot prices in tankers and bulk carriers. The main question that they were trying to answer was to identify which model is more accurate depending on the vessel size. They compared univariate (ARIMA, GARCH) and multivariate models (VAR, VECM) and they reached to the conclusion that: "…the combining methodology of previous univariate and multivariate models provide lower forecasting errors in seven out of eight categories (except Handysize) of ships using the simple average of forecasts instead of the forecasts of each individual model." (Geomelos and Xideas, 2017). For them the use of a hybrid methodology could reduce significantly the forecasting errors. Munim and Schramm in 2016 made a research that was aiming to forecast container freight rates on the major trade route Far East- Northern Europe. They employed an ARIMA model and a hybrid model of ARIMA and GARCH named as ARIMARCH. They concluded that the hybrid model gives significantly better results than the existing freight rate forecasting models regarding short term forecasts (Munim and Schramm,2016).

Diakodimitris in 2019 made a research on comparing different forecasting models for the tanker industry. The research included all four tanker vessel sizes namely, Panamax, Aframax, Suezmax, VLCC/ULCC. The comparison between the forecasting approaches was commenced between five different models namely, ARCH, GARCH, ARMA-GARCH, VAR and VEC. The results of the analysis showed that ARIMA model was producing better forecasts when examining the crude oil spot freight rates. On the other hand, when he examined tanker time charter rates VAR-VECM where providing better forecasts for all the tanker vessel sizes (Diakodimitris,2019). In his study he suggested that further research on different exogenous variables form different categories, in the forecasting performance of one or more of the proposed models could be a great research subject.

2.4.4 Empirical studies using Exogenous Variables

A new model built by Lyridis, et al in 2004 was the ANN (Artificial Neural Network). The specific model is multivariate and includes exogenous variables that are capable of influence the spot prices. They concluded that "… in an industry as dynamic as shipping, multivariable models interpret more precisely the freight markets in relation to univariate models." (Lyridis et al,2004).

The purpose of the paper by Polimenopoulos in 2006 was to create forecasts for the freight rates of different sizes of vessels using multiple forecasting models. The models employed were

ARIMA, GARCH and ARIMAX model. For the ARIMAX model as exogenous variable were used Crude Oil Purchase prices, Scrap, Second Hand and Newbuilding prices and other ship class time charter rates. It has been proven that neither the standard explanatory variables associated with time charter rates, or lagged time charter rates themselves contain useful information to be able to forecast ARIMA, ARIMAX and GARCH models successfully over long time periods (Polimenopoulos, 2006).

Chen in 2010 made a research on comparing modern time series models, emphasizing to the underlying structure features and economic activities of different variables and different markets. To identify models that provide forecasts of spot prices in the dry bulk market, several time series models were used, including the ARIMA, ARIMAX, VAR, VARX, VECM and VECMX. US Dollar Index is employed into forecasting models as the exogenous variable along with the LIBOR. When comparing the models, it is found that the VEC model with significant coefficients of error correction terms can give better results on forecasting daily spot and daily forward prices than the other models. On the other hand, for longer horizons, the ARMA model seems to outperform the VAR model (Chen,2011).

Baser et al, in 2018 commenced a research on Predicting the Baltic Dry Index (BDI) with Leading Indicators. In this study a special type of ARIMA model which contains exogenous variables is employed which is called ARIMAX model. They selected specific exogenous variables in order to build their model. The variables that they selected were the BDI, the US 10-year bond rate, food commodity price index, minerals, ores and metals commodity price index, crude oil prices, index, world consumer price index, world industrial production, gold prices, silver prices, and US$/SDR exchange rate. They concluded that an ARIMAX model with explanatory variables of price of golds, price of silver and price of iron has been a useful tool to monitor both freight markets and economic conditions (Baser et al, 2018).

Chen, Merman and van de Voorde in 2014 wanted to compare different models in order to recognize which model is the one that can provide the most accurate forecasts of spot prices in the dry bulk market. They examined the spot price movement and made an attempt to forecast spot rates at main trading routes in the Capesize, Panamax and Handymax markets. For achieving that they used multiple time series models such as auto regressive integrated moving average ARIMA, vector auto regression (VAR). For examining the exogenous variables in their forecast they used univariate auto regressive integrated moving average with exogenous variables (ARIMAX) and vector auto regression with exogenous variables (VARX) models. The exogenous variables that they selected to include in their forecasts were the US Dollar index and the exchange rate of US dollar against EURO. They concluded that "the findings of forecasting models suggest that VAR model and a VARX model perform better on the out-of-sample forecast against the univariate ARIMA model and ARIMAX (Chen et al 2014).

Gavriilidis et al in 2018 examined whether the use of the oil price shocks as an exogenous variable could improve the accuracy of a volatile forecast. They selected to deploy a GARCH-X model to forecast the spot and 1-year time-charter tanker freight rates on different vessel sizes. Their findings indicate that a GARCH-X models significantly improves their forecasting power for both the spot and 1-year time charter tanker freight rates when forecasting supply demand shocks. Additionally, the use of oil supply shocks as an exogenous variable leads to only weak improvements in forecasting the volatility in the tanker freight markets for all the vessel sizes that were examined (VLCC, Suezmax, Aframax, MR) (Gavriilidis,2018). Finally, Bertolloto and Oliveira in 2020 made a paper on the performance verification of dynamic models in the short-term for the spot market of crude oil export route. They concluded that ARIMA models are adequate on the forecast of oil tanker freight rates (Bertolloto and Oliveira,2020).

2.4.5 Remarks Relevant to our Study

As it is obvious from the above literature review of empirical studies it is difficult to identify one methodology or econometric model that provides decisively/conclusively superior results. Performance of different econometric models depends on many factors such as quality of data, time period, segments of the market, independent and exogenous variables etc. The evolution of econometric methods and models is an ongoing process. Similar to this the improvement of forecasting capabilities with the inclusion of different exogenous variables in different segments of the market is one direction for further investigation.

The above literature review was an important contributor to my familiarity of different studies that try to analyze various aspects of the shipping industry. Important insights were obtained on many econometric models and approaches that applied in order to forecast and analyze aspects of the maritime industry such as spot or T/C rates or several indexes. More importantly, it improved my knowledge and understanding about the methods and models used specifically for the forecast of tanker freight rates. Through the study of these research papers the choice of the econometric model of this thesis was selected. A lot of these studies emphasized on the comparison of the forecasting performance of different univariate and multivariate econometric models. However, the purpose of our study is not the comparison of the forecasting performance of different models about freight rates but the impact of different exogenous variables on the determination of tanker freight rates. According to Cullinane (1992) ARIMA models are performing better in short-term forecast while Batchelor et al concluded that ARIMA models were capable of providing forecasts with smaller error compared to the VECM model. Also, Fan et al (2013) concluded that "for the short-term forecasting on BDTI there was no major difference between WNN and ARIMA models". Based on these finding and taking into account that our study intends to analyze the short-term forecast of one-month ahead we decide that the choice of a univariate model such the ARIMA as a base for measuring the impact of the exogenous variables is the most appropriate for our thesis. The recommendation by Diakodimitris (2019) that "…the inclusion of exogenous economic variables might affect the formation of the values of the freight rates." (Diakodimitris 2019) was the main reason of our decision to proceed to analyze the impact of exogenous variables on the forecasting performance of tanker freight rates. By the relevant literature above Polimenopoulos (2006), Chen (2010), Baser (2018) etc. useful information was gained on the exogenous variables relevant for this study. This together with the availability of data and an assessment of which exogenous variable may provide the best insight on the formation of the crude oil tankers freight rates determined our choice of exogenous variables as it is presented in details in the relevant section 3.6 below.

Finally, our methodology is similar to work of Baser et. (2018) where they analyze the impact of different exogenous variables by using the ARIMAX model. However, in this thesis we are interested in analyzing T/C rates while they examined BDI.

3. Methodology

The aim of this study is to compare the forecasting performance of an ARIMA model versus an ARIMAX model that incorporates exogenous variable(s) regarding the freight rates of four size of vessels (VLCC, Suezmax, Aframax, Panamax). Twelve exogenous variables from three different categories, Financial, Oil and Commodities will be used for the period January 1999-December 2019 on a monthly base. At the beginning the impact of each exogenous variable on the freight rates of each size of vessel will be analyzed separately. Then, the effect of the simultaneous inclusion of more than one of the exogenous variables based on the assessment of their individual forecasting effect will be evaluated.

3.1 Time series

3.1.1 Definition of A Time Series

Time series is “a sequential set of data points, measured typically over successive times…” (Adhikari, Agrawal, 2013). Mathematically can be expressed as a set of vectors $x(t)$, $t = 0,1, 2,$ where t represents the time elapsed and the variable $x(t)$ is considered as a random variable (Adhikari, Agrawal, 2013).

Multivariate-Univariate

Time series can be categorized into univariate and multivariate. When a time series contains observations of one and only one variable that varies over time then this is characterized as univariate time series. On the opposing side, when we have a time series that contains observation of more than one variable that varies over time then this set of time series are considered as multivariate. In multivariate time series each variable does not depend solely on the previous values but there is dependency and between the other variables. This dependency can be used for forecasting future values (Adhikari, Agrawal, 2013).

Continuous-Discrete

Another distinction of time series is the categorization in continuous or discrete. The difference between these two categorizations is the fact that in the discrete time series the observations are measured at a specified time while in the continuous the observations are measured in all times. A usual practice in discrete time series is to record the consecutive observations and split them in equal time periods (monthly, quarterly, annually) (Adhikari, Agrawal, 2013). On the other hand, a time series is considered as continuous when observations are made continuously through time even when the measured variable can only take a discrete set of values. A continuous time series can be converted into a discrete by merging the data all together over a specific time interval.

3.1.2 Components of a Time Series

Four are the main components that are capable of affecting the time series. These components are the following:

Trend

The tendency of time series to either increase, decay or remain stable over a long period of time is named as Secular Trend or Trend. Consequently, it can be inferred that the trend is a long-term movement in a time series (Adhikari, Agrawal, 2013). The form of the trend pattern may be linear or non-linear. Linear trend patterns are not only the simplest, but also the most commonly encountered trend pattern (Gerbing, 2016).

Cyclical

The cyclical deviation in time series can describe the medium-term movement of the series, which occurred under repetitive circumstances in cycles (Adhikari, Agrawal, 2013). The unpredictable nature in multiple economic variables creates fluctuation that lead to a series of certain phases (peak, recession, trough, recovery). All cycles taken together illustrate this pattern in the economy.

Seasonal

Seasonal variations in time series are variations occurred during the course of a year. The major factors that generate the seasonal variations are considered to be traditional habits, climate and weather conditions and customs (Adhikari, Agrawal, 2013). Usually, for the majority of the business and their economic data the measurement of the seasonal component is in quarters originating by the four seasons (Gerbing, 2016).

Irregular components

This error component describes unpredictable events which are not regular and also do not repeat in a particular pattern. These variations are caused by incidents such as war, strike, earthquake, flood, revolution, etc. There is no defined statistical technique for measuring random fluctuations in a time series (Adhikari, Agrawal, 2013).

The trend, cyclical, and seasonal components combine to form the pattern underlying the time series data, namely, the values of Y ordered over time, although not all these components characterize every data set. An important purpose of time series analysis is to isolate each of these three components and demonstrate how each affects the value of Y over time, including forecasts for the future. The identification of the pattern of a time series, as well its predictable aspect is complicated by the presence of random error (Gerbing, 2016).

3.2 Econometric Time Series Models

Generally, a time series model can have multiple forms for time series data and represent different stochastic processes. The most widely used models are the Autoregressive (AR) and Moving Average (MA) models (Adhikari, Agrawal, 2013).

3.2.1 Box-Jenkins Approach

The original Box-Jenkins modelling procedure involved a three-stage process: Model selection, Parameter estimation, Model checking (Hyndman, 2001). During the course of the years there are multiple modern explanation referring to the Box-Jenkins methodology, aiming to simplify the above process by adding two more steps, preliminary stage of data preparation and a final stage of model application (or forecasting). Some of these enhancements that lead to new versions of the methodology created by Markakis and Hibon in 1997 and Wheelwright and Hyndman in 1998 (Hyndman, 2001).

The steps of Box – Jenkins methodology that will be followed in our research are described below:
The first step of the process is to prepare the data for transforming it and differencing it. The main question that the researcher tries to answer at this stage is whether the data is stationary. If the values of a time-series seem to fluctuate with constant variation around a constant mean, then it is reasonable to suppose that the process is stationary otherwise, it is nonstationary (Umberto Triaca, 2018). In addition to check the plot of a time series in order to determine stationarity or not, this is possible to be accomplished with the use of the plot of the ACF. If the ACF of the time series

values either cuts off or dies down quickly then the time series values should be considered stationary. On the other hand, if the ACF of the time series values either cuts off or dies down extremely slowly then it should be considered non-stationary (Diem Ngo,2013).

The Box-Jenkins methodology provides recommendations for making the series stationary in both its mean and variance (Makridakis and Hibon, 1997). The standardization process of the data through its transforming and differencing aiming to achieve stabilization of the variance. The purpose of differencing is to remove any seasonal or trend patterns in our data series because in that way the modelling of the original data is easier to get achieved (Hyndman, 2001). The specified forecasting methodology is considered to be sensitive to errors in differencing. Additionally, the long-term behavior of the model can be determined by the amount of differencing and the addition of a constant variable in the model (John Frain, 1992).

According to Palachy (2019) the series is called stationary if satisfies the following three formal conditions:

1. Mean of Y_t ($E(Y_t)$ remain same over time or time invariant. i.e.
    a. $E(Y_t) = u, \forall t$
    b. Where the symbol ∀, is use for all and (u) is any scalar
2. Variance of Yt ($V(Y_t)$ is time invariant. i.e.
    a. $V(Y_t) = \sigma^2, \forall t$
3. $Cov\ of\ Y_t$ and Y_{t-S}($cov\ (Y_t, Y_{t-S})$ is time invariant, but can be depend upon the lag length. i.e $Cov\ (Y_t, Y_{t-S}) = Y_s$

The stationarity tests will analyze below in the relevant section.

The second step of the Box-Jenkins methodology is the selection of the appropriate model. This can be achieved through the use of autocorrelations and partial autocorrelation coefficients for determining the most suitable values of p and q (Makridakis, Hibon 1997). The Box-Jenkins framework uses various graphs based on the transformed and differenced data that obtained in Step 1 in order to identify the most suitable ARIMA process that will give a good fit to the data (Hyndman, 2001).

The third step is the estimation of the parameters through the use of computational algorithms of ordinary least square (OLS) and Maximum Likehood (ML). Through the use of computational algorithms, the parameters of the model could be estimated. In this study all the computational work will be performed with R software.

The fourth step is the Diagnostic Check of the model. After the values of p, q was estimated, a diagnostic check must be commenced in order to determine whether or not the residuals e_t was white noise (Makridakis and Hibon 1997). If the model is found to be inadequate, the Box-Jenkins approach has to be repeated by returning to the second step of the process. If the Diagnostic Check shows that the model was consistent with the observed features, then the forecast could be computed.

Stationarity Tests

There are different tests in order to examine whether stationarity of the data has achieved:

- Unit root tests, such as the Dickey-Fuller test and its augmented version, the augmented Dickey-Fuller test (ADF). The null Hypothesis is that a unit root is present in a time series sample. The alternative hypothesis is usually stationarity or trend-stationarity.
- The Phillips-Perron test (PP), for which the null hypothesis is that the series possesses a unit root and hence is not stationary
- The KPSS test that consider as null hypothesis that an observable time series is stationary around a deterministic trend.

The Dickey-Fuller Test

The DF test was the first statistical tests that checked through the null hypothesis that a unit root is present in an autoregressive model of a given time series, so the process is thus not stationary. The original test treats the case of a simple lag-1 AR model. The test has three versions that differ in the model of unit root process they test for;

- Test for a unit root: $\Delta y_i = \delta y_{i-1} + u_i$
- Test for a unit root with drift: $\Delta y_i = a_0 + \delta y_{i-1} + u_i$
- Test for a unit root with drift and deterministic time trend:
$$\Delta y_i = a_0 + a_1 * t + \delta y_{i-1} + u_i$$

Improvements and extensions of the DFT were developed for models that were more complex, such as the Augmented Dickey-Fuller (ADF) that uses AR of any p-th order and models seasonal/time trends.

$$\Delta y_t = c + \beta_t + a y_{t-1} + \varphi_1 \Delta Y_{t-1} + \varphi_2 \Delta Y_{t-2} .. + \Phi_p \Delta Y_{t-p} + \varepsilon_t$$

In all the versions of DF tests the null hypothesis remains the same namely, it accepts the existence of a unit root (α=1). The estimated p-value must be lower than the significance level (i.e. 0.05) for rejecting the null hypothesis which means that the data series is stationary.

Phillips-Perron Test (PP)

Another unit root test is the Phillips-Perron test (PP) that examines the stationarity of the data. The test has unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation. (Phillips, Perron, 1988). In contrast to the ADF approach, the PP tests deal with serial correlation in the errors by employing a nonparametric serial correlation correction factor, which is based on a consistent estimate of the long run variance of the error process." (Castro et al,2013).

The KPSS Test

All the tests mentioned above are testing the null hypothesis that the time series y_t is integrated of order one, $I(1)$. The opposite case, i.e. testing the null hypothesis that the time series y_t is I(0), is described by the KPSS test (Kwiatkowski, Phillips, Schmidt and Shin, 1992). To the Dickey-Fuller family of tests, the null hypothesis assumes stationarity around a mean or a linear trend, while the alternative is the presence of a unit root. This test is based on linear regression, breaking up the series into three parts: a deterministic trend (*βt*), a random walk (*rt*), and a stationary error (*εt*), with the regression equation:

$$x_t = r_t + \beta_t + \varepsilon_t$$

where $r_t = r_{t-1} + u_t$ and $\boldsymbol{u} \sim (0, \sigma^2)$ and are white noise(*iid)*.

In this research for checking the stationarity of the time series the ADF and KPSS test will be applied. The reason behind the selection of the specified tests were that according to Palachy

(2019) the KPSS test is often used to complement Dickey-Fuller-type tests. Additionally, Davidson and MacKinnon (2004) reported that the PP test performs worse than ADF test in the case of finite samples. Finally, according to Arltová and Darina (2016) “The most appropriate test for length T = 100-400 was the ADF test compared to the PP. Consequently, we will proceed to our research with the ADF and the KPSS tests (Arltová and Darina, 2016).

Seasonality

Seasonal effect is one of the multiple factors that can influence the time series. These effects are the result of different natural and social rhythms (duration of the day, seasons, holidays, etc.) in the peoples living. In time series also calendar effects are noticeable when we have repetitive days in a month (working days’ effect), or the leap-year effect or the holiday effect where some holidays are considered as a day off and some others not. In the occasion where these effects are statistically significant in our time series, they have to be removed in order to have seasonally adjusted time series. In that way we manage to make the time series easier for interpretation, because seasonal effects create fluctuation that can shadow other important fluctuation of the time series (Golmajer, Smukavec, 2019).

Diagnostic Tests

The diagnostic test will be used to check the validity of our models. It will be checked if the residuals of our models are white noises. A white noise is a time series with two simple properties, independence in its values and homoscedasticity (Invariant Variance).

Box-Pierce test

The Box-Pierce test is used for examining if the residuals of a ARMA model are independent. The null hypothesis is that the model does not show lack of fit. On the other hand, the alternate hypothesis is that the model does show a lack of fit. The criterion of the Box-Pierce test is that a significant p-value in this test rejects the null hypothesis that the time series isn’t autocorrelated.

Goldfeld-Quandt test

The Goldfeld-Quandt test applies for testing the homoscedasticity of the residuals. This test compares the variances of two subgroups one set of high values and a set of low values. The null Hypothesis of the test is the existence of homoscedasticity. The test criterion is a large F-statistic, which indicates the existence of heteroscedasticity (Goldfeld and Quant 1965).

Finally, the Box-Jenkins methodology initially was designed for ARIMA modelling however, is used in multiple statistical modeling situations. That happens because it gives the opportunity to the researcher to identify the most suitable model for its research.

3.2.2 Autoregressive Model

Autoregressive models have been developed on the idea that the current value of the time series, can be explained as a function of their past values.

$$\chi_t = \varphi_0 + \varphi_1 \chi_{t-1} + \varphi_2 \chi_{t-2} + \cdots + \varphi_p \chi_{t-p} + \varepsilon_t$$

The p-value defines the number of steps into the past for forecasting the current value. The extent to which it might be possible to forecast real data series from its own past values can be assessed by examining the autocorrelation function (ACF) and the scatterplot matrices after taken the lag (Shumway and Stoffer, 2016). A p-th order autoregressive process represented as AR(p), and is a process that can be represented by p-th order stochastic difference equation as presented above, where the process of ε_t is white noise with mean zero and constant variance σ^2 (Pfaff, 2006).

3.2.3 Moving Average Model

A process that is modelling the finite moving average of its shocks is called MA(q), where the parameter q refers to the maximum lag of shocks that can be included in such a process. A q-th order moving average denotes as MA(q), is a process that can be represented as

$$\chi_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \varphi_q \varepsilon_{t-q}$$

Where the process of ε_t is white noise with mean zero and constant variance equal to σ^2 (Zhang, 2018).

One of the first researchers that managed to merge the Autoregressive and moving average approaches, was Wold in 1938 in his study "A Study in the Analysis of Stationary Time Series" (Wold, 1938). In this way he showed that by combining these approaches it is possible to model the stationary time series as long as AR(q) & MA(p) were specified. "This means that any series χ_t can be modelled as a combination of past χ_t values and/or past e_t errors" (Makridakis and Hibon, 1997).

$$x_t = \varphi_1 \chi_{t-1} + \varphi_2 \chi_{t-2} + \cdots + \varphi_p \chi_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 e_{t-2} - \cdots \theta_q \varepsilon_{t-q}$$

ARIMA model with all its different variations are based on the famous Box-Jenkins principle, this being the reason that all broadly known as the Box-Jenkins models. (Adhikari, Agrawal, 2013). A main characteristic of the Box-Jenkins methodology is the fact that encompasses the identification of an appropriate ARIMA process. It fits this process to the data and then it performs the forecasting by using the same model. Notice, that AR and MA are two widely used linear models that work on stationary time series and I is a preprocessing procedure to "stationarize" time series if needed. The equation of a non-seasonal ARIMA (p, d, q) process is the following:

$$\varphi(B)(1 - B^d) y_t = c + \theta(B) \varepsilon_t$$

where e_t is white noise with mean zero and variance σ^2, B is the backshift operator, and φ(z) and θ(z) are polynomials of p-order and q-order (PFAFF, 2006).

3.3 ARIMAX Model

A further development in the ARIMA model was the incorporation of an exogenous variable. Such models are of the form

$$\begin{aligned} y_t &= \beta x_t + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 z_{t-1} - \cdots - \theta_q z_{t-q} + z_t y_t \\ &= \beta x_t + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 z_{t-1} - \cdots - \theta_q z_{t-q} + z \end{aligned}$$

where χ_t is a covariate at time t and β is its coefficient. The existence of lagged values of the explanatory variable on the right hand side of the equation shows that β can only be interpreted on the value of previous values of the response variable (Hyndman, 2010).

The ARIMAX model requires that all exogenous variables also show stationary time series pattern. In comparison to the ARIMA model, the ARIMAX model takes the exogenous variables into account, so the forecasting method of the ARIMAX model does not solely depend on the historical data of its own endogenous variables (Chen, Meersman et al 2014). For the purpose of our research we selected the following version of ARIMAX

$$y_t = \beta\chi_{t-1} + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 z_{t-1} - \cdots - \theta_q z_{t-q} + z_t y_t$$
$$= \beta x_{t-1} + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 z_{t-1} - \cdots - \theta_q z_{t-q} + z$$

This version will allow us to examine if the exogenous variable can predict in one-month horizon the price of the freight rates.

3.4 Forecasting Model Selection

For comparison reasons the following models will be run for the purpose of our study.

- A NAÏVE model. Our model free approach is a very simple approach to predict one month ahead by using the previous observed value of our data series. This is taken in order to have a baseline for comparing models allowing us to understand the value of our models and the predictability of them.
- An ARIMA model following the Box-Jenkins methodology.
- An ARIMAX model with different exogenous variables.

3.5 Forecasting Performance Indicators

The result of the previous selected models will be evaluated based on the following performance indicators:

3.5.1 AIC

When comparing models fitted by maximum likelihood to the same data, the smaller the AIC the better the fit. The theory of AIC requires that the log-likelihood has been maximized: whereas AIC can be computed for models not fitted by maximum likelihood, their AIC values should not be compared. The AIC score is useful only when its used to compare two models (Sakamoto et al, 1986).

3.5.2 RMSE

RMSE is nothing but the square root of calculated Mean Squared Errors (MSE). It is a quadratic error metric indicator that also measures the average importance of the error. The root-mean-square deviation or root-mean-square error is a frequently used measure of the differences between values predicted by a model or an estimator and the values observed. The equation of this metric is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2}$$

Where n is the number of forecasted observations , y_j are the real values at period j and $\hat{y}_j$ are the forecasted values at period j. RMSE is a non-negative measure, and a value of 0 indicates that the data have a perfect fit. Consequently, the lower the value the better for the results. RMSE is very sensitive to extreme values and outliers. That is happening because the impact that each error has to RMSE is proportional to the size of the squared error.

3.5.3 MAE

The Mean Absolute Error (MAE) is also called as the Mean Absolute Deviation (MAD). It measures the average importance of the absolute errors in a set of predictions. Namely, it measures the average absolute deviation of forecasted values from original ones. It shows the size of the overall error that occurred because of the forecasting procedure. For a good forecast, the obtained MAE should be as small as possible. The equation of MAE is:

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right|$$

Where n is the number of forecasted observations, y_j are the real values at period j and $\hat{y}_j$ are the forecasted values at period j (Adhikari, Agrawal, 2013).

3.5.4 MAPE

Another indicator will be the Mean Absolute Error Percentage (MAPE). As we can derive from its name, it measures the percentage of the error between the actual variables and the forecasted ones. MAPE is independent of the scale of measurement but is affected by the transformation of the data. This measure represents the percentage of average absolute error occurred.

$$MAPE = \frac{100\%}{n}\sum_{j=1}^{n}\left|\frac{y_j - \hat{y}_j}{y_j}\right|$$

Where n is the number of forecasted observations, y_j are the real values at period j and $\hat{y}_j$ are the forecasted values at period j.

In this study our main indicator for the selection of the best forecasting model will be the AIC. The rest of the performance indicators described above is going to help us have a broader image on the forecasting results. Furthermore, due to the fact that the Naïve approach that we follow does not provide us a AIC because it is a model free approach, the comparison between the Naïve approach and the ARIMA models will be based on MAPE.

3.6 Data Selection and Data Source

Data of all variable for this study covers the period 1/1/1999 – 31/12/2019 on a monthly base. Data used for the tanker freight rate is the "1 Year Time Charter Rate" that was obtained from the Clarkson's Database for all four vessel sizes. The choice of the specific 12 exogenous variables was made based on the review of literature of relevant studies, the availability of data and an assessment of which exogenous variable may provide the best insight on the formation of the crude oil tankers freight rates. These exogenous variables are falling into three major categories. Financial, Oil, and Commodity Variables.

Oil Variables

The choice of the Oil Variables was made based on the research paper of Polimenopoulos (2006) where he used the Crude Oil Price as an exogenous. On top of that we selected to include the Worldwide Oil Production and the Oil Stocks as exogenous variables as we believe they will give useful insights in our research. Here, we have to note the limitation that we faced on the data series of the Oil Stocks as we were unable to find the Worldwide Oil Stocks thus we used only the US Oil Stocks. This limitation might impact the result of our forecast on the specific variable.

Financial Variables

As presented in the literature almost all the researches have used financial variables in order to explore the relation of freight rates or BDI with and different exogenous variables. The US Index is found in the paper of Baser et al (2018), Chen (2010) and Chen et al (2014). Additionally, we selected different FOREX such as the US-UK and the US-EU. Finally, the choice of the LIBOR was made because Chen (2010) used it and we selected to add the 10 yrs. Bond and the VIX index in order to examine correlations between them and the freight Rates for different size of vessels.

Commodity Variables

For the choice of the commodity variables we took into consideration the research by Baser et al (2018) where they used a lot of different variables of different categories in order to create a multivariate ARIMAX model.

The table below presents the list of the twelve exogenous variables, the category they belong, their definition and data sources for each one.

Variable Name	Variable Category	Definition	Source
Global Oil Production	Oil Variables	Crude oil production refers to the quantities of oil extracted from the ground after the removal of inert matter or impurities(OECD ,2015)	Clarkson's
US oil Stocks	Oil Variables	Crude oil stocks, also known as inventory, are reserves of unrefined petroleum measured in numbers of barrels. Crude stockpile data for the United States is published every week by the Energy Information Agency (EIA)(Chen,2018)	U.S. Energy Information Administration
Global Price of WTI oil	Oil Variables	West Texas Intermediate (WTI) can refer to a grade or a mix of crude oil, and/or the spot price, the futures price, or the assessed price for that oil; colloquially WTI usually refers to the price of the New York Mercantile Exchange (NYMEX) WTI Crude Oil futures contract or the contract itself (Purvin & Gertz Inc. p. 24.)	FRED® Economic Data
Global price of Silver	Commodity Variables	The price of silver as traded in US$/Metric Ton	https://www.investing.com/commodities/silver-historical-data
Global Price of Gold	Commodity Variables	The price of Gold as traded in U.S. Dollars per Troy Ounce	FRED® Economic Data
Global Price of Aluminium in US$	Commodity Variables	The price of silver as traded in US$/Metric Ton	https://www.investing.com/commodities/silver-historical-data
Global Price Index of All Commodities	Commodity Variables	A commodity price index is a fixed-weight index or average of selected commodity prices, which may be based on spot or futures prices. It is designed to be representative of the broad commodity asset class or a specific subset of commodities, such as energy or metals	FRED® Economic Data
FOREX US-EU	Financial Variables	The currency pair tells the reader how many U.S. dollars are needed to purchase one Euro(Chen,2018)	FRED® Economic Data
FOREX US-UK	Financial Variables	The currency pair tells the reader how many U.S. dollars are needed to purchase one British pound .(Chen,2018)	FRED® Economic Data

US$ INDEX	Financial Variables	U.S. Dollar Index is an index of the current value of the United States dollar in relation with a lot different foreign currencies.	FRED® Economic Data
VIX INDEX	Financial Variables	VIX is the name for the Chicago Board Options Exchange's CBOE Volatility Index, a popular measure of the stock market's expectation of volatility based on S&P 500 index options(Kueper,2020)	FRED® Economic Data
Aaa Corporate Bond Yield Relative to Yield on 10-Year	Financial Variables	The Moody's Seasoned Aaa Corporate Bond Yield measures the yield on corporate bonds that are rated Aaa	FRED® Economic Data
1-Month London Interbank Offered Rate (LIBOR), based on U.S. Dollar	Financial Variables	One-Month LIBOR means the London interbank offered rate for deposits in U.S. dollars with the maturity of one month.	FRED® Economic Data

Table 1: Exogenous Variables

4. Data Analysis

Applying the above methodology in this section, first we will analyze our data with the use of descriptive statistics. Then the process of the formation of the ARIMA model after having achieve stationarity will be analyzed as well as their forecasting results for each size of vessel. In turn, we will incorporate in the ARIMA model of each vessel size an exogenous variable each time. Therefore, a new model for each of the twelve exogenous variables will be defined and run. In order to do that each of the twelve exogenous variables will be checked for stationarity. The results of each model will be evaluated based on their statistical significance and their ability to accurate forecast the future tanker freight rates through the performance indicators measures. Then, by selecting the exogenous variables that provide the best models in each category of vessels we proceed to define a model with all of them as exogenous variables and examine how this model performs compared with the ones with only one exogenous variable for each category of vessels. Finally, we compare the best model for each category of vessel in order to identify the best performing model in terms of the best fit.

4.1 Descriptive Statistics

Summary Statistics for Vessel Sizes

Through the descriptive statistics we will calculate the coefficient of variation (CV) which can provide us the variation range by taking into account the mean of the data sample. This should be equal with the standard deviation (σ) of the data divided by the mean of it.

	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum	St. Deviation	CV
VLCC	18,000	26,500	33,875	38,669	50,406	90,000	15,749	40.72%
Suezmax	15,246	18,666	26,025	28,919	38,781	58,750	10,825	37.43%
Aframax	12,000	15,375	19,413	22,142	28,500	43,500	7,844	35.42%
Panamax	10,900	13,352	14,638	16,787	19,572	30,500	4,944	29.45%

Table 2: Descriptive Statistics for VLCC, Aframax, Suezmax, Panamax

As shown in the above table we can identify that the minimum value of the VLCC freight rates is 18,000 and the maximum is 90,000, so the range of our data is 72,000. The σ is of 15,749 and the

CV is 40.72%. On the Suezmax Vessels the minimum value is 15,246 and the Maximum is 58,750. The σ is of 10,825 and the CV is 37.43%. On the Aframax Vessel the minimum value is 12,000 and the Maximum is 43,500. The σ is of 7,844 and the CV is 35.42%. On the Panamax Vessel size, the minimum value is 10,900 and the Maximum is 30,500. The σ is of 4,943 and the CV is 29.45%. What we can derive from the Descriptive statistics of all the vessel sizes is that the time series have a lot of fluctuations in a very wide range. The higher the vessel size the higher the σ indicating more volatile markets of the bigger vessel sizes. This behavior verifies the dynamic nature of the tanker freight rate market.

Summary Statistics for Exogenous Variables

It is evident in the table below that the exogenous variables exhibit different values for CV which range from 9% to 97% depending on the characteristics of each variable. The fact that half of them have a value higher than 40% indicates the dynamic and volatile nature of most of the variables examined.

	Minimum	1st Q	Median	Mean	3rd Q	Maximum	St. Deviation	CV
Oil Production	72.48	82.06	86.42	87.37	94.04	102.07	7.92	9.06%
Oil Price	11.99	35.57	57.13	59.74	80.02	133.93	27.12	45.39%
Oil Stocks(US)(000's)	1,445.81	1,615.80	1,445.81	1,615.80	1,445.81	1,615.80	1,445.81	8.93%
FX USEU	0.85	1.10	1.22	1.20	1.32	1.58	0.17	13.75%
FX USUK	1.22	1.45	1.58	1.59	1.68	2.07	0.20	12.70%
US IND	71.80	81.30	89.63	91.11	98.47	120.24	11.67	12.81%
VIX	10.13	14.05	17.74	19.74	23.65	62.64	8.06	40.84%
AAA 10yrs	0.64	1.30	1.60	1.56	1.85	2.68	0.43	27.41%
Silver	4.13	6.21	14.60	14.51	17.94	48.58	8.68	59.81%
Gold	256.20	403.58	948.65	903.54	1,283.48	1,780.65	474.69	52.54%
LIBOR	0.15	0.26	1.39	2.09	3.46	6.69	2.02	96.54%
Aluminium	1,179.86	1,550.00	1,824.77	1,889.07	2,100.69	3,067.46	426.19	22.56%

Table 3: Descriptive Statistics for the Exogenous Variables

4.1.1 Oil Variables

For the exogenous variables of the oil category in the above table we notice that the variable with the highest CV is the Oil price (45%) while the variable od Oil production and Oil stocks have low CV of 9% each.

4.1.2 Financial Variables

In the category of Financial exogenous variables that exhibit significant high values for the CV is the LIBOR and the Volatility Index (VIX) with a value of 97% and 41% respectively. The range of variation of the other variables between 13% and 27%.

4.1.3 Commodity Variables

In this category the variable which has high CV is the Silver (60%) while Gold has close value of CV (53%). The dispersion of aluminum Price is relatively; its CV is 23%.

4.2 Level of Correlations Between Variables

These results below represent the level of correlation coefficients between each category of vessels freight rates and each of the exogenous variables. In Appendix Table 1 you can find tables with the correlation levels between all variables for all vessel categories. In the VLCC category from the list of the exogenous variable the LIBOR is the one that exhibits the highest level of Correlation at 15.29%. The next highest correlation rate is showed by the Oil Production variable at a level of 8.86% while the third is with FOREX US-UK at 7.53%. It is noticeable that a big difference exist in the behavior of two FOREX variables as the US-EU variable is significantly lower at -1.76% compared with the US-UK of 7.53%. From the commodity variables aluminum and silver have exactly the same correlation percentage at 1.68% while the Gold is at a negative correlation rate of -6.23%. From the Financial Variables we note that VIX and the 10 yrs. Bond are a little bit below, -7% where the US index does not seem to provide important insights with only -1.82%. For the Suezmax vessels the variable with the highest level of correlation is the LIBOR. Then Oil Production and FOREX USUK have the second and third best level of correlation accordingly.

Exogenous Variables	VLCC	Suezmax	Aframax	Panamax
T/C Rate	1	1	1	1
Oil Production	0.0886(2)	0.1334(2)	0.2197(1)	-0.021
Oil Price	0.0472	-0.022	0.088	-0.0264
Oil Stocks (US)	-0.0442	-0.0741	-0.099	-0.0623
FOREX USEU	-0.0176	-0.0072	0.0407	0.0613(3)
FOREX USUK	0.0753(3)	0.1235(3)	0.175(3)	0.1496(2)
US Index	-0.0182	0.0264	-0.0083	-0.0232
VIX	-0.0688	0.0355	0.0313	0.0225
10 Yrs. Bond	-0.0699	0.0112	-0.0409	0.0577
Silver	0.0168	-0.056	-0.0102	-0.0326
Gold	-0.0623	-0.0572	-0.0573	-0.0684
LIBOR	0.1529(1)	0.1601(1)	0.1884(2)	0.1545(1)
Aluminium	0.0168	-0.037	0.0873	-0.0321

Table 4: Level of Correlation Between Vessel Sizes& Exogenous Variables

Regarding the Aframax vessels the variable with the highest level of correlation is the Oil Production followed by the Libor and FOREX USUK. Finally, regarding the Panamax vessel the variable with the highest level of correlation is the LIBOR followed by the FOREX US-UK and FOREX US-EU in the second and third best level.

Summarizing, the exogenous variables with the three higher correlation values in every category of vessels is LIBOR, FOREX US/UK and the oil production, except for the Panamax category where the FOREX US/EU exhibits the second highest correlation.

4.3 Stationarity Tests for Exogenous Variables

The results for stationarity of ADF and KPSS test for all exogenous variables are presented in the table below.

	KPSS	ADF
Oil Production	0.01	0.1301
Oil Price	0.01	0.5605
Oil Stocks (US)	0.01	0.1036
FOREX USEU	0.01	0.6714
FOREX USUK	0.01	0.5409
US Index	0.01	0.7669
VUIX	0.01	0.0838
10 Yrs. Bond	0.1	0.4223
Silver	0.01	0.5741
Gold	0.01	0.7150
LIBOR	0.01	0.3888
Aluminium	0.01	0.3759

Table 5: KPSS & ADF Test for Exogenous Variables

Based on the obtained p-value by each test and their relevant criteria all the exogenous variables tested are not stationary. Therefore, the data has to be stationarized by taking the first order difference of each variable and check again for the existence of a unit root.

After taking the first order difference it is evident in the results presented in the table below that the data for all variables became stationary. This permit us to proceed in the estimation of ARIMAX model for each exogenous variable for each category of vessels.

	KPSS	ADF
Freight Rates	0.1	0.01
Oil Production	0.1	0.01
Oil Price	0.1	0.01
Oil Stocks (US)	0.1	0.01

FOREX USEU	0.1	0.01
FOREX USUK	0.1	0.01
US Index	0.1	0.01
VUIX	0.1	0.01
10 Yrs. Bond	0.1	0.01
Silver	0.1	0.01
Gold	0.1	0.01
LIBOR	0.1	0.01
Aluminium	0.1	0.01

Table 6: KPSS&ADF Tests with lag (1)

4.4 VLCC

4.4.1 ARIMA Model for VLCC

In order to examine the stationarity of the data for VLCC freight series we carry out the ADF and KPSS test. The results of these test are presented below.

	P-values
ADF Test	0.0119
KPSS Test	0.2398

Table 7: KPSS & ADF Tests for VLCC Time series

The p-value of ADF test is 0.01 < 0.05 level of significance therefore, the null hypothesis of existence of unit root (non-stationarity) is accepted. The p-value of KPSS test is 0.23 > 0.05 level of significance hence, the null hypothesis of stationarity is rejected. Since both tests agree to the existence of a unit root, we proceed to the stationarization of the data by taking the first order difference and check again for a unit root. The new results we got show stationarity of the data as the p-value of the ADF test is 0.01 and the KPSS p-value equals 0.1 and we can proceed to the forecast of our data.

Having stationarized the series by taking a first order difference the next step in selecting the appropriate order for ARIMA (p, d, q) model is to determine by examining the ACF and PACF plot the need for any AR or MA components in order to correct any possible autocorrelation that still remains in the series after differencing it. Precisely, based on AR(p) and MA(q) order for the appropriate ARIMA model we have the PACF plot to identify the p-order and the ACF to identify the q-order. From the specific plot below we observe that the current values are correlated with the previous ones and the PACF plot exhibits a significant spike only at lag 1 which implies that all higher order autocorrelations are efficiently explained by the lag1 autocorrelation. Consequently, p=1 for the AR.

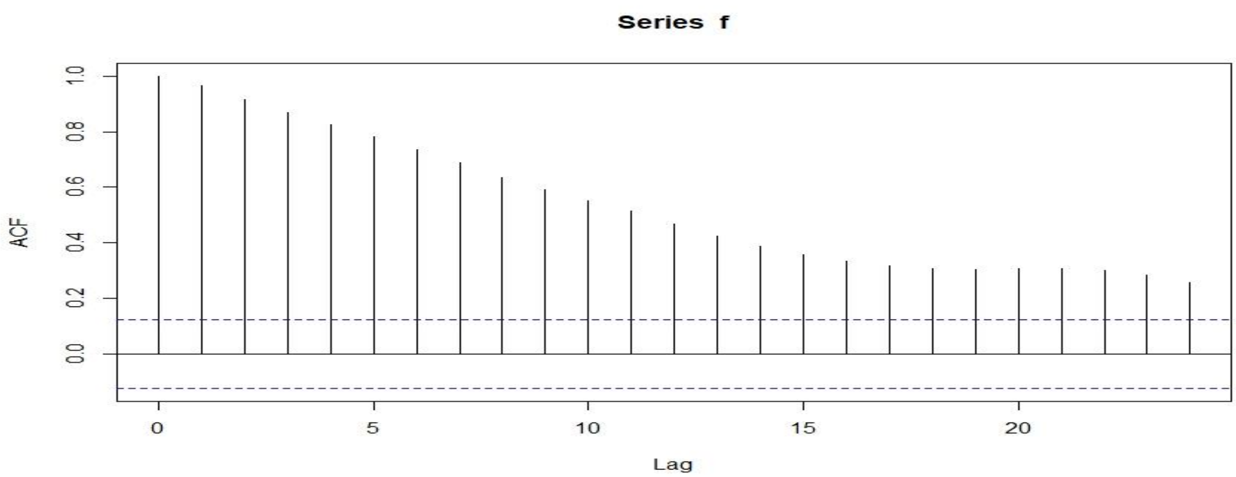

Figure 3: ACF Plot for VLCC Time series

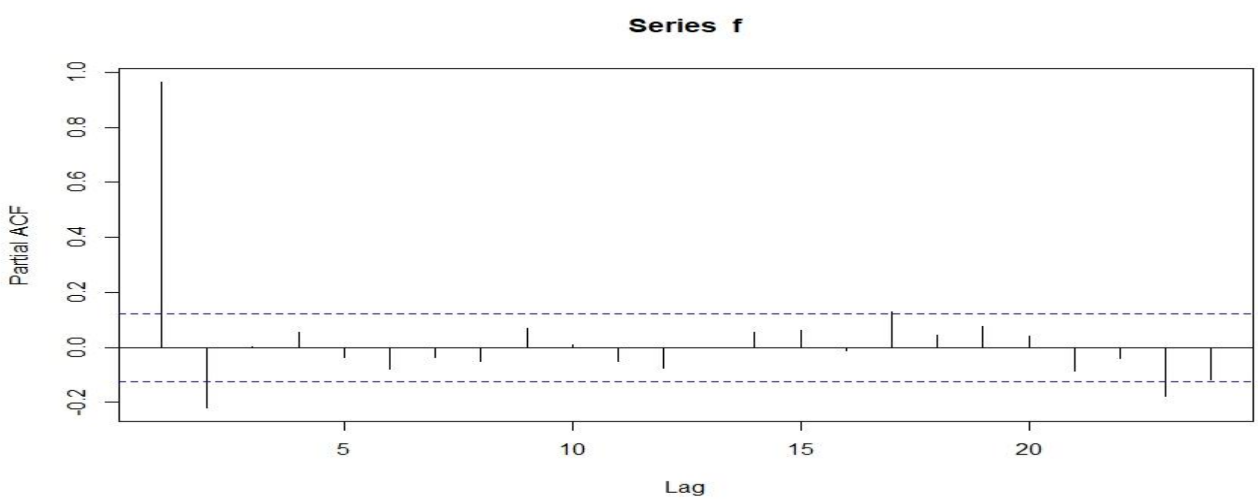

Figure 4: PACF Plot for VLCC Time series

From the ACF plot we notice that there is a decreasing trend. Thus, we do not have evidence that the model has MA terms. Additionally, form, the PACF plot we can note that there are 2 bars that excess the limits (dot lines) that indicates for VLCC T/C rates an AR (2). Due to the fact that we have a unit root we understand that q should be equal to zero (q=0). Since we take only the first order difference in order the data to become stationary, the order of integration is d=1. All these observations suggest that the appropriate order of the model for fitting is ARIMA (1,1,0). In order to verify that this is the best fitting model we have to test it with a lag +/- 2. As a result, for the VLCC vessels we obtain the order of (1,1,0). The table below presents the results of the ARIMA (1,1,0) compared with the Naïve approach based on the performance indicator measures.

	Naïve	ARIMA(1,1,0)
RMSE	4,056.16	3,963.12
RMSE/MEAN	10.48%	10.24%
MAE	2,660.40	2,574.15
MAPE	6.36%	6.06%

Table 8: Naïve & ARIMA(1,1,0) Forecasting Performance for VLCC

It is noticeable that the ARIMA (1,1,0) model performs slightly better than the Naïve approach. The MAPE is slightly better in the ARIMA (1,1,0) at a percentage of 6.06% compared with the 6.36% of the Naïve approach. Moreover, the MAE of the ARIMA model is 2574.15 while for the NAÏVE approach is 2660.40 indicating a slight reduction of the errors in the forecast. The diagnostic tests for this model could be found in Appendix Table 2.

4.4.2 ARIMAX model for VLCC

In order to analyze the impact of each exogenous variable in the forecasting performance of the ARIMA (1,1,0) model we added an explanatory variable to the model each time and compared the results of all twelve ARIMAX (1,1,0) models. The first step is to identify which model provides the lowest value of the Akaike information criterion (AIC) which indicates the better in-sample prediction error. The next step is to check for the accuracy of the ARIMAX models through the performance indicators. The table below shows the relevant results.

	AIC	RMSE	RMSE/MEAN	MAE	MAPE
VLCC Naive	-	4,056.16	10.48%	2,660.40	6.06%
VLCC ARIMA(1,1,0)	4,855.91	3,971.08	10.26%	2,574.15	6.06%
Oil Production	4,857.91	3,979.06	10.28%	2,573.31	6.16%
Oil Price	4,852.30	3,934.70	10.17%	2,571.05	6.07%
Oil Stocks(US)	4,857.88	3,978.83	10.28%	2,575.19	6.10%
FOREX USEU	4,857.44	3,975.35	10.27%	2,579.50	6.07%
FOREX USUK	4,857.86	3,978.66	10.28%	2,576.16	6.07%
US INDEX	4,857.32	3,974.41	10.27%	2,577.25	6.09%
VIX	4,857.33	3,974.44	1027%	2,577.66	6.06%
10yrs Bond	4,857.91	3,979.08	10.28%	2,574.15	6.19%
Silver	4,856.73	3,969.64	10.26%	2,600.17	6.11%
Gold	4,857.76	3,977.85	10.28%	2,582.08	6.08%
LIBOR	4,855.39	3,959.07	10.23%	2,569.42	6.12%
Aluminium	4,856.80	3,970.28	10.26%	2,584.97	6.06%

Table 9: Forecasting Performance for VLCC with Exogenous Variables

According to the AIC results the lowest values are exhibited by the model with the exogenous variable of Oil price (4852.3) and the exogenous variable of LIBOR (4855.39). The third model with the lowest AIC value is the model with no exogenous variable (4855.91). All the other models have a bit higher AIC than the model with no exogenous variables at levels between 4856 and 4857,91. Based on this we conclude that the only variables that their incorporation provides a ARIMAX model with slightly better fit than the model with no exogenous variable (ARIMA) are the LIBOR and the Oil Price. However, this better performance is not so significant to outperform the ARIMA model.

4.4.3 ARIMA &ARIMAX models comparison for VLCC

Recognizing the relative low impact of the exogenous variables in the fitting of our models we decide to incorporate the two exogenous variables (Oil price, LIBOR) with the most significant positive impact on the forecasting performance of the model simultaneously, in order to examine their joined impact on the forecast of freight rates.

	AIC	RMSE	RMSE/MEAN	MAE	MAPE
ARIMA(1,1,0)	4,855.91	3,971.08	10.26%	2,574.15	6.06%
ARIMAX Oil Price,LIBOR)	4,852.65	3,929.705	10.15%	2,560.834	6.14%
ARIMAX(Oil Price)	4,852.30	3,934.70	10.17%	2,571.05	6.16%
ARIMAX(LIBOR)	4,855.39	3,959.07	10.23%	2,569.42	6.08%

Table 10: Comparison Between ARIMA & ARIMAX Best Fit models for VLCC

The obtained results and the value of AIC as presented in the table above indicate that still the best fit is provided by the ARIMAX (Oil price) as the fit in the model of ARIMAX (Oil Price, LIBOR) is slightly worse than the one with only one variable. In other words, the simultaneous incorporations of these two exogenous variables did not improve the fit of the model.

In turn we proceed to apply the same methodology that was applied for the VLCC vessels above in the remaining categories of vessel by defining the order of ARIMA model and proceed with the incorporation of the same exogenous variables in the ARIMAX model.

4.5 Suezmax

The results in the table below indicate that the ARIMA (1,1,0) model performs slightly better than the Naïve approach. The ACF and PACF plots can be found in Appendix Figure 1. The value of MAPE for ARIMA (1,1,0) is 4,42% which is less than 4,77% of the MAPE of NAÏVE model. The stationarity tests as well as the diagnostic test can be found in Appendix Table 3 & 4 respectively.

	AIC	RMSE	RMSE/MEAN	MAE	MAPE
Suezmax Naive	-	2,393.23	8.27%	1,484.29	4.77%
ARIMA(1,1,0)	4,585.59	2,312.54	7.99%	1,380.20	4.42%
Oil Production	4,584.01	2,300.61	7.95%	1,395.05	4.54%
Oil Price	4,580.55	2,284.83	7.89%	1,400.22	4.58%
Oil Stocks(US)	4,587.51	2,316.81	8.00%	1,380.31	4.43%
FOREX USEU	4,587.58	2,317.13	8.00%	1,380.00	4.42%
FOREX USUK	4,586.57	2,312.46	7.99%	1,378.85	4.43%
US INDEX	4,587.23	2,315.55	8.00%	1,379.40	4.43%
VIX	4,586.98	2,314.38	7.99%	1,384.38	4.45%
10yrs Bond	4,587.53	2,316.92	8.00%	1,383.67	4.44%
Silver	4,587.55	2,316.99	8.00%	1,382.44	4.43%
Gold	4,587.59	2,317.18	8.00%	1,379.77	4.42%
LIBOR	4,587.15	2,315.15	8.00%	1,386.99	4.45%
Aluminium	4,585.36	2,306.89	7.97%	1,400.06	4.52%

Table 11: Forecasting Performance for Suezmax with Exogenous Variables

It is obvious based on the values of AIC in the above table the models with the exogenous variables of Oil price and Oil production provide better results than the ARIMA model. The model with the exogenous variable of Aluminium has lower AIC value than the ARIMA model as well. All the rest of the models have a bit higher AIC than the model with no exogenous variables. Based on this we conclude that the only variables that their incorporation provides a model with slightly better fit than the model with no exogenous variable are the Oil Production the Oil Price and the Aluminium.

4.5.1 Comparison Between ARIMA & ARIMAX models for Suezmax

The simultaneous incorporation of the exogenous variables with the most significant positive impact on the forecasting performance of the model (Oil price, Oil Production, Aluminium) it will be provided in the following table:

	AIC	RMSE	RMSE/MEAN	MAE	MAPE
ARIMA(1,1,0)	4,585.59	2,312.54	7.99%	1,380.20	4.42%
ARIMAX(Oil Production)	4,584.01	2,300.61	7.95%	1,395.05	4.54%
ARIMAX(Oil Price)	4,580.55	2,284.83	7.89%	1,400.22	4.58%
ARIMAX(Aluminium)	4,585.36	2,306.89	7.97%	1,400.06	4.52%
ARIMAX (Oil Production, Oil Price)	4,579.71	2,276.45	7.86%	1,401.06	4.61%
ARIMAX (Oil Production, Oil Price, Aluminum)	4,581.62	2,280.65	7.87%	1,402.34	4.61%

Table 12: Comparison Between ARIMA&ARIMAX Best Fit models for Suezmax

The above AIC indicates that the ARIMAX (Oil price, Oil Production) model provides slightly better fitting than the other models.

4. 6 Aframax

As it is showed the table below based on the MAPE results the ARIMA (1,1,0) model performs slightly better than the Naïve approach. The ACF& PACF plots, the stationarity tests as well as the diagnostic test can be found in Appendix Figure 2 and Tables 5,6 respectively.

	AIC	RMSE	RMSE/MEAN	MAE	MAPE
Aframax Naive		1,456.336	6.57%	933.61	3.96%
Aframax ARIMA(1,1,0)	4,298.21	1,301.19	5.87%	801.48	3.37%
Oil Production	4,295.02	1,290.31	5.82%	809.05	3.43%
Oil Price	4,293.33	1,285.99	5.80%	805.55	3.44%
Oil Stocks(US)	4,299.17	1,301.08	5.87%	798.43	3.36%
FOREX USEU	4,300.21	1,303.79	5.88%	801.87	3.37%
FOREX USUK	4,299.78	1,302.67	5.88%	801.68	3.37%
US INDEX	4,299.74	1,302.57	5.87%	802.83	3.38%
VIX	4,297.53	1,296.84	5.85%	810.07	3.42%
10yrs Bond	4,298.88	1,300.34	5.86%	808.58	3.40%
Silver	4,299.85	1,302.86	5.88%	801.52	3.37%
Gold	4,300.21	1,303.80	5.88%	801.52	3.37%
LIBOR	4,299.85	1,302.88	5.88%	804.56	3.38%
Aluminium	4,299.79	1,302.71	5.88%	801.92	3.37%

Table 13: Forecasting Performance for Aframax with Exogenous Variables

According to the AIC results the lowest values of ARIMAX model are exhibited by the model with the exogenous variable of Oil price (4293.33) and the exogenous variable of Oil Production (4295.02). All the rest models have a bit higher AIC that the ARIMA model. Based on this we conclude that the only exogenous variables that their incorporation provides a slightly better fit than the ARIMA model are the Oil Production and the Oil Price.

4.6.1 Comparison Between ARIMA &ARIMAX models for Aframax

The results of the simultaneous incorporation of the two exogenous variables with the better positive impact (Oil price, Oil Production) in the model and their comparison with the results of the other models are presented in the table below.

	AIC	RMSE	RMSE/MEAN	MAE	MAPE
ARIMA(1,1,0)	4,298.21	1,301.19	5.87%	801.48	3.37%
ARIMAX(Oil Price)	4,293.33	1,285.99	5.80%	805.55	3.44%
ARIMAX(Oil Production)	4,295.02	1,290.31	5.82%	809.05	3.43%
ARIMAX AFRAMAX (Oil Production, Oil Price)	4,290.98	1,277.39	5.76%	803.46	3.43%

Table 14: Comparison Between ARIMA & ARIMAX Best Fit models for Aframax

It is obvious that based on the AIC figures the ARIMAX (Oil production, Oil price) Model provides slightly better results than the other models.

4.7 Panamax

For this category of vessels, the order of ARIMA model is different than in the other categories. It is ARIMA (5,1,0). This model performs slightly better than the Naïve approach as all the values of its performance indicators are lower than the ARIMA model. The ACF& PACF plots, the stationarity tests as well as the diagnostic test can be found in Appendix Figure 3 and table 7,8 respectively.

	AIC	RMSE	RMSE/MEAN	MAE	MAPE
NAIVE		865.58	51.56%	532.48	2.93%
ARIMA(5,1,0)	4,046.17	779.49	4.64%	477.30	2.65%
Oil Production	4,048.01	780.85	4.65%	477.65	2.65%
Oil Price	4,045.32	776.69	4.62%	471.02	2.62%
Oil Stocks(US)	4,048.12	781.02	4.65%	477.10	2.65%
FOREX USEU	4,047.95	780.74	4.65%	477.33	2.65%
FOREX USUK	4,047.81	780.54	4.65%	477.28	2.65%
US INDEX	4,046.82	778.98	4.64%	482.40	2.70%
VIX	4,047.68	780.30	4.64%	479.57	2.67%
10yrs Bond	4,046.89	779.05	4.64%	482.49	2.69%
Silver	4,047.60	780.18	4.64%	477.64	2.66%
Gold	4,047.83	780.55	4.65%	477.39	2.65%
LIBOR	4,048.13	781.03	4.65%	477.73	2.65%
Aluminium	4,047.11	779.45	4.64%	475.45	2.63%

Table 15: Forecasting Performance for Panamax with Exogenous Variables

The above table indicates that the model with exogenous variable of Oil price is the only one that shows a value of AIC that is lower than the ARIMA (5,1,0) model. All the rest models have a bit higher AIC than the model with no exogenous variables. Therefore, the only variable that its incorporation provides a model with slightly better fit than is the Oil Price. Consequently, there is no reason of creating a model with more than one explanatory variable as in the previous categories of vessel since it will not improve the existing best-fit model.

Before we proceed to the comparison among the models with the best forecasting performance in each vessels category it is important to evaluate the significance of the exogenous variable in the improvement of the forecasting capabilities of the ARIMA model. The summary of our results is presented in the table below.

	VLCC	Suezmax	Aframax	Panamax
Oil Production		✓	✓	
Oil Price	✓	✓	✓	✓
Oil Stocks(US)				
FOREX USEU				
FOREX USUK				
US INDEX				
VIX				
10yrs Bond				
Silver				
Gold				
LIBOR	✓			
Aluminium		✓		

Table 16: Summary of Variables that improves ARIMA models

The variables with a positive impact are the oil price and Libor in the VLCC category, the Oil production the Oil price and the Aluminium in the Suezmax Category, the Oil production and oil price in the Aframax vessels and the oil price in the Panamax. Therefore, it is important to mention that the exogenous variable that is present in all ARIMAX models in each category of vessels that performed better than the ARIMA ones is the Oil price. The oil production is present in all categories of vessels except the VLCC and Panamax category while the LIBOR provide better fit only in the VLCC category. This indicates that the category of exogenous variables that slightly improves the forecasting performance of ARIMA models is the Oil category. From the other two categories of exogenous variable, only the Libor from the Financial category shows a positive effect in the VLCC vessels type while from the commodity category only the Aluminium shows a slight better fit in the Suezmax category.

Due to the fact that the aforementioned variables were providing better fit than the ARIMA model, we decided to incorporate the best in each category of vessels simultaneously in the same ARIMAX model for this size of vessel in order to examine if the fit of the models was improving. The obtained results indicate that in the Suezmax and Aframax categories the incorporation of more than one exogenous provided slightly better fit in the models. On the other hand, in the VLCC category the ARIMAX with one variable (Oil Price) had better fit than the VLCC ARIMAX (Oil Price, LIBOR). For the Panamax category there was only one variable (Oil Price) that was performing better than the ARIMA (5,1,0) model so we did not create any model with two exogenous variables.

4.7.1 Comparison Between Best Fit Models for all Categories of Vessels

In the table below we presented a comparison of the models with the best forecasting performance in each category of vessel size.

	AIC	RMSE	RMSE/MEAN	MAE	MAPE
ARIMAX VLCC(Oil Price)	4,852.30	3,934.70	10.17%	2,571.05	6.16%
ARIMAX AFRAMAX (Oil Production , Oil Price)	4,290.98	1,277.39	5.76%	803.46	3.43%
ARIMAX SUEZMAX(Oil Production, Oil Price)	4,579.71	2,276.45	7.86%	1,401.06	4.61%
ARIMAX Panamax (Oil Price)	4,045.32	776.69	4.62%	471.02	2.62%

Table 17: Comparison Between best-fit models for all categories of vessels

The best performing model compare to others is in the Panamax type of vessels with the oil price as exogenous variable. Almost similar forecasting results are provided by the model in the Aframax size of vessels that includes the oil production as exogenous variable besides the Oil price. This indicates that the best impact of exogenous variables appears by the variables in the Oil category.

4.8 Comparison of Results with other Similar Studies

In this section we will try to compare the results of our study with those of other relevant studies using exogenous variables.

Lyridis in 2004 by using WNN model concluded that "multivariate models interpret more precisely the freight markets in relation to univariate models." Our results for all categories of vessels are marginally aligned with their conclusions even though their analysis was on spot freight rates and not T/C rates. However, the modest effect that the inclusion of the exogenous variables provide are in line the conclusion of Gavriilidis (2018) on the negligible effect of an exogenous variable in the forecasting performance and Polymenopoulos in 2006 where he concluded that neither the standard explanatory variables associated with time charter rates, or lagged time charter rates themselves contain useful information to be able to forecast ARIMA, ARIMAX and GARCH models successfully especially over long time periods.

Our results seem to be different than Baser et al (2018) where by using BTI concluded that by adding more exogenous variables in an ARIMAX model then we can have useful insights on monitoring both freight markets and economic conditions. They found that an ARIMAX model with explanatory variables of price of golds, price of silver and price of iron has been a useful tool to accomplish that. In our case the commodity variables do not provide important insights on the freight rates mechanism. By adding more exogenous variables in the model we did not gain significant improvement of our forecast in order to identify freight market characteristics and patterns.

In summary, attention has to be paid to the comparability of the results of the results of our study with others due to different of the period of the analysis, data used, segment of the market, etc.

5. Conlusions

The importance of transportation of Oil for the global economy was recognized very early, even before the globalization of the economy. For geographical reasons this is accomplished even today mostly by shipping. As a result, this initiated a huge scientific research around the determination and forecast of freight rates. Many empirical studies with the use of evolving sophisticated econometric methods and models try to identify the variables that determine the freight rates and forecast their future value. All these studies conducted over various time periods, different vessel sizes as well as routes in different geographical locations. Diakodimitris (2019) comparing the forecasting performance of different of the above econometric models and explaining their relatively low performance, proposed as a topic for further research the inclusion of exogenous economic variables as they might provide important insight on the formation of freight rates. Continuing in the tradition of empirical studies that try to analyze the future behavior of freight rates based on their past performance with the use of ARIMA econometric model, in this thesis we examined the main question of how the incorporation of one or more exogenous variables in an ARIMA model will influence the forecast of freight rates. Subsequently, is was examined how this inclusion of exogenous variables behave for different size of vessels and which ARIMAX model with one or more exogenous variable provide better forecasting performance.

5.1 Answers to Research and Sub-Research Questions

In the section below we will present the answers to sub-research questions and the main research question:

Sub-Research Question 1: *To what extend the different exogenous or group of exogenous variables affect the tanker freight rates?*

Answer: The use of certain exogenous variables seems to improve slightly the predictability of tanker freight rates. From the twelve exogenous variables examined in this thesis only four provide a positive impact namely, Oil price, Oil production, Libor, Aluminum. Among the three categories of exogenous variables (Oil, Financial, Commodity) the one that exhibits the best forecasting improvement is the Oil category. However, it needs to be noticed that this improvement in forecasting is not significant.

Sub-Research Question 2: *How will the inclusion of exogenous variable(s) in a model affect its prediction power regarding the forecasting performance of the freight rates for different size of vessels.*

Answer: Different exogenous variables provide a small improvement in the forecast of the fright rates for all size of vessels. From the Oil category, the oil price for all size of vessels while the Oil production only for the Suezmax and Aframax vessels, the Libor from the Financial category for the VLCC vessels and Aluminum from the commodity category for the Suezmax vessels. In other words, in the forecast of tanker freight rates slight positive impact is exhibited for VLCC vessels by two exogenous variables (Oil price, Libor) for Suezmax by three variables (Oil price, Oil production, Aluminum), for Aframax by two variables (Oil price, Oil production) and for Panamax by one variable (Oil price).

The joint incorporation of the exogenous variables that provided slightly better fit in the models for each size of vessel indicated better results only in the Suezmax and Aframax categories through the combined effect of Oil price and Oil production variables. In the VLCC category the Oil Price had better fit than the combined effect of Oil Price, and LIBOR, while in the Panamax category there was only one variable (Oil Price) that was performing better than the ARIMA (5,1,0).

Having answered the above two sub-research questions, we can proceed to the main research question:

Main Research Question: *How will the incorporation of one or more exogenous variables in an ARIMAX model influence the forecasting performance of tanker freight rates vs the ARIMA model.*

Answer: Our results indicate that there are four out of the twelve exogenous variables examined that improve slightly the forecasting performance of the ARIMA model regarding tanker freight rates for all size of vessels. The best performing ARIMAX model among all categories of vessels is in the Panamax with the oil price as exogenous variable. The second-best model is for the Aframax size of vessels that includes the Oil price and Oil production as exogenous variable. The third best fit model is for the Suezmax type of vessels with the same Oil variables as in the case of the Aframax. The lowest fit model is the VLCC with Oil Price as an exogenous. Thus, only exogenous variables from the Oil category is capable of providing slightly better forecasting performance among all examined exogenous variables.

It is obvious from the derived results that the inclusion of certain exogenous variables like oil price and oil production improves the forecasting performance of ARIMAX models in comparison to ARIMA one but not too much. The forecasting performance of ARIMAX model could not surpass the one of ARIMA models. The identification of the relatively low impact of the exogenous variables in the forecast of freight rates could be attributed to the highly dynamic nature of the shipping industry and the freight rate market. A characteristic of this kind of studies is that are sensitive to many stochastic parameters, data quality, time period of the analysis, market segments etc. This is confirmed by the high level of variability and coefficient of variation in many of the time series used in this study as it was confirmed by the descriptive statistics.

5.2 Limitations and Recommendations for further Research

Before we proceed to the recommendation for further research, I would like to address some limitations faced during this thesis. The first limitation was a lack of data as specified in Chapter 3. More specifically, we had to include only the US Stocks of Oil as we could not manage to find the Worldwide Stocks of oil in monthly data for the period of the research. Furthermore, I faced a lot of difficulties with the software I selected to run my statistical analysis. Even if I managed to run the whole research in R Software the process of understanding and running the software was demanding and time-consuming as programming was an unexplored field for myself. Moreover, my econometric knowledge was also below the required level for such a study, that made me to spent a lot of time and effort in order to comprehend the ideas and the logic behind the theory in order to complete this study. Finally, another serious difficulty that I encountered was the unprecedented issues that the appearance of Covid-19 created especially, in terms of scientific interaction, exchange of ideas and the accessibility of facilities and databases etc.

Further research is needed in terms of the categories of exogenous variables. The use of different econometric models either univariate (ARCH type) or multivariate (VAR, VECM) for the forecasting of the spot and T/C freight rates of vessels of the same size but for different markets/routes within the shipping sector could be a great research topic. Finally, the use of ANN or WNN is also strongly advised for further research.

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Appendix

Appendix Table 1-Correlation on Differentiated Data

	VLCC T/C	Oil Production	Oil Price	Oil Stocks(US)	FOREX USEU	FOREX USUK	US INDEX	vix	10yrs Bond	Silver	Gold	LIBOR	Aluminium
VLCC T/C	1	0.0886	0.0472	-0.0442	-0.0176	0.0753	-0.0182	-0.0688	-0.0699	0.0168	-0.0623	0.1529	0.0168
Oil Production	0.0886	1	-0.011	-0.0141	0.0122	0.0008	0.0105	0.0639	0.0086	0.0219	-0.0875	0.0128	0.0075
Oil Price	0.0472	-0.011	1	-0.1657	0.3613	0.3903	-0.2528	-0.3329	-0.2763	0.2159	0.1032	0.0373	0.4674
Oil Stocks(US)	-0.0442	-0.0141	-0.1657	1	-0.0791	-0.0388	0.029	-0.0038	0.0677	-0.0535	-0.0154	-0.0842	-0.1399
FOREX USEU	-0.0176	0.0122	0.3613	-0.0791	1	0.6959	-0.6543	-0.1789	-0.009	0.226	0.309	-0.0944	0.4041
FOREX USUK	0.0753	0.0008	0.3903	-0.0388	0.6959	1	-0.3762	-0.1127	-0.126	0.1161	0.2076	0.0875	0.4175
US INDEX	-0.0182	0.0105	-0.2528	0.029	-0.6543	-0.3762	1	0.2273	0.0412	-0.3034	-0.2102	-0.0139	-0.2149
VIX	-0.0688	0.0639	-0.3329	-0.0038	-0.1789	-0.1127	0.2273	1	0.486	-0.1281	0.1165	0.1835	-0.2724
10yrs Bond	-0.0699	0.0086	-0.2763	0.0677	-0.009	-0.126	0.0412	0.486	1	-0.0904	0.1407	0.0134	-0.2369
Silver	0.0168	0.0219	0.2159	-0.0535	0.226	0.1161	-0.3034	-0.1281	-0.0904	1	0.3591	-0.0827	0.2115
Gold	-0.0623	-0.0875	0.1032	-0.0154	0.309	0.2076	-0.2102	0.1165	0.1407	0.3591	1	-0.0459	0.237
LIBOR	0.1529	0.0128	0.0373	-0.0842	-0.0944	0.0875	-0.0139	0.1835	0.0134	-0.0827	-0.0459	1	-0.0071
Aluminium	0.0168	0.0075	0.4674	-0.1399	0.4041	0.4175	-0.2149	-0.2724	-0.2369	0.2115	0.237	-0.0071	1

	Suezmax T/C	Oil Production	Oil Price	Oil Stocks(US)	FOREX USEU	FOREX USUK	US INDEX	vix	10yrs Bond	Silver	Gold	LIBOR	Aluminium
Suezmax T/C	1	0.1334	-0.022	-0.0741	-0.0072	0.1235	0.0264	0.0355	0.0112	-0.056	-0.0572	0.1601	-0.037
Oil Production	0.1334	1	-0.011	-0.0141	0.0122	0.0008	0.0105	0.0639	0.0086	0.0219	-0.0875	0.0128	0.0075
Oil Price	-0.022	-0.011	1	-0.1657	0.3613	0.3903	-0.2528	-0.3329	-0.2763	0.2159	0.1032	0.0373	0.4674
Oil Stocks(US)	-0.0741	-0.0141	-0.1657	1	-0.0791	-0.0388	0.029	-0.0038	0.0677	-0.0535	-0.0154	-0.0842	-0.1399
FOREX USEU	-0.0072	0.0122	0.3613	-0.0791	1	0.6959	-0.6543	-0.1789	-0.009	0.226	0.309	-0.0944	0.4041
FOREX USUK	0.1235	0.0008	0.3903	-0.0388	0.6959	1	-0.3762	-0.1127	-0.126	0.1161	0.2076	0.0875	0.4175
US INDEX	0.0264	0.0105	-0.2528	0.029	-0.6543	-0.3762	1	0.2273	0.0412	-0.3034	-0.2102	-0.0139	-0.2149
VIX	0.0355	0.0639	-0.3329	-0.0038	-0.1789	-0.1127	0.2273	1	0.486	-0.1281	0.1165	0.1835	-0.2724
10yrs Bond	0.0112	0.0086	-0.2763	0.0677	-0.009	-0.126	0.0412	0.486	1	-0.0904	0.1407	0.0134	-0.2369
Silver	-0.056	0.0219	0.2159	-0.0535	0.226	0.1161	-0.3034	-0.1281	-0.0904	1	0.3591	-0.0827	0.2115
Gold	-0.0572	-0.0875	0.1032	-0.0154	0.309	0.2076	-0.2102	0.1165	0.1407	0.3591	1	-0.0459	0.237
LIBOR	0.1601	0.0128	0.0373	-0.0842	-0.0944	0.0875	-0.0139	0.1835	0.0134	-0.0827	-0.0459	1	-0.0071
Aluminium	-0.037	0.0075	0.4674	-0.1399	0.4041	0.4175	-0.2149	-0.2724	-0.2369	0.2115	0.237	-0.0071	1

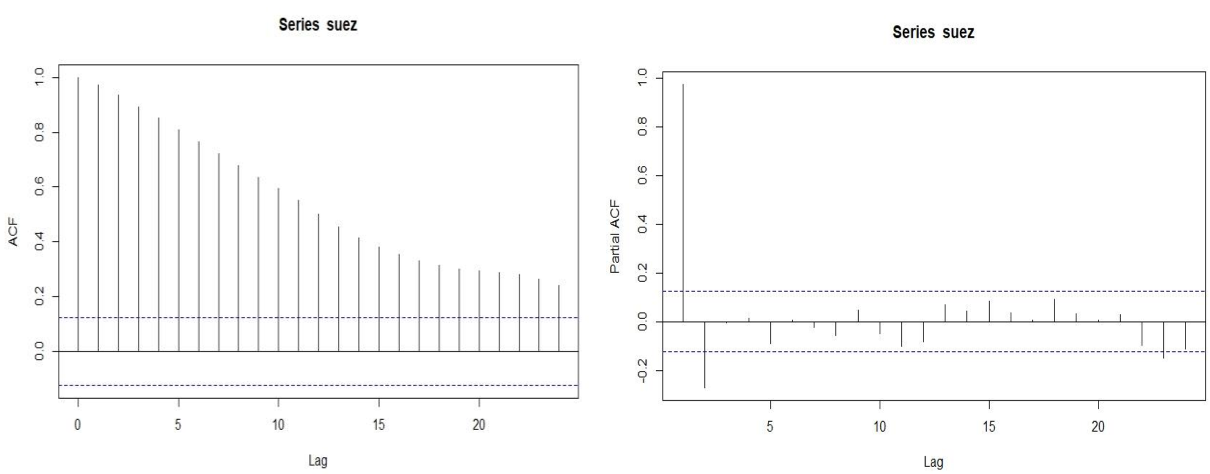
	Aframax T	Oil Production	Oil Price	Oil Stocks(US)	FOREX USEU	FOREX USUK	US INDEX	vix	10yrs Bon	Silver	Gold	LIBOR	Aluminium
Aframax T/C	1	0.2197	0.088	-0.099	0.0407	0.175	-0.0083	0.0313	-0.0409	-0.0102	-0.0573	0.1884	0.0873
Oil Production	0.2197	1	-0.011	-0.0141	0.0122	0.0008	0.0105	0.0639	0.0086	0.0219	-0.0875	0.0128	0.0075
Oil Price	0.088	-0.011	1	-0.1657	0.3613	0.3903	-0.2528	-0.3329	-0.2763	0.2159	0.1032	0.0373	0.4674
Oil Stocks(US)	-0.099	-0.0141	-0.1657	1	-0.0791	-0.0388	0.029	-0.0038	0.0677	-0.0535	-0.0154	-0.0842	-0.1399
FOREX USEU	0.0407	0.0122	0.3613	-0.0791	1	0.6959	-0.6543	-0.1789	-0.009	0.226	0.309	-0.0944	0.4041
FOREX USUK	0.175	0.0008	0.3903	-0.0388	0.6959	1	-0.3762	-0.1127	-0.126	0.1161	0.2076	0.0875	0.4175
US INDEX	-0.0083	0.0105	-0.2528	0.029	-0.6543	-0.3762	1	0.2273	0.0412	-0.3034	-0.2102	-0.0139	-0.2149
VIX	0.0313	0.0639	-0.3329	-0.0038	-0.1789	-0.1127	0.2273	1	0.486	-0.1281	0.1165	0.1835	-0.2724
10yrs Bond	-0.0409	0.0086	-0.2763	0.0677	-0.009	-0.126	0.0412	0.486	1	-0.0904	0.1407	0.0134	-0.2369
Silver	-0.0102	0.0219	0.2159	-0.0535	0.226	0.1161	-0.3034	-0.1281	-0.0904	1	0.3591	-0.0827	0.2115
Gold	-0.0573	-0.0875	0.1032	-0.0154	0.309	0.2076	-0.2102	0.1165	0.1407	0.3591	1	-0.0459	0.237
LIBOR	0.1884	0.0128	0.0373	-0.0842	-0.0944	0.0875	-0.0139	0.1835	0.0134	-0.0827	-0.0459	1	-0.0071
Aluminium	0.0873	0.0075	0.4674	-0.1399	0.4041	0.4175	-0.2149	-0.2724	-0.2369	0.2115	0.237	-0.0071	1

	Panamax T/C	Oil Production	Oil Price	Oil Stocks(US)	FOREX USEU	FOREX USUK	US INDEX	vix	10yrs Bond	Silver	Gold	LIBOR	Aluminium
Panamax T/C	1	-0.021	-0.0264	-0.0623	0.0613	0.1496	-0.0232	0.0225	0.0577	-0.0326	-0.0684	0.1545	-0.0321
Oil Production	-0.021	1	-0.011	-0.0141	0.0122	0.0008	0.0105	0.0639	0.0086	0.0219	-0.0875	0.0128	0.0075
Oil Price	-0.0264	-0.011	1	-0.1657	0.3613	0.3903	-0.2528	-0.3329	-0.2763	0.2159	0.1032	0.0373	0.4674
Oil Stocks(US)	-0.0623	-0.0141	-0.1657	1	-0.0791	-0.0388	0.029	-0.0038	0.0677	-0.0535	-0.0154	-0.0842	-0.1399
FOREX USEU	0.0613	0.0122	0.3613	-0.0791	1	0.6959	-0.6543	-0.1789	-0.009	0.226	0.309	-0.0944	0.4041
FOREX USUK	0.1496	0.0008	0.3903	-0.0388	0.6959	1	-0.3762	-0.1127	-0.126	0.1161	0.2076	0.0875	0.4175
US INDEX	-0.0232	0.0105	-0.2528	0.029	-0.6543	-0.3762	1	0.2273	0.0412	-0.3034	-0.2102	-0.0139	-0.2149
VIX	0.0225	0.0639	-0.3329	-0.0038	-0.1789	-0.1127	0.2273	1	0.486	-0.1281	0.1165	0.1835	-0.2724
10yrs Bond	0.0577	0.0086	-0.2763	0.0677	-0.009	-0.126	0.0412	0.486	1	-0.0904	0.1407	0.0134	-0.2369
Silver	-0.0326	0.0219	0.2159	-0.0535	0.226	0.1161	-0.3034	-0.1281	-0.0904	1	0.3591	-0.0827	0.2115
Gold	-0.0684	-0.0875	0.1032	-0.0154	0.309	0.2076	-0.2102	0.1165	0.1407	0.3591	1	-0.0459	0.237
LIBOR	0.1545	0.0128	0.0373	-0.0842	-0.0944	0.0875	-0.0139	0.1835	0.0134	-0.0827	-0.0459	1	-0.0071
Aluminium	-0.0321	0.0075	0.4674	-0.1399	0.4041	0.4175	-0.2149	-0.2724	-0.2369	0.2115	0.237	-0.0071	1

Appendix Table 2:VLCC Diagnostic Tests

	Box-Pierce Test	GQ Test
VLCC T/C	0.8694	1
Oil Production	0.87904	1
Oil Price	0.86942	1
Oil Stocks(US)	0.86914	1
FOREX USEU	0.86479	1
FOREX USUK	0.86055	1
US INDEX	0.83302	1
VIX	0.86944	1
10yrs Bond	0.85611	1
Silver	0.8697	1
Gold	0.92653	1
LIBOR	0.86771	1

Appendix Figure 1:Suezmax ACF&PACF Plots



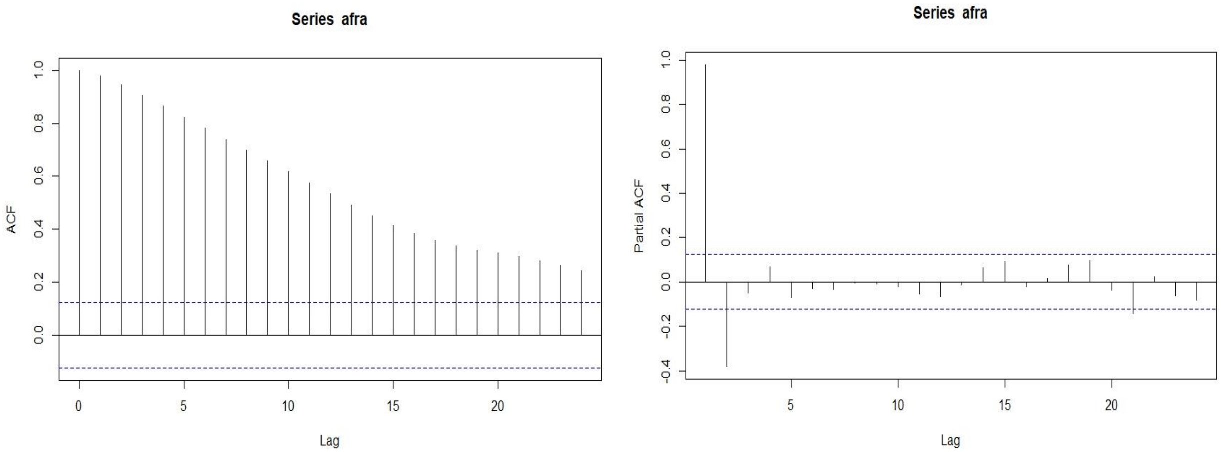
Appendix Table 3: Suezmax Stationarity Tests

Suezmax	P-values
ADF Test	0.2513718
KPSS Test	0.01

Appendix Table 4 :Suezmax Diagnostic Tests

	Box-Pierce Test	GQ Test
Suezmax T/C	0.8470	0.9973
Oil Production	0.8114	0.9986
Oil Price	0.9006	0.9905
Oil Stocks(US)	0.8470	0.9977
FOREX USEU	0.8494	0.9985
FOREX USUK	0.8519	0.9980
US INDEX	0.8585	0.9985
VIX	0.8506	0.9977
10yrs Bond	0.8483	0.9979
Silver	0.8406	0.9981
Gold	0.8486	0.9981
LIBOR	0.8656	0.9981
Aluminium	0.8424	0.9973

Appendix Figure 2:Aframax ACF & PACF Plots



Appendix Table 5:Aframax Stationarity Test

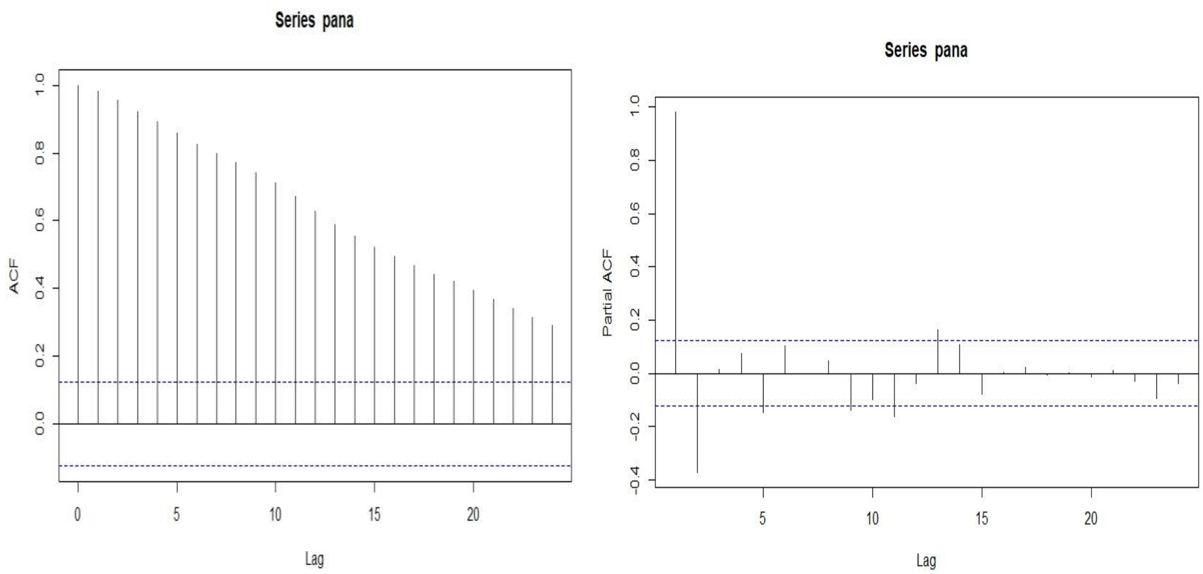
Aframax	P-values
ADF Test	0.2910887
KPSS Test	0.01035394

Appendix Table 6:Aframax Diagnostic Test

	Box -Pierce Test	GQ Test
Aframax T/C	0.63361	1
Oil Production	0.54933	1
Oil Price	0.68367	0.999999
Oil Stocks(US)	0.62587	1
FOREX USEU	0.63186	1
FOREX USUK	0.64963	1
US INDEX	0.62982	1
VIX	0.65144	1
10yrs Bond	0.65256	1
Silver	0.62043	1
Gold	0.63325	1

LIBOR	0.64412	1
Aluminium	0.62679	1

Appendix Figure 3: Panamax ACF&PACF Plots



Appendix Table 7:Panamax Stationarity Tests

Panamax	P-values
ADF Test	0.2513718
KPSS Test	0.01

Appendix Table 8: Panamax Diagnostic Test

	Box-Pierce Test	GQ Test
Panamax T/C	0.9900	1
Oil Production	0.9899	1
Oil Price	0.9988	1
Oil Stocks(US)	0.9885	1
FOREX USEU	0.9880	1
FOREX USUK	0.9809	1
US INDEX	0.9971	1
VIX	0.9912	1
10yrs Bond	0.9911	1
Silver	0.9925	1
Gold	0.9897	1
LIBOR	0.9917	1
Aluminium	0.9985	1