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AN ECONOMETRIC MODEL OF TANKER SPOT FREIGHT RATES

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Preface

The thesis was prepared in cooperation with the Department of Operations Management at the Copenhagen Business School, Denmark in fulfilment of the requirement for acquiring the Cand.merc. / MSc. Economics and Business Administration within the field of Supply Chain Management – Maritime Business.

The thesis is dedicated to the research areas – applied econometrics and macroeconomics and subject to Baltic Dirty Tanker Index routes in Worldscale units, in regards to Ve*ry Large Crude-, Suezmax*- and *Aframax carriers.* Frist, the paper introduces the subject and outlines the strategic objectives. Further, familiarises the reader with the maritime business, in regards to segments, in particular, the crude tanker segment, tanker market model, freight rates, contracts and shipping market cycles. Additionally, a general tanker market literature review and a specific outline concerning econometric modelling and forecasting is presented. Moreover, data used for the subsequent analytical sections is described and discussed. Furthermore, univariate- and multivariate models are displayed. Finally, the forecasted models are benchmarked and critically discussed, concerning their validity, reliance and implication.

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Abstract

The paper titles *An econometric model of tanker spot freight*, applies econometric time-series models to model and forecast Baltic Exchange Dirty Tanker Index routes in Worldscale units. The focal point is the crude oil tanker segment; *Very Large Crude-, Suezmax-* and *Aframax carriers*, in regards to Intra-European, Asian and North American crude oil trade routes. The data was sourced in co-operation with the World Maritime University, Malmö, Sweden and the world's leading maritime data provider Clarksons Research Shipping Intelligence Network. A relatively limited amount of studies has been so far subject to econometrics modelling in the spot freight tanker market context, thus providing exceptional aspiration to fill such gap within the academia. The appliance of spot rates strive from the notion that these tend to reflect a uniform worldwide accessible current price in a marketplace at which a commodity can be sold or bought for immediate delivery. Regarding, seaborne trade spot freight rates, these depict the price charged for the carriage of cargo. Companies linked to global supply chains can enhance their competitiveness, in relation to accurately evaluating and forecasting these spot rates.

'Can crude tanker spot freight rates be modelled and forecasted by an econometric model?'

The first section applies the univariate autoregressive moving average (ARMA) model, based on the Box-Jenkins framework. Further, the concept of stationarity, relation to the Dicky Fuller test is thoroughly discussed. Based on the acceptance of the null hypothesis of a present unit root, the time-series are transformed to log-returns, thus achieving satisfactory estimates. Additionally, in the second section, crude oil prices and –production, in regards to allocated BDTI routes are introduced. Frist, the vectorised AR (VAR) model is utilised, which takes into account the dynamic relationship between the routes in Worldscale units and the crude oil price benchmarks *Brent* and *West Texas Intermediate* (WTI). The Granger causality test confirms that crude oil prices have predictive causality on BDTI rates. Cointegration is rejected by the majority of the models, which included crude oil prices, BDTI routes and respective geographical linked crude oil production, with the exception of two Intra-European routes. In the latter section, the WTI-related, Brent-related VAR- and ARMA models are subject to dynamic and static forecasting methods. Benchmarking is conducted via a random walk model. The criteria for evaluating forecast performance, in particular, the mean absolute error (MAE) and root mean squared error (RMSE), are applied. The WTI-related VAR model seems to be on average superior across the Baltic Dirty Tanker Index routes while showcasing sufficient forecasting performance for the *South East Asia to East Coast Australia* route.

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Abbreviations and Notations

Abbreviations (Models):

ACF (*Autocorrelation Function*)
PACF (*Partial Autocorrelation Function*)
ADF (*Augmented Dicky-Fuller test*)
AIC (*Akaike Information Criterion*)
AR (*Autoregressive model*)
MA (*Moving average model*)
ARMA (*Autoregressive moving average model*)
ARIMA (*Autoregressive integrated moving average model*)
VAR (*Vector autoregressive model*)
VECM (*Vector error correction model*)
ARCH (*Autoregressive conditional heteroscedasticity*)
GARCH (*Generalized ARCH*)
MAE (*Mean absolute error*)
RMSE (*Root mean squared error*)

Abbreviations (Terms):

BDTI (*Baltic Dirty Tanker Index*)
BITR (*Baltic International Tanker Route*)
DWT (*Dead weight tonnes*)
COA (*Contract of affreightment*)
GDP (*Gross Domestic Product*)
LNG (*Liquid Natural Gas carriers*)
LPG (*Liquid Petroleum Gas carriers*)
TC (*Time charter*)
TCE (*Time charter equivalent*)
VLCC (*Very Large Crude Carriers*)
WS (*Worldscale*)
WTI (*West Texas Intermediate)*
Mbpd (*Million barrels per day*)

Notations:

The research paper, strives to enforce consistency regarding quotations, highlighting and formulas. Quotes are emphasised by *cursive text* and framed in primes, while specific focal points or internal references in the text are written in *cursive*. Formula guidelines are set by Verbeek (2004) - *A Guide to Modern Econometrics*.

Chapter 1 - Introduction

'*Every individual... neither intends to promote the public interest, nor knows how much he is promoting it... he intends only his own security; and by directing that industry in such a manner as its produce may be of the greatest value, he intends only his own gain, and he is in this, as in many other cases, led by an invisible hand to promote an end which was no part of his intention.*' - Adam Smith (1759, p. 184-185)

The book *The Theory of Moral Sentiments*, suggests that that free markets regulate themselves by self-interest, competition and – supply and demand. The maritime industry as one of the '*four cornerstones of globalisation, along with communications, international standardisation, and trade liberalisation*' (Kumar & Hoffmann, 2002, pp. 35-62), provides excellent opportunities to investigate the *invisible hand*. To understand the *invisible hand* is crucial in macroeconomic theory, thus enhances common understanding of the expression of such, in regards to seaborne spot freight rates and their fundamentals. These freight rates illustrate the general seaborne transportation market level. The evaluation and prediction of such rate is fundamental to various stakeholders in the maritime sector, who's livelihood depend on a positive bottom line result, which can only be achieved with some foresight.

In previous decades researchers have dedicated multiple analysis to such subject. However, the usage of econometric modelling and forecasting is relatively scarce, while having the potential to enhance the common understanding of certain economic variables (Reutlinger, 1966), such as spot freight rates and maritime business cycles. As one of the largest maritime segments, the dirty tanker business, which refers to seaborne crude oil transportation, shall provide as a vehicle, the opportunity to shed light on the usage of econometric models and their appropriate appliance for such case.

In general, dirty tankers are cargo vessels dedicated to carry crude oil and are classified by size, measured in deadweight tonnage (DWT). These are chartered via voyage charter or time charter (TC). This paper delimits itself to examine only voyage charter agreements, which are defined as the process of hiring vessels for carriage of cargo from a loading- to a discharge port. Voyage charter agreements include as an integral part, the freight rate, which is specified in Worldscale (WS) or time charter equivalent (TCE). These two measurements are reported by the Baltic Exchange on a daily basis and are publically accessible. Representing the '*daily level of settled voyage charter agreements for transporting crude oil on different voyage routes*' (Steen, 2013, p. 4).

The Baltic Dirty Tanker Index (BDTI), illustrates the crude oil tanker segment's spot market environment, in regards to major trade routes and vessel type in DWT. It is published by the Baltic Exchange via information stemming from shipping brokers and reported in Worldscale. The Worldscale rate, abbreviated form Worldwide Tanker Normal Freight Scale and established by the Worldscale Associations of London and New York, represents the baseline price for the carriage of crude oil in metrics tonnes between loading- and discharging ports in the world. In negotiations between charterers and operators, the freight rate will be determined based on a Worldscale rate percentage. It is a tool reference tool for chartering tanker vessels and provides ship-owners '*with the same net return per day irrespective of voyage performed for the Worldscale Standard Vessel at WS100'* (Worldscale Association, 2016, p. 1). Thus, offering a fairly exact representation of the tanker market environment.

Based on the Baltic Dirty Tanker Index, univariate and multivariate models are applied to model and forecast the time-series. The multivariate models, introduce additionally crude oil prices and -production as explanatory variables, to evaluate the relationship between crude oil tanker spot freight rates and explanatory variables.

1.1 Problem statement

Freight rate forecasting in the crude oil market has been conducted since decades with rather flawed results, showcased by the impact of the recession in 2007 - 2009 on the relative unprepared maritime market players. In fact, virtually no ship-owner was able to forecast the freight rate level. Stopford (2009, p. 132), supplied an answer to this inherent problem, stating that a '*prediction process should be seen as clarifying risk rather than creating certainty*'. The shipping industry is rather complex, thus diminishes the forecasting ability. Au contraire, the ability to predicting freight rates would be highly beneficial. Therefore this paper dedicates itself to identify following strategic objectives;

Can crude oil tanker spot freight rates be modelled and forecasted via econometric models?

In regards, to the univariate model the main Baltic Exchange Dirty Tanker Index routes in Worldscale units - *Very Large Crude Oil Tankers (VLCC), Suezmax* and *Aframax* and to the multivariate models, crude oil prices - *West Texas Intermediate* and *Brent* and crude oil production in the *North Sea*, the *Former Soviet Union* and the *Middle East*, are assessed.

The primary objective of this thesis is to develop econometric modelling- and forecasting frameworks for crude oil tanker spot freight rates. Therefore, the research is separated into three distinct sections;

I. *Univariate time-series model section* includes the autoregressive moving average model (ARMA), based on the Box-Jenkins framework, which purely utilizes the information contained in past observations of the Baltic Dirty Tanker Index routes.

II. *Multivariate time-series model section* introduces crude oil prices and crude oil production as explanatory variables. Hence, to evaluate the relationship between crude oil prices and tanker spot freight rates, a vector autoregressive models (VAR) model is applied. Further, the Granger causality test is utilised to assess this relationship. Moreover, the Johansen cointegration test, vector error correction model (VECM), investigates the relationship running from the explanatory variables, crude oil prices and – production to the Baltic Exchange Dirty Tanker Index routes.

III. *Forecasting*, previously outlined models are benchmarked to a random walk model and evaluated by the performance criteria - mean absolute error (MAE) and root mean squared error (RMSE).

1.2 Delimitations

The problem statement outlined the primary target, which questions whether econometric models are capable to models and forecast spot freight rates. To create an academic value, this paper needs to limit its scope.

Regarding data selection, the Baltic Dirty Tanker Index routes which are subject to univariate- and multivariate modelling, are chosen based on tanker transportation demand by routes in *table 4.1*. These routes aim to mirror the tanker market environment, rather than specific circumstances, to achieve a holistic overview. Additionally, the metric of Worldscale units, rather than the time-charter equivalent, is selected, due to its property to model market levels, instead of actual freight rates. Further discussion is displayed in *section 2.3*. Regarding the tanker segments, merely VLCC, Suezmax- and Aframax vessels, are considered crude oil tankers while acknowledging that a minority of Suezmax and Aframax vessel transport also oil products. The multivariate analysis utilises crude oil prices and –production, based on previous literature, rather than data mining. Therefore, this paper accepts delimitation in variable choice, which may have a linkage to the indexed routes. Econometric models and concepts are evaluated and discussed to a least minimal extent, to limit this thesis to the focal point of research. Thus, presume the reader's familiarity with such concepts.

1.3 Methodology

This section aims to present an assessment of the data acquisition and the basic concepts and procedures of the econometric analysis. Based on the research statement, this paper, dedicates itself to a quantitative framework, in regards to secondary data. In *chapter 2* and *chapter 3*, the reader is briefly introduced to the tanker market, - environment, - model and mechanisms, to assure a common understanding. The purpose is to highlight the Baltic Dirty Tanker Index's linkage to the tanker freight market. Additionally, displaying the reasoning behind the usage of explanatory variables. Further, the literature overview strives to give an outline, which provides guidance and reasoning for the appropriate choice of analytical frameworks. The *chapter 4*, presents the time-series used in this paper, which consist of observations in a time sequence over equal time increments. These time-series were primarily sourced from the world's leading maritime data provider, Clarksons Research Shipping Intelligence Network (Greenwood & Hanson, 2013) [Link] and other highly accredited sources such as the Federal Reserve Bank of St. Louis [Link] and the U.S. Energy Information Administration [Link]. To mitigate the risk of biased results, the datasets were neither adjusted nor alerted in any fashion.

1.3.1 Econometric models

In regards to the *section 1.1* and the strive to create a cohesive structure, the methodology of the applied models is elaborated alongside their application in *chapter 5* and *chapter 6*, while the general functionality of econometric models is showcased in the following paragraph.

Verbeek (2004, p. 2), introduces econometric models by classifying them into three distinct categories. *The first class* strive to model a time-series while taking the assumption that its past observations are linked to the present ones. This model can be utilised to forecasts future values, in regards to the corresponding volatility or uncertainty. *The second class* models the fluctuation between economic quantities in relation to other quantities and its primary concern is to present insights into processes. Lastly, the *third class* aims to describe the linkage between multiple observations sets at a specific point in time. These models target the question, if observation x_t shifts, how will the observation y_t correspond to this movement. The primary objective of econometric models is to quantify either univariate or multivariate relationships. The models in itself provide a tool, based on economic theory, to reach the required goals. Elements, such as parameters are estimated from the time-series. To investigate the validity of the resulting models, diagnostic tests are applied to check whether the models are appropriate for their particular usage. Finally, econometric models are based on hypothesis, which determine the outcome of the model.

1.4 Outline

The thesis incorporates eight chapters, excluding introduction and bibliography; The *second chapter* provides the shipping market overview, in particular, focusses on the tanker segment. Further, the tanker market model, freight rates, contracts and the shipping market cycles are outlined. The *third chapter* acts as an introduction to previous tanker market studies and includes a separate section concerning econometric models. The *fourth chapter* introduces the data used throughout the paper, including the Baltic Exchange Dirty Tanker Index routes in Worldscale units, in regards to *VLCC, Suezmax-,* and *Aframax* vessels and the explanatory variables for the multivariate models. The *fifth chapter* consist of the parameter estimation- and evaluation process of the univariate ARMA model. The *sixth chapter* is subject to the multivariate modelling in regards to the explanatory variables, crude oil prices and geographical crude oil production. The VAR model in connection with the Granger causality test, the Johansen cointegration test, and VECM, are applied. The *seventh chapter* forecasts and benchmarks the proposed models. The *eight chapter* provides a critical perspective on the models in connection to econometrical issues, implication for the auditions, and further research to optimise the performance of the applied concepts. The *ninth chapter* summaries in a sophistic fashion the analytical outcome.

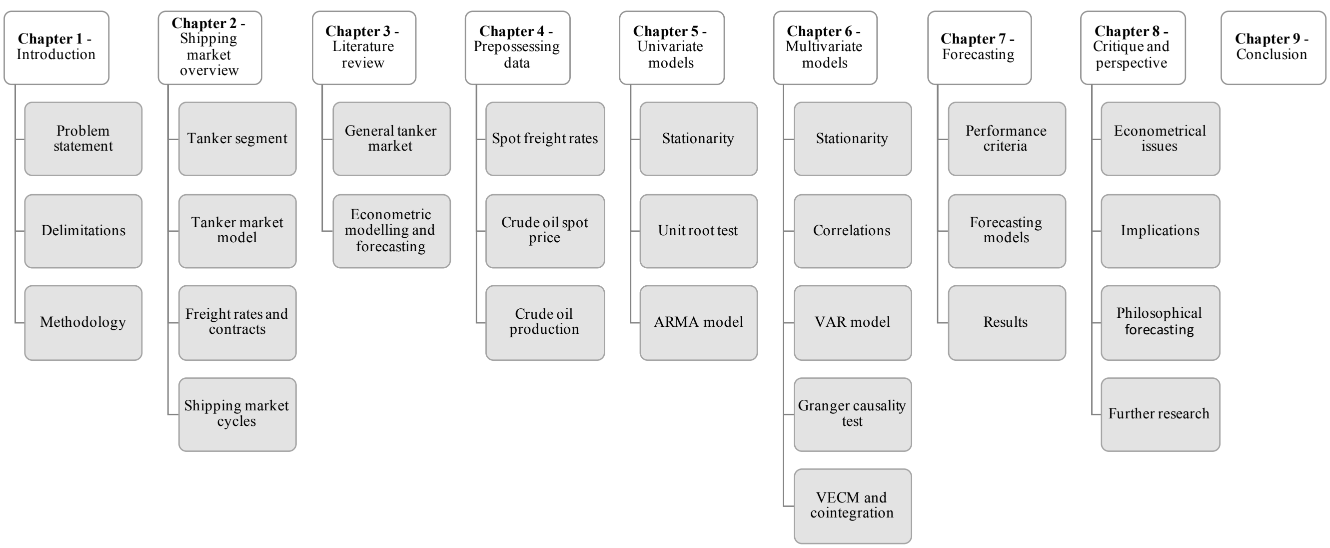

Figure 1.1 Thesis outline

Chapter 2 - Shipping market overview

The shipping market overview presents a general perspective on the maritime business and is based on Stopford's (2009) research *Sea Transport and the Global Economy*. Maritime transportation dates back over 5,000 years and shaped the world's economic evolutionary path significantly. The economist, Adam Smith, first recognised shipping in his publications as a necessity to stimulate economic development, thus interlinking shipping, economic growth and trade. Stopford separates the maritime history into three distinct phases;

I. The *first phase* in the late fifteenth century seaborne supply chains commenced operations in the Mediterranean and North Western Europe while spreading via the silk road to China and India.

II. The *second phase* in the eighteenth century was initiated by the industrial revolution in Western Europe and U.S.. In this phase, major inventions revolutionised the shipping industry, concerning shipbuilding – steam engine, communication networks and the commercialization of trade through the Baltic Exchange. In relation to onshore progress, infrastructure project such as the Suez Canal further enhanced the efficiency of shipping. In connection to colonial empires, trade lanes expanded and the demand for seaborne transportation grew rapidly.

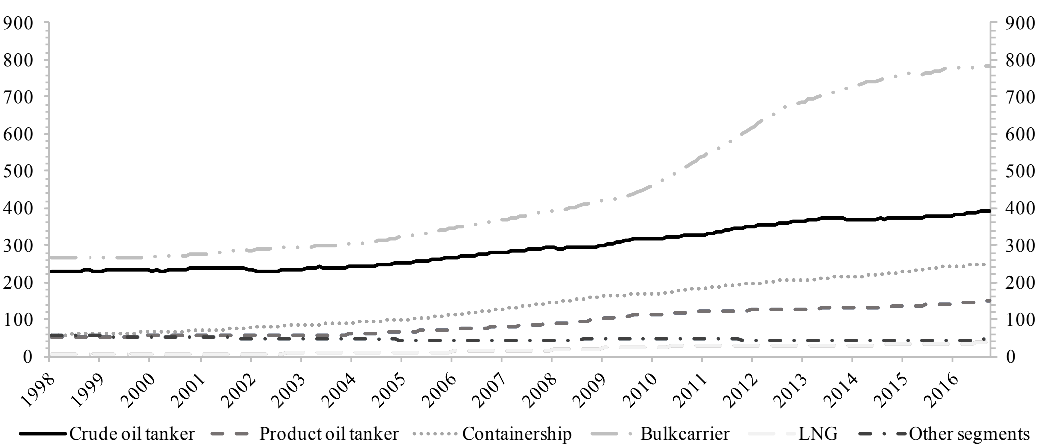

Figure 2.1 Development of merchant fleet January 1998 - September 2016 (million dead weight tonnes)
Source: © Clarkson Research Services Limited 2016

III. The *third phase* was triggered after the second world war, inducted by the corrosion of the colonial empires and trade liberalisation policies, such as the Bretton Woods system. Globalisation affected manufacturing companies, primarily in the occidental parts of the world, which sought to diversify their supply chains, to decrease production costs and expand to new markets. Initiated by such progress, the bulk carrier markets experienced a period of growth, in term of containerization and specialist shipping. Another major event in this phase was the shift towards the flags of convenience, thus the liberalisation of regulatory policies.

Seaborne transportation endured constant cyclical- and structural shifts and is interlinked with the global economy and trade flows. In the 21st century, shipping facilitates globalisation and connects the global business community.

2.1 Tanker segment

This section offers a throughout overview of the tanker fleet, in particular, the crude oil tanker segment, to enhance the understanding of spot freight rates. Moreover, presents the tanker market specific aspects, in regards to the *Elements of the Tanker Market* by Velonias (1995).

The world tanker fleet is composed of crude oil-, product-, liquid gas tankers and hybrid carriers and constituted in September 2016 for approximately 38% of the total merchant fleet (Clarksons Reserach, 2016). Tankers are categorised by size;

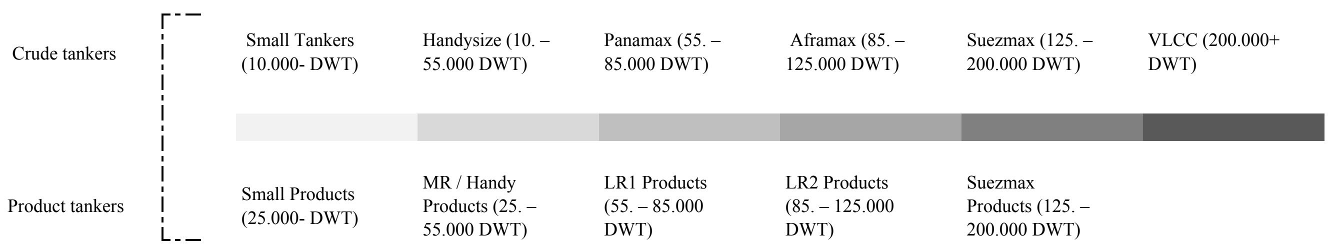

Figure 2.2 Tanker segments (million dead weight tonnes)

Source: © Clarkson Research Services Limited 2016

The fundamental distinction between crude- and product carriers; Crude tanker carry unrefined oil from the extraction facilities to the refineries while product tankers transport the refined oil from the refineries to the end consumer. In general, tanker shipping represents an economical mean to transport liquid bulk (Venus Lun, et al., 2013).

The uniqueness of the tanker segment is given by its perfect competitive market, due to the identical shipping services provided by tanker ship-owners. Additionally, the transparency and availability of information based on the Baltic Index mitigates the risk of price manipulations. Further, entry barriers in the form of regulations are minor in the tanker shipping industry, while capital investments concerning the new-build market are high.

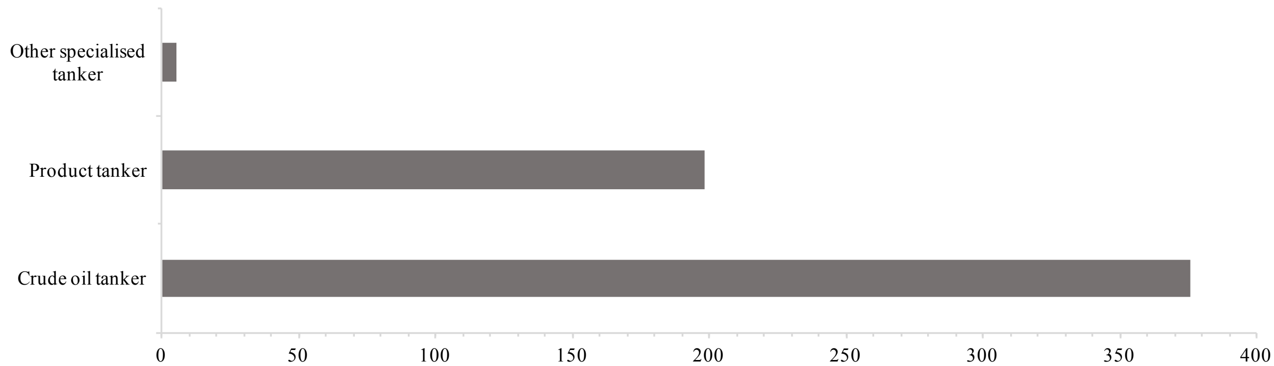

Figure 2.3 Tanker fleet by September 2016 (million dead weight tonnes)

Source: © Clarkson Research Services Limited 2016

Note: Crude oil tanker (Tanker, Shuttle), Product tanker (Products, Chem & Oil) and Other specialised tanker (Fruit Juice, M. Sulphur, Phosphoric A., Waste, Palm Oil, Sulphuric A., Edible Oil, Prod./RoRo, Water, Wine, Chem & LPG, Oil & LPG, Products/MPP, Asp.& Bit., Bunkering, Slop Reception, Methanol)

2.1.1 Crude oil tankers

Crude oil was first hauled 1859 in Titusville, North America and the first seaborne transport of such cargo commemorated in 1861. Due to the delicate handling of this flammable cargo, barrels were used to store crude oil, which was later replaced by tanks. Thus, labelling crude oil vessels – *tankers*. In September 2016, crude oil tankers accounted for approximately 24% of the merchant fleet, therefore constituting as the one of the largest segment in the fleet. These vessels are designated to transport liquid bulk, crude oil from their extraction location to the refineries, which then is converted to liquid fuels, LPG or other oil products. The crude oil tanker segment also includes shuttle tankers, which are designated to carry the crude oil from offshore facilities to onshore storages or refineries.

Tankers are separated by size and deployment capabilities, in regards to trade lanes. In general, VLCCs are designated to transport crude oil from the Middle East to Europe, United States or Asia, while avoiding canals. Suezmax tankers carry their cargo from West Africa, the North Sea, and East Europe to the American Gulf Coast and U.S. West Coast. Aframax tankers operate in the Intra-Asian trade, Black Sea, North Sea and the Caribbean. Smaller crude oil tankers engage mostly in short hauls or costal areas, due to onshore infrastructure delimitations. These vessels can shift between dirty- and clean oil, thus blurring the line between product- and crude tankers.

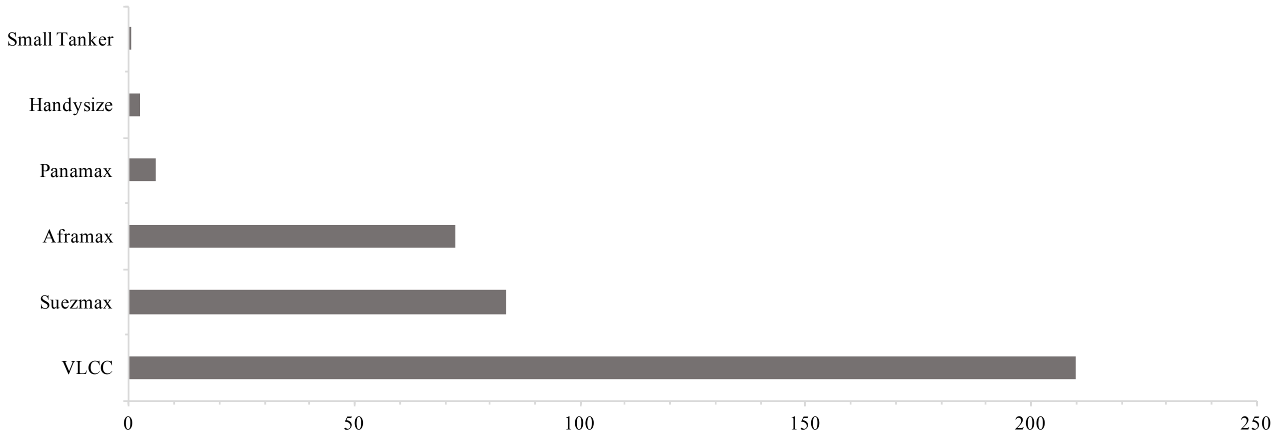

Figure 2.4 Crude oil tanker fleet by September 2016 (million dead weight tonnes)

Source: © Clarkson Research Services Limited 2016

The crude oil tanker deployment depends on the geographical production location, thus dictating also the trade pattern. In the previous decades, the Middle East has been the largest exporting region with approximately 60% of global discovered crude oil reserves. Stopford (2009, p. 439) referred to the geographical location of the Middle East as a '*ship demand multiplier*'. In the case of global crude oil export grows – the market share of Middle East - and the average haul increases, while affecting these variables vice versa, in case global crude oil export decreases. Meaning, that the cyclical oil trade swings are intensified and passed over to the crude oil tanker market. Therefore, showcasing the significance of supply pattern for oil, when predicting seaborne crude oil demand. Other clusters of crude oil production are located in the North Atlantic, West Africa, Russia and North America.

On the other side, significant importers are Europe, United States and Asia, in particular, China. Factors influencing seaborne crude oil demand, are significantly related to political frameworks, in which oil is traded, in regards to market economics and geostrategic notions. Since the beginning of the 20th century, a few major oil conglomerates controlled the entire crude oil supply chain, include the seaborne transport. After the oil crisis in the 1980s, oil-producing nations started to nationalise their production and handled the distribution on their own, including their tanker fleets. In the 21st century, the majority of seaborne crude oil transport is split between governmental-, private oil producers and independent traders. Transported crude oil, is shipping often on a voyage by voyage basis and traded on the spot market.

2.1.2 Other tankers

This section gives a brief overview of the other tanker segments, such as product-, chemical-, liquid gas tankers and hybrid carries.

Product oil tankers, constitute as an own fleet segment, although are capable of transporting crude oil, therefore distorting the line between this segment and crude oil tankers. However, differentiate themselves by size; Product tankers are rarely larger than Aframax tankers. Additionally, the oil product trade, also referred to as clean product trade, comprises the transportation of refined oil products, such as liquid fuel or gas. Until the 1960s, most seaborne oil trade was clean, i.e. crude oil was refined before shipped to their destination. Afterwards, oil firms adopted a new strategy and located refineries closer to the end consumer, thus increasing the dirty products trade. This shift was supported, by unique local demands and geopolitical disruptions in the Middle East, which triggered especially European nations to became more risk adverse. Hence, promoted the development in particular of European-based refineries. Since the beginning of the 21st century, the trend to regional refineries reversed in correlation to the expansion of Middle Eastern and Indian refineries.

Other specialised tankers are liquid gas tankers, which are divided into *LPG- and LNG carriers*. The major difference between these two carriers is the type of gas; LNG trade in general on specific routes between natural production facility and the end consumer while LPG transport gases derived from oil production facilities. The LPG- and LNG fleet constituted for approximately 22 million DWT and 37 million DWT, in the respective order in September 2016 (Clarksons Reserach, 2016). *Chemical tankers* carry a variety of liquid bulk, such as vegetable oils, juice, wine and special chemical. These tankers have in general a capacity below 50.000 DWT. Lastly, *hybrid carriers*, also referred to as combined carriers, switch between wet and dry bulk, such as coal, ore or crude oil, depending on the market environment, regarding the payoff. These vessels may contribute to sudden changes in the supply curve of the respective fleet segment.

2.2 Tanker market model

The tanker market model is derived from Stopford's (2009) shipping market model and acts as a solid introduction into freight rates and chosen explanatory variables. The major difference between the shipping- and the tanker market model are the distinctive characteristics of seaborne liquid bulk trade, which will be showcased in the following section. The model by Stopford includes a supply- and demand function, in relation to the freight rate mechanism. Demand is impacted by seaborne transportation demand, while the supply side is represented by the fleet capacity. An imbalance in the market is expressed in the freight rate mechanism. With this, freight rates represent under the assumption of a perfectly competitive market the equilibrium between demand and supply in the seaborne liquid bulk trade. Modelling this equilibrium dates back to Koopmans (1939), who strived to illustrate the supply and demand in the tanker segment. Oher fundamental literature pieces include the NORTANK model, which analysed the freight market for VLCCs (Norman & Wergeland, 1981) and the econometric tanker model (Beenstock & Vergottis, 1989). A more sophistic discussion of such research is provided in *chapter 3*.

2.2.1 Seaborne demand

Tanker demand stems from multiple factors, which are interconnected with the global economy, creating an inherent problem to determine exactly the impact and implication. The following key parameters built up on Stopford's (2009) shipping market model, in regards to seaborne crude oil transport demand. Wijnoslst & Wergeland (1997) assessed that the overall tanker demand is subject to global energy consumption, geopolitical disruptions and the oil price. Additional factors are showcased;

World economy, which is driven by economic growth, industrial development and population growth, generates seaborne transportation demand and directly interlinks them with total energy demand. *Seaborne commodity trade* is divided into short- and long-term trade pattern shifts. In short-term, the crude- and oil product trade is subject to seasonal changes, in regards to heating demand in autumn and winter. Long-term shifts are driven by geographical crude oil reserves depletion, demand distribution of energy sources, environmental policies and technology advances. T*onne-mile ratio* is defined as the multiplication of transported cargo in tonnes and the transportation distance in nautical miles. In particular, the tanker segment's average haul is directly affected by pipelines or canals, which decrease the transportation demand, e.g. onshore infrastructures such as the Eastern Siberia–Pacific Ocean oil pipeline or Sino-Myanmar pipeline and the Suez Canal or Panama Canal, impact the tonne-mile ratio. *Geopolitical disruptions*, which refer to random shocks are classified as unexpected events impacting crude oil tanker demand. These include wars, labour strikes, environmental policies (Dirzka, 2015). *Freight rates*, which represent the transportation costs, impact the seaborne demand by enhancing or diminish the competitiveness of such transport mode.

2.2.2 Seaborne supply

The tanker supply is linked to the amount of vessel capacity in active service. The shipping service supply is determined by multiple factors, which apply also in some cases to seaborne demand. The following list of determining seaborne supply factors builds up on the research by NORTANK model by Norman & Wergeland (1981) and the shipping market model by Stopford (2009).

World tanker fleet, is defined as the total amount of crude – and oil product vessels and measured in DWT, while being impacted by the demolition- and deliver market. Due to long building times of approximately 1-2 years, the impact on supply growth is lagged. In particular, the tanker segment supply is impacted by hybrid carriers and floating storages, which skew the supply function. These vessels, adjust their state in relation to the freight rate environment. *Tonne-mile ratio*, affects supply in terms of fleet productivity, DWT utilisation, loading- and discharging time and speed. *Freight rates,* impact the profitability of tankers. Higher rates incentives investors to engage in the delivery market, therefore increasing supply and vice versa in periods of low rates. In general, vessels are trading, if freight rates are higher than break-even point regarding total operating expenses or if an upswing is anticipated.

2.3 Freight rates and contracts

This sections, introduces the subject of freight rates and charter contracts, in relation to the freight rate mechanism with the specific focus on the spot freight market and is based on Stopford (2009, p. 182). In regards, to the analytical section of this paper is it crucial to understand the mechanics behind this market.

As previously specified, the freight market is impacted by supply- and demand factors and incorporates a network out of organisations and governments, which demand- and supply seaborne transportation services. The actors are referred to as, charterers, which own the cargo, and ship-owners, which lend their vessel. The negotiation between the two parties is commonly conducted by a shipbroker and concludes most commonly in one of the two kinds of transactions, the *Time charter-* or *Freight contract*;

Time charter contract refers to an agreement in which the charterer dictates the voyage route, in relation to the terms of the contract. The time charter price, usually given in U.S. Dollar per day, is determined by the ship-owner, based on the evaluation of previous expenses and future spot market expectations and benchmarked to the time charter equivalent. The latter process can be conducted by analysing freight rates via econometric models or freight rate derivatives. The time-charter contracts can be divided into two types of agreements; In the *first one*, the charterer hires the vessel, including the crew for a specified period and is accountable for the voyage costs, which include bunker fuel, and port- or canal fees. The actual owner of the vessel has to cover the operational expense, such as repairs. In the *second one*, the charterer hires the vessel and is in responsible for all operational- and non-operational duties. The ship-owner is in most cases a financial investor, and the vessel is given to the charterer in the form of a lease agreement. The advantage is hereby that the ship-owner is not required to have maritime specific knowledge and the charterer can acquire a vessel without significant capital investments. Due to the long-term nature of such agreements, the time charterer hedges against anticipated changes in the spot freight market, which in itself might pose a risk factor, in case spot rates levels are below the arranged time charter rates price.

Freight contract refers to a spot contract, which is defined as an agreement between the charterer and ship-owner about a cargo transport in price per tonne, rather than the vessel. In general, freight contracts are traded within two to four weeks before the loading of the cargo onto the ship. There are two kinds of contracts, the *contract of affreightment*, which specifies multiple cargo voyages in a fixed period and the *voyage charter*, which relates to a single cargo voyage. In both cases, the ship-owner and charterer negotiate the exact loading- and discharging port. The negotiated price per tonne, is based on the daily updated freight rate of traded spot contracts and is established either via the Worldscale units - or time charter equivalent rates. Both are accessible via the Baltic Exchange [Link].

The *Worldscale rate* is published by the World Scale Association [Link] and based on the previous year's expenses of a particular voyage, including port- or canal fees and bunker prices. It acts as the payment system for oil tanker services. This rate is measured on a cargo weight basis in tonnes. In an actual negotiation between ship-owner and charterer Worldscale rate is used as a baseline. The negotiated freight rate will be a percentage of this baseline, depending one the amount the charterer’s will to pay and the ship-owner's will to offer transportation services.

The *time charter equivalent rate*, which is also published by the Baltic Exchange represents the average daily revenue performance of a particular tanker segment per voyage. It is calculated by subtracting the voyage expense from the trip revenue and divided by round trip voyage in days. These voyage expenses, include bunker costs, port- or canal fees and commissions.

The freight contracts are interlinked with time charter contracts. In the case of a negatively growing spot market, freight contracts are more demanded by the charterers. Based on this notion there is no interest to commit to long-term time charter agreements. Ship-owners have neither an interest in the previously specified spot market conditions to commit to long-term contracts, due to the issue that the contract would be settled on a low level. The only case, when charterers prefer time charter contracts is when there is an anticipated or an actual positive price surge in the spot market, and charterers strive to hedge against this environment.

2.3.1 Freight Rate Mechanism

The freight rate mechanism, based primarily on *section 2.2*, describes the adjustment mechanism, which regulates the imbalances between seaborne demand and available shipping capacity and is expressed by transport costs and freight rates. In the case of a shipping service surplus, rates tend to fall, while in the event of a shortage, rates tend to rise. In regards to the introduction of *chapter 2*, the literature piece from Adland (2012), determined that the freight market has a homogenous character, due to the substitutability of transportation services by individual market players. Moreover, the diversity of market operators, which offer tanker serveries and the transparency of information via the Baltic Exchange and other entities, make '*freight rate manipulation*' difficult (Hordnes & Furset, 2013) and foster an entirely competitive market.

Venus Lun, et al. (2013) determined that there are only minor competitive advantages for larger ship-owners, regarding entering the tanker market, while the second-hand-, demolition market as well as the geographical mobility of vessels ensures a relatively easy exit from the market or an unprofitable trade route. To understand the mechanism, the demand-, as well as the supply function are illustrated in the following section, based on Stopford's elaborations;

Demand function features the adjustment of seaborne service demand, in regards to freight rate changes. According to Stopford (2009), the demand for such service is very inelastic, due to the substitutable characteristic of the seaborne transport mode. Cargo-owners have to transport their goods via vessel, regardless of the freight rate. Moreover, transportation costs as a share of the cargo value are marginal. Therefore an increase in freight rates has little to none impact on the total costs.

Supply function features the adjustment of fleet capacity supply in regards to freight rate changes and is measured in the tonne-mile supply. The supply from an individual vessel is constrained by multiple factors such as age, operational costs, size and vessel speed. In case operational costs are higher than the freight rate, vessels tend to stop trading or decrease their speed, to save bunker fuel cost, thereby diminish supply in terms of tonne-mile capacity. On the other hand, the vessel age is interlinked with the operational costs; Older vessel are in general less efficient, therefore will be layup first, in the case the freight rate reaches an unsustainable level. Otherwise, if operational costs are lower than the freight rate than a vessel increases its speed, thus the supply in terms of tonne-mile capacity.

2.4 Shipping market cycles

The last section of the second chapter relates to shipping market cycles, which aims to explain the volatility in the freight market. These cycles follow the path of four stages, '*trough, a recovery, a peak, and a collapse*' and their length and timing of these stages are inconsistent (Stopford, 2009, p. 98). Therefore, raising the argument that this uncertainty makes freight rate forecasts unreliable (Cufley, 1972).

Stopford argues the market is impacted by short-term-, as well as longer-term cycles. The short-term cycle states that a fleet supply shortage triggers higher freight rates, which increases the activity in the new-build market, while a surplus diminishes freight rates and results in higher demolition activity, which cures the imbalance of the market. In each of these cycles, the '*supply lurches after demand like a drunk walking a line that he cannot see very clearly*' (Stopford, 2009, p. 134). The longer-term cycle is driven by technical shipping developments, resulting in higher efficiency and productivity of the fleet, such developments are steam engines and containerization.

In a long-run study, between 1741 and 2007, 22 cycles with an average span of 10.4 years were detected, occurring within the framework of economic fundamentals. The common feature of these cycles are periods of high freight level, which were triggered by unexpected events and crisis resulted from macroeconomic shocks. Another factor impacting shipping market cycles is over-capacity, arising from overinvestment by e.g. irrational onshore investors (Hampton, 1991).

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Chapter 3 - Literature review

The literature review adopts the content analysis structure from Jain, et al. (2010, p. 16), which '*enables one to determine the nature of content, identify the patterns, and estimate the relationships between the research papers being analysed*'. Therefore, this chapter is divided into three content-wise distinct section; *General tanker market-, Spot freight rate-* and *Econometric modelling* research. As previously mentioned in *section 1.3*, the literature review fulfils the purpose of familiarising the reader on the one hand with the tanker market while additionally showcasing the general application of econometric models in the maritime sector.

3.1 General tanker market

The publication *Tanker Freight Rates And Tankship Building* by Koopmans, (1939), proposed as one of the first studies a framework for modelling tanker supply and – demand. Based on microeconomic theory, which defines the freight rate as the intersection point of the supply – and demand curve, Koopmans determined that tanker service demand and freight rates are only to a minor extent correlated. The verification for such claim was derived from the notion that oil consumption is price inelastic. Therefore the need to facilitate transportation, can not be substituted, at least in the short-run. Additionally, seaborne oil transportation costs constitute for a minor part of the end-consumers oil price. Therefore freight rate changes can be neglected. On the other hand, tanker service supply is correlated to available fleet capacity. Supply shortages trigger higher freight rates and can not be adjusted in the short-run by the new-build market. Elasticity is to a certain degree provided by increasing speed or decreasing loading- and discharging times. Supply surplus leads to lower freight rates, which drives out the vessel from the market, into passive trading ships or to the demolition market.

Another decisive study in the tanker segment, *The Theory of Oil Tankship Rates* by Zannetos (1964), forecasted charter rates, based on the assumption that the seaborne market contains enough information on it own to be utilised for forecasting. The study found evidence that vessel size and freight rates are significant negatively correlated, while time charter- and spot rates are uncorrelated, except in recessions periods. In times of high spot rates, the trend towards a longer length of a charter contract is negative while the order-book activity and time charter rates are positively correlated.

Further, the book *Ships and Shipping* by Nersesian (1981), took another approach concerning the evaluation of tanker freight rates and proposed a six sections demand- and supply model. These sections incorporated factors such as total energy demand, in relation to the source of energy, seaborne fossil fuel trade and patterns, global crude oil trade patterns, transportation demand in tonne-mile and future vessel demand.

Another academics contribution for the tanker segment was the NORTANK model by Norman & Wergeland (1981), which is defined as an approach to model the individual supply curve of a vessel, thus creating an aggregated market curve. Beenstock & Vergottis (1989) suggested an econometric tanker model, which treated the freight- and shipping market independently, to determine the fleet size, freight rates, second-hand- and new-build activity. Other general tanker market models focused on the issue of bunker prices and speed. The study by Assman (2012), investigated the linkage between freight rates, bunker prices and speed for VLCCs and found no evidence of a present relationship. On the contrary, Jonkeren, et al. (2012), concluded in the bulk segment that freight rates and speed are correlated. In the case of a freight rate increase, the vessel speed will rise to satisfy demand, and vice versa. Moreover, bunker fuel prices impact the vessel speed.

3.1.1 Spot freight rate

Spot freight rates, as defined in *section 2.3*, have been under investigation for decades. One of the earliest studies by Strandenes & Wergeland (1981) analysed the impact of spot freight rates on the new-build- and second-hand prices and time charter rates. Another work by Strandenes (1986), linked the tanker- and dry bulk market and developed a model in relation to spot freight rates and factors such as new-build- and second-hand market activity, regarding volumes and prices.

In 1995, Tamvakis, examined the impact of environmental policies, specifically the U.S. Oil Pollution Actin in 1990 on the spot freight market using the Worldscale units. Another crucial publication concerning the tanker spot freight market was conducted by Kavussanosa & Alizadeh-M (2002), which resulted in the validation of deterministic seasonality. The study indicated that spot freight rate, depending on vessels size and the tanker market environment increases in November and December while declines from January to April.

The paper by Tvedt (2003), analysed the time charter equivalent spot rate, in relation to its structure and tonne miles per day. Adlanda & Cullinane (2006), found that tanker spot freight rates can be best modelled via a non-linear stochastic process and that the volatility rises with the freight level. Adland & Strandenes (2007), presented an equilibrium model for VLCC spot freight rates, concerning their future probability distribution and fleet size, order-book and age profile. Batchelora, et al. (2007), examined spot freight rates and concluded that VECM performs well in-sample fit appliance while underperforming in time-series forecasts. Therefore, suggesting that

ARIMA- and VAR model shall be used instead for predicting spot freight rates. Additionally VECM, ARIMA and VAR models are outperformed by a random walk process. Devanney (2010), provided evidence for the linkage between VLCC spot freight rates and bunker fuel prices. In the short-run, rising bunker fuel prices triggered spot freight rates spikes.

3.2 Econometric modelling and forecasting

The following sub-section, introduces relevant literature on econometric modelling and forecasting, thereby interlinking it partially to spot freight rate modelling and maritime research.

The subject of econometric modelling and forecasting has been for long prevailing in the macro- and energy economics literature, about issues such as GDP and energy consumption (Soytas & Sari, 2003) (Ghali & El-Sakka, 2004), including issues of export (Narayan & Smyth, 2009) (Sultan, 2012) and labour, capital (Shahbaz, et al., 2013) (Shahbaz, et al., 2013) (Lean & Smyth, 2010). Additionally, a wide selection of econometric forecasts has been conducted; Box-Jenkins method (Uri, 1978) (Uri & Flanagan , 1979) (Saab , et al., 2001), non-linear dynamic forecasting (Kaboudan, 1989) and exponential forecasting (Tamimi & Kodah, 1993).

The existence of a daily updated index, the Baltic Exchange indexes, makes econometric modelling for researcher attractive. While the Baltic Dry Index, which compromises dry bulk cargo trade existed already since 1985, the Baltic Dirty Tanker Index, was published quite recently in 2001. Therefore, econometric studies for the dry bulk segment dominate this research area.

One of the earlier forecast studies, in regards to the Baltic Exchange Indexes via Box-Jenkins approach, has been conducted by Cullinane (1992) and validated the reliability of an ARIMA model in comparison to other predictive frameworks. Evans (1994), analysed the interrelation between supply and demand in the dry bulk segment via a dynamic econometric process. Kavussanos (1996), utilised the autoregressive conditional heteroskedasticity (ARCH) model and suggested that oil- and tanker vessel prices are negatively interrelated in the rate of change, while positive associated in volatilities, in regards to vessel size. Berg-Andreassen (1997), applied an Augmented Dickey–Fuller (ADF)- and Johansen likelihood ratio test, to investigate the validity of the five assumptions, put forward by the previous research of Zannetos (1964). Veenstra & Franses (1997), used dry bulk freight rates data to demonstrate non-stationarity and applied the VAR model to predict freight rates. Glen & Martin (1998), utilised the GARCH model to point out investment tanker size risks, in relation to the spot- and time charter market. The study concluded that the investment risk rise in relation to the tanker vessel size, and is greater if the ship operates in the spot freight market. Veenstra (1999), introduced the VAR model to visualise the spot freight- and time charter rate differences. Wright (1999), also applied the VAR model to investigate the cointegration relationship between tanker spot freight indexes and one-year time charter rates.

Tvedt (2003), found evidence that the time charter equivalent spot rate can be described as a geometric mean reversion process. Wright (2003), utilised the cointegration analysis and exhibited the existence of a long-run relationship in the tanker freight rates. Kavussanos (2003), introduced a cointegrating error correction ARCH model, to investigate the difference between owning – and operating tanker vessels' risks in the spot freight- and time charter market. In comparison, spot freight rates have higher volatilities than time charter rates and smaller vessels freight rate have lower volatilities than larger vessels. Therefore concluding that ship-owner should operate in the time charter market and favour smaller vessels, to minimise risks. Kavussanos & Nomikos (2003), applied Baltic Indexes and found that ARMA and VAR model underachieve, while VECM performs well. Kavussanos & Visvikis (2004), determined via the Augmented Dickey–Fuller-, Johansen test and the VECM, the long-run relationship of Forward Freight Agreements and the Baltic Panamax Index.

Adland & Cullinane (2006), applied a general non-parametric Markov diffusion process to evaluate spot freight rates and found evidence that the volatility of change rises with the level of freight rate. Syriopoulos & Roumpis (2006), utilised an exponential GARCH model to analyse the linkage between dry bulk- and tanker sales and found evidence that vessel prices impact trade. Cariou & Wolff (2006), applied the VAR model and Granger causality test to investigate the relationship between bunker fuel prices, spot freight- and time charter rates. Goulielmos & Psifia (2007), used the BDS test, which detects nonlinear serial dependence in time-series and concluded that linear models are not able to model indices. Sødal, et al. (2008), characterised shipping freight rates as non-liner and non-stationary, questioning the forecasting accuracy of traditional stochastic modelling methods. Poulakidas & Joutz (2009), analysed the interrelation between spot freight rates and oil price surges via a cointegration- and Granger causality analysis. The study determined that there is a significant link between these variables. Zhang, et al. (2014), utilised the Granger causality- and Brownian distance correlation analysis and found that during rescission periods the new-build market is closer related to the second-hand- and freight market.

In addition to normal econometric models, such as ARMA or VAR, research has more recently focused on hybrid frameworks and their reliability to model and forecast. ARIMA-ARCH model, Haque Munim & Schramm (2016), investigated container freight rates for the Far East to Northern Europe trade lane and provided evidence for the superiority of an ARIMA-ARCH model in relation to a pure ARIMA model. ARMA-GARCH model, Steen

(2013), modelled a Baltic Dirty Tanker index route via the ARMA-GARCH model and found no evidence that it outperforms a random walk model.

The literature review, outlined general maritime models, in relation to tanker supply- and demand research. Followed by a thorough spot freight rate research overview, overlapping it partially with general applied econometrics literature, in regards to VAR, VECM, ARMA, ARIMA, Granger-causality-, cointegration and hybrid models. In regards to *section 1.3*, a sophisticated research framework of tanker spot freight rates, is based on the previously outlined literature and incorporates the evaluation of different models, which are rooted in the econometric literature, to target the research question most efficiently.

Chapter 4 - Prepossessing data

The datasets in this paper are divided along the application in univariate- and multivariate models. With this, the centrepiece are crude oil tanker spot freight rates, Baltic Exchange Dirty Tanker Index (BDTI), which are quoted in Worldscale units. The Baltic Exchange currently provides assessments on several routes, however rather than investigating each route, seven were allocated to mirror a significant propitiation of seaborne crude oil transportation demand, in regards to the *VLCC-, Suezmax-* and *Aframax* segment.

Based on previous literature, namely Fan, et al.'s (2013) publication *Forecasting Baltic Dirty Tanker Index by Applying Wavelet Neural Networks* and Jugović, et al. (2015), explanatory variables are chosen. This study analysed via a Wavelet Neural Network model the internal- and external determinants of the Baltic Exchange Dirty Tanker Index.

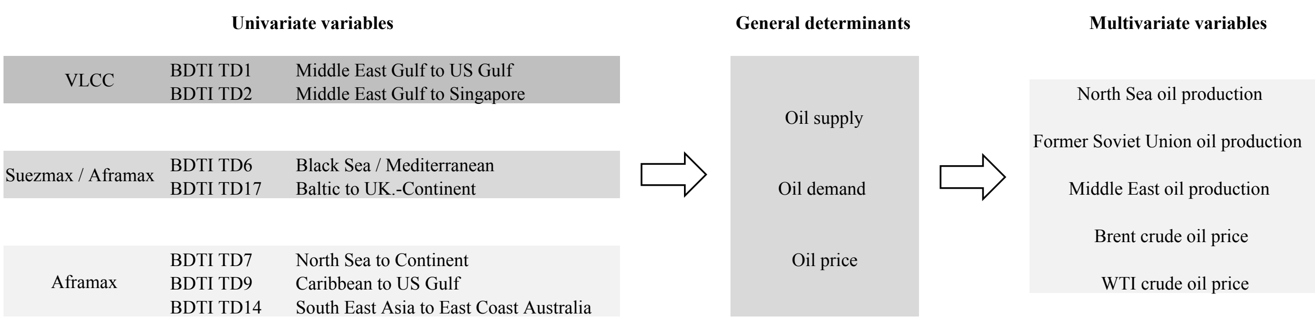


Figure 4.1 Crude oil tanker Worldscale routes - General determinants

Source: Modified Fan, et al. (2013)

The Baltic Dirty Tanker Indexes are derived from internal factors such as, the route, in terms of geographical production patterns, costs and revenue, such port- and canal fees, bunker fuel and freight rates .

Lastly, the specific vessel types, in terms of fuel consumption, capacity and size, impact the internal component. The paper by Fan, et al. (2013), lists in total six variables, which determine BDTI, however for the purpose of this papers' multivariate analysis section only two were allocated; Crude oil prices and -production, in regards to seaborne transportation demand and supply.

4.1 Spot freight rates

This section introduces Baltic Exchange Dirty Tanker Index (BDTI) routes, hereby referring to *section 2.3*. The BDTI mirrors the crude oil market environment for freight rates, in regards to selected routes. Clarksons Research reports twenty-one tanker route indexes in Worldscale while fifteen of them are primarily dirty tanker related. These are published on a daily schedule and are publically available (Baltic Exchange, 2016). The dirty tanker spot freight rate indexes indicate seaborne crude oil transportation service cost, in regards to trade routes.

The average freight rate F_{a_i} per route is provided by the Baltic Exchange, which receives information via shipbroking firms. Further a weighted factor W_i for each route is applied. The sum of the multiplications is symbolised by the *equation 4.1*;

$$BDTI = \sum_{i}^{n} (F_{a_i} * W_i) \tag{4.1}$$

The Baltic Exchange Dirty Tanker Index (BDTI) routes are affected by trade routes, costs, revenue and vessel type. Trade routes in the BDTI are determined by fleet supply and transportation demand, which are influenced by the loading- and discharging location and different costs, such as port- and canal fees and the voyage duration. The vessel type impacts the BDTI, in regards to DWT, capacity, speed and bunker fuel consumption. *Au contraire*, to the dry bulk segment, where freight rates are measured in USD$ per tonne, the tanker segment expresses freight rates in Worldscale (WS) units.

Worldscale supports the negotiation process of the oil transportation freight rate (Worldscale Association, 2016) and represents the freight market levels. This measurement incorporates voyage expenses, such as bunker fuel prices, port- and canal fees (Goulas, 2010). Based on the significant impact of bunker fuels on the operational vessel costs, crude oil prices play a crucial role. In practical terms, a Worldscale rate of 100, which is also defined as the flat rate, i.e. freight rate is as issued by the Worldscale Association, while a rate of 120 means 120% of the issued freight rate. The usage of Worldscale units fosters comparability and transparency, in regards to trade route and vessel segment. The Worldscale rate can be therefore expressed by the *equation 4.2*;

$$WS\ \frac{USD\$}{Metric\ tonne} = \frac{(Daily\ hire * Round\ voyage\ day) + voyage\ expenses}{Cargo\ quantity\ in\ metric\ tonne} \tag{4.2}$$

For the purpose of this paper seven routes where chosen, based on the coverage of significant seaborne crude oil transportation service demand, showcased in *table 4.1* (Clarksons Reserach, 2017).

		Million barrels per day / million DWT					
	Routes	2013	2014	2015	2016	2017	%
VLCC	Middle East Gulf to China, Japan, Korea	7,7	7,8	8,1	8,5	8,7	2%
	Middle East Gulf to Other Asia/Pacific	3,4	3,3	3,5	3,7	3,9	3%
	Middle East Gulf to North America	2,0	1,7	1,4	1,6	1,5	-10%
	Caribbean to China / India	1,2	1,3	1,6	1,6	1,7	8%
	West Africa to Far East	1,1	1,2	1,2	1,3	1,4	6%
	West Africa to India	0,4	0,5	0,6	0,5	0,5	-5%
	Others	1,2	1,3	1,5	1,4	1,4	-5%
	Total, million barrels per day	**17,0**	**17,1**	**17,9**	**18,6**	**19,1**	**2%**
	Total, million DWT	**161,0**	**161,2**	**165,5**	**174,0**	**176,2**	**1%**
	%, growth	-2,4%	0,1%	2,7%	5,1%		
Suezmax	West Africa to North America	0,5	0,3	0,2	0,3	0,3	-13%
	Middle East Gulf to Mediterranean	0,9	1,0	1,1	1,2	1,3	-3%
	Caribbean to North America	0,8	0,7	0,7	0,7	0,6	-10
	West Africa to Mediterranean/UK.-Continent	1,1	1,1	1,2	1,0	0,9	-8%
	Middle East Gulf to India	0,5	0,6	0,6	0,7	0,8	11%
	Mediterranean/UK.-Continent to North America	0,3	0,2	0,2	0,2	0,2	-8%
	Mediterranean/Black Sea to UK.-Continent	0,3	0,3	0,3	0,3	0,3	-2%
	Mediterranean/Black Sea to Mediterranean	0,9	0,7	0,8	0,8	0,8	-2%
	Others	2,4	2,9	2,9	2,9	3,0	3%
	Total, million barrels per day	**7,7**	**7,8**	**8,0**	**8,1**	**8,2**	**-1%**
	Total, million DWT	**54,2**	**55,2**	**56,7**	**58,6**	**58,5**	**0%**
	%, growth	3,5%	2,0%	2,7%	3,2%	0,0%	
Aframax	Baltic to UK.-Continent	1,6	1,5	1,7	1,8	1,7	-5%
	UK.-Continent to UK.-Continent	2,1	2,2	2,1	2,3	2,2	-4%
	Black Sea/Mediterranean to UK.-Continent	1,4	1,2	1,3	1,2	1,2	-2%
	Intra Far East	1,2	1,2	1,4	1,7	1,8	5%
	Caribbean to North America	1,5	1,5	1,5	1,5	1,3	-9%
	Middle East Gulf to Asia/Australia	0,9	0,7	0,7	0,8	0,8	6%
	Others	2,5	2,5	2,4	2,4	2,5	6%
	Total, million barrels per day	**11,2**	**10,8**	**11,1**	**11,7**	**11,5**	**-1%**
	Total, million DWT	**56,0**	**54,8**	**55,6**	**57,2**	**57,4**	**0%**
	%, growth	-7,9%	-2,2%	1,5%	3,0%	0,3%	

Table 4.1 Crude tanker demand by route

Source: © Clarkson Research Services Limited 2016, Oil & Tanker Trades Outlook, Vol. 22, No.1, January 2017

The dataset was provided by the WMU, Malmö, Sweden and originates from the Clarksons Research Shipping Intelligence Network. The Dirty Tanker Index trade routes in Worldscale incorporate; VLCC – *BDTI TD1*, *BDTI TD2*. *Clarksons ID. 41093 and 41094*, Suezmax / Aframax - *BDTI TD6*, *BDTI TD17*. *Clarksons ID. 41099 and 69763*, and Aframax - *BDTI TD7*, *BDTI TD9*, *BDTI TD14*. *Clarksons ID. 41100, 41102 and 41107.*

The entire time-series span from March 2016 through February 2017, and each series contains 132 monthly averaged observations. The following *table 4.2*, displays the descriptive summary for the seven BDTI routes – VLCC, Suezmax, Aframax.

	Aframax			Suezmax / Aframax		VLCC	
	BDTI TD7	BDTI TD9	BDTI TD14	BDTI TD6	BDTI TD17	BDTI TD1	BDTI TD2
	North Sea to Continent	Caribbean to US Gulf	South East Asia to East Coast Australia	Black Sea / Mediterranean	Baltic to UK.-Continent	Middle East Gulf to US Gulf	Middle East Gulf to Singapore
Mean	114,35	135,30	110,66	101,93	102,54	45,83	67,30
Standard Erroı	3,02	4,58	3,46	3,79	3,51	2,31	3,15
Median	103,76	116,76	101,02	88,53	90,04	37,40	59,00
Standard Devi	34,71	52,57	39,75	43,59	40,29	26,58	36,14
Sample Variar	1204,69	2763,26	1579,89	1899,93	1623,39	706,44	1306,18
Kurtosis	2,90	1,50	3,56	4,33	1,15	5,14	8,79
Skewness	1,63	1,35	1,61	1,82	1,27	2,10	2,63
Range	187,68	257,63	238,06	252,03	190,41	147,39	215,19
Minimum	64,60	61,03	52,87	48,38	48,00	18,04	29,30
Maximum	252,28	318,66	290,93	300,41	238,41	165,43	244,50
Sum	15094,68	17859,71	14607,35	13455,27	13534,81	6050,20	8883,58
Count	132	132	132	132	132	132	132

Table 4.2 BDTI routes descriptive statistics

Source: © Clarkson Research Services Limited 2016

4.1.1 BDTI – VLCC

The Baltic Dirty Tanker Indexes - VLCC includes the routes; *Middle East Gulf to Singapore* from Ras Tanura, Saudi Arabia to Singapore with 270,000 DWT vessels and maximum age of 20 years. *Middle East Gulf to US Gulf* from Ras Tanura, Saudi Arabia to Louisiana Offshore Oil Port (LOOP), United States 280,000 DWT and maximum age of 20 years.

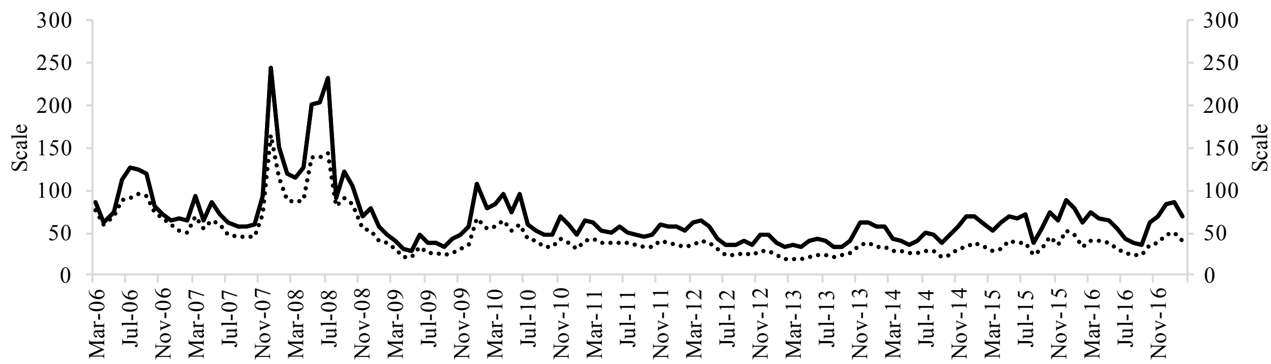


Figure 4.2 Very Large Crude Carrier, monthly Worldscale rate, March 2006 - February 2017

Source: © Clarkson Research Services Limited 2016

The time-series span from the March 2006 through February 2017 and includes 132 observations. Throughout the period its peak was reached for the route *Middle East Gulf to Singapore* in December 2007 with 244.5 points and for *Middle East Gulf to US Gulf* in December 2007 with 165.4 points. The lowest level was reached for the first route in May 2009 with 29.3 and for the second route in April 2013 with 18.1 points. From March 2006 through February 2017 the route *Middle East Gulf to Singapore* in Worldscale units decreased by -21% and the route *Middle East Gulf to US Gulf* by -47%.

4.1.2 BDTI – Suezmax/Aframax

The Suezmax/Aframax routes; *Black Sea/Mediterranean*, Novorossiysk, Black Sea, Russia to Augusta, Sicily, Italy with 135,000 DWT vessels and maximum age 20 years. *Baltic to UK-Continent*, Primorsk, Russia to Wilhelmshaven, Germany with 100,000 DWT vessels and maximum age 15 years.

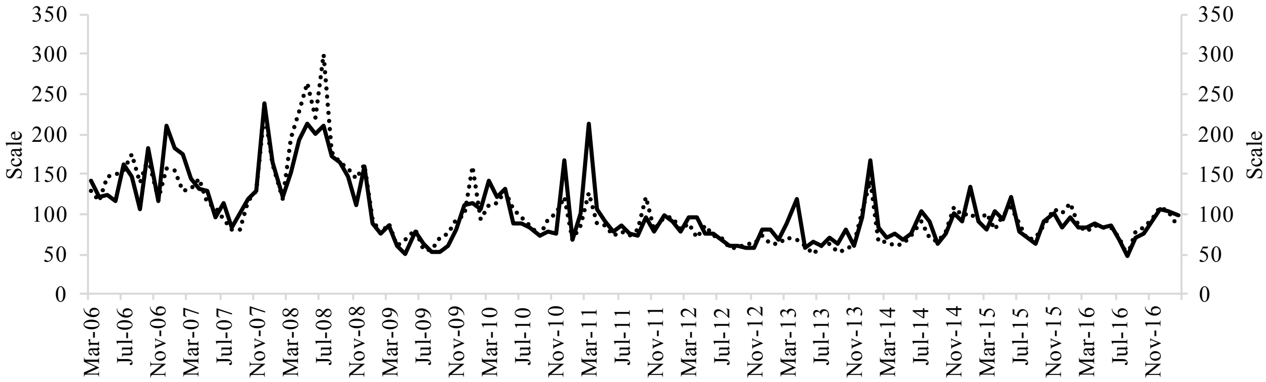


Figure 4.3 Suezmax/Aframax, monthly Worldscale rate, March 2006 - February 2017

Black Sea / Mediterranean   Baltic to UK-Continent

Source: © Clarkson Research Services Limited 2016

The BDTI routes time-series span from the March 2006 through February 2017 and compromises 132 observations. Throughout the period its highest value was reached for the route *Black Sea/Mediterranean* in July 2008 with 300.4 points and *Baltic to UK-Continent* in December 2007 with 238.4 points. Both routes touched their lowest point in August 2016, with 48.3 and 48.0 points, in the respective order. From March 2006 through February 2017 the route *Black Sea/Mediterranean* in Worldscale units decreased by -35% and the route *Baltic to UK-Continent* by -31%.

4.1.3 BDTI – Aframax

The Baltic Dirty Tanker Index for Aframax incorporates three routes, *North Sea to Continent*, Sullom Voe Terminal, Scotland, the United Kingdom to Wilhelmshaven, Germany with 80,000 DWT vessels and maximum of age 20 years. *Caribbean to US Gulf*, Port of Jose Petroterminal, Venezuela to Corpus Christi, United States Gulf with 70,000 DWT vessels and maximum of age 20 years. *South-East Asia to East Coast Australia*, Seria Oil Terminal, Brunei to Sydney, Australia with 80,000 DWT vessels and maximum of age 15 years.

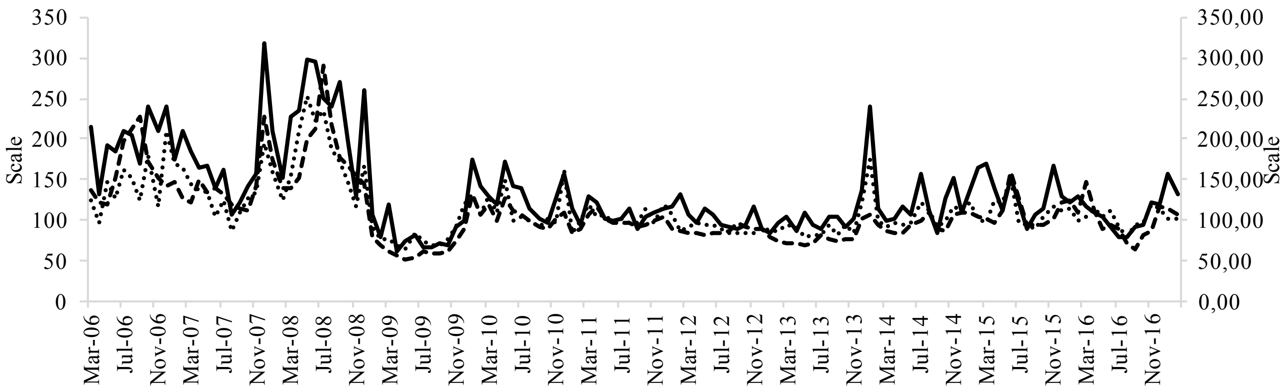


Figure 4.4 Aframax, monthly Worldscale rate, March 2006 - February 2017

Source: © Clarkson Research Services Limited 2016

The BDTI routes time-series span from the March 2006 through February 2017 and include 132 observations. Throughout the period its highest peak was reached for the route *Caribbean to US Gulf* in December 2007 with 318.7 points, *North Sea to Continent* in May 2008 with 252.3 points and *South-East Asia to East-Coast Australia* on July 2008 with 290.9 points. The *Caribbean to US Gulf* reached its lowest level in April 2009 with points, while the other two route progressed to this level in May 2009, with 64.6 and 52.8 points. From March 2006 through February 2017 the route *Caribbean to US Gulf* in Worldscale units decreased by -38%, N*orth Sea to Continent* by -18% and *South-East Asia to East Coast Australia* by -23%.

4.2 Crude oil spot price

Crude oil prices are expressed as benchmarks, which include *Brent*, *West Texas Intermediate* (WTI) or *Dubai crude*. These benchmarks differ mainly by their sulphur content, refinery process, hauling location and transpiration cost. Thus affecting the pricing of crude oil. The major crude oil benchmarks are *West Texas Intermediate* and *Brent* and used as a standard reference price for the entire global crude oil market. (Daryanani, et al., 2013). Due to shifting trading patterns, the literature is undecided, which of the two benchmarks act as a superior representation of oil prices. (Smith, 2012). This paper favours the usage of both benchmarks - *West Texas Intermediate* and *Brent* as the spot crude oil price. The price symbolises the equilibrium outcome, determined by the quantity of production and consumption (Nakov & Nuño, 2011). Due to trading on the Futures Exchange, it can be excepted that spot oil prices incorporate to some extent future expectations. The crude oil price is impacted by various factors, such as supply disruptions in the form of war, terrorism or labour strikes (Dirzka, 2015), explorations of new reserves, changes in demand patterns, in the form of alternative energy recourses or global economics growth. The link to the Baltic Dirty Tanker Index is established via the general trade volume of crude oil. Additionally, direct considerations concerning bunker fuels are taken into account. An increase in crude oil prices correlates with higher bunker fuel prices and therefore rising operational shipping cost, thus affecting the BDTI. Based on the connection to the BDTI, the *WTI* and *Brent* will be introduced in the multivariate analysis.

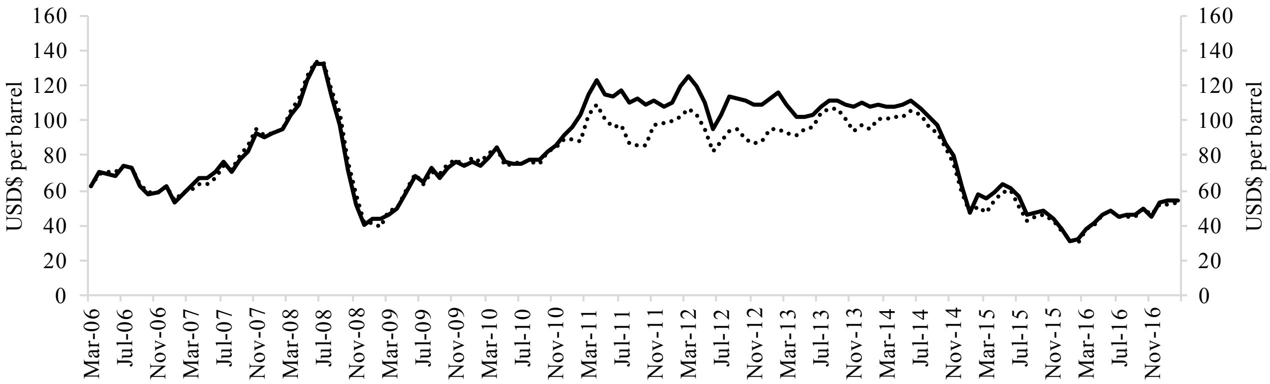


Figure 4.5 WTI- and Brent crude oil price, average monthly USD$ per barrel, March 2006 - February 2017

Brent crude oil price ······ WTI crude oil price

Source: Federal Reserve Bank of St. Louis and U.S. Energy Information Administration

The dataset for the *West Texas Intermediate* was drawn from the Federal Reserve Bank of St. Louis database and includes the monthly average and non-seasonally adjusted *WTI* crude oil price in USD$ per barrel. The entire dataset spans from the March 2006 through February 2017 and contains 132 observations. Throughout the period its highest peak was reached in June 2008 with 133.8 USD$ per barrel, while its lowest level was in February 2016 at 30.3 USD$ per barrel. From March 2006 through February 2017 the *WTI* decreased by -15%. On the other hand, the *Brent* crude oil price is reported on a monthly-, non-seasonally adjusted base and originates from the U.S. Energy Information Administration, spanning from March 2006 through February 2017 and containing 132 observations. Throughout the period its highest level was reached in June 2008 with 132.7 USD$ per barrel, while its lowest point was in January 2016 at 30.7 USD$ per barrel. From March 2006 through February 2017 *Brent* decreased by -12%.

4.3 Crude oil production

The notion that global economic growth facilitates energy trade has been widely discussed in previous researches. (Corbett & Winebrake, 2008). The relationship between trade, GDP, and energy trade, has been a focal point of macroeconomic research since the last decade. Energy trade is defined by the volume of trade flow. Supply is expressed by the quantity of energy reserves and origin of commerce, while demand is derived from the source of energy consumed and destination of trade (Thanopoulou & Strandenes, 2015). Therefore, global energy transport is determined by demand and production, in relation to the respective geographical settings (Levine, et al., 2014). Regarding maritime transport, demand is subject to tonne-mile consideration, which determines the anticipated fleet deployment and their productivity. Therefore, impacting also the Baltic Dirty Tanker Index. In the case of rising crude oil production, demand for transportation service increases relative synchronically. The geographical production location, selected for research strive to mirror to a certain extent the chosen BDTI routes for VLCC-, Suezmax- and Aframax vessels. The *Middle East crude oil production* relates to - *BDTI TD1 - Middle East Gulf to US Gulf* and *BDTI TD2 - Middle East Gulf to Singapore*. While *Former Soviet Unions crude oil production* relates to *BDTI TD6 - Black Sea / Mediterranean* and *BDTI TD17 - Baltic to UK-Continent*. The *North Sea production* is only related to *BDTI TD9 - North Sea to Continent*.

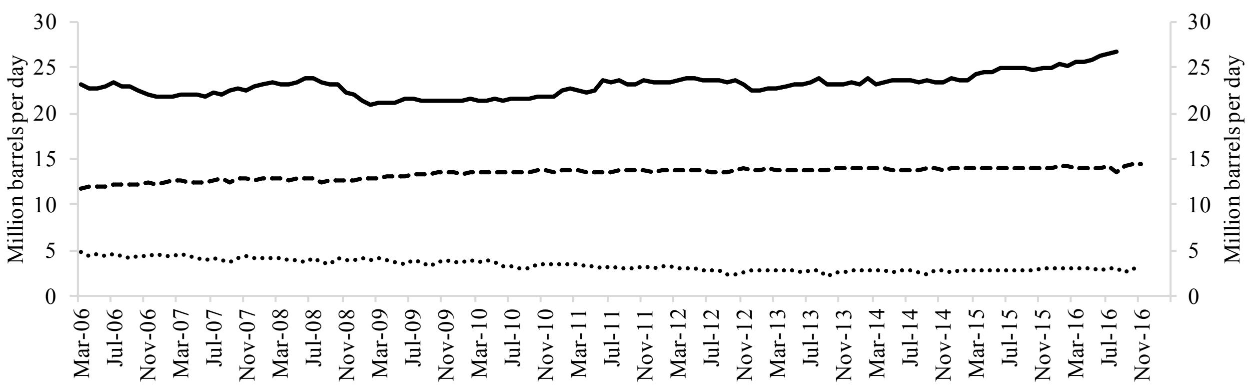


Figure 4.6 Crude oil production, monthly million barrels per day, March 2006 - February 2017

North Sea Fromer Soviet Union Middle East

Source: © Clarkson Research Services Limited 2016

The dataset originates from Clarksons Research and illustrates the monthly crude oil production. The time-series are not uniform in length, the variable *North Sea*- and *former Soviet Unions production* span from March 2006 till November 2016 and includes 129 observations, while the time-series *Middle East* reaches only till August 2016 and contains 126 observations. The *Middle East crude oil production*, had its peak in August 2016 with 26.6

million barrels per day (mbpd), while its lowest level was reached in February 2009 at 20.8 mbpd. The *Former Soviet Unions crude oil production* peaked in October 2016 with 14.5 mbpd, while its lowest level was in March 2006 at 11.8 mbpd. *North Sea crude oil production* had its peak at the beginning of the time-series in March 2006 at 4.8 mbpd and its lowest level in September 2013 at 2.3 mbpd.

4.4 Data overview

The univariate- and multivariate models are based on 126 observations, rather than 132. The six remaining variables are reserved for the forecast in *chapter 7*, to measure the performance concerning sample fit. The separations of the time-series into two distinct sets enables to derive the statistical process from the first set and utilises the second set for testing, thus avoiding bias results. Due to the appliance of monthly observations and their relatively large number a forecast over approximately a half year can be justified.

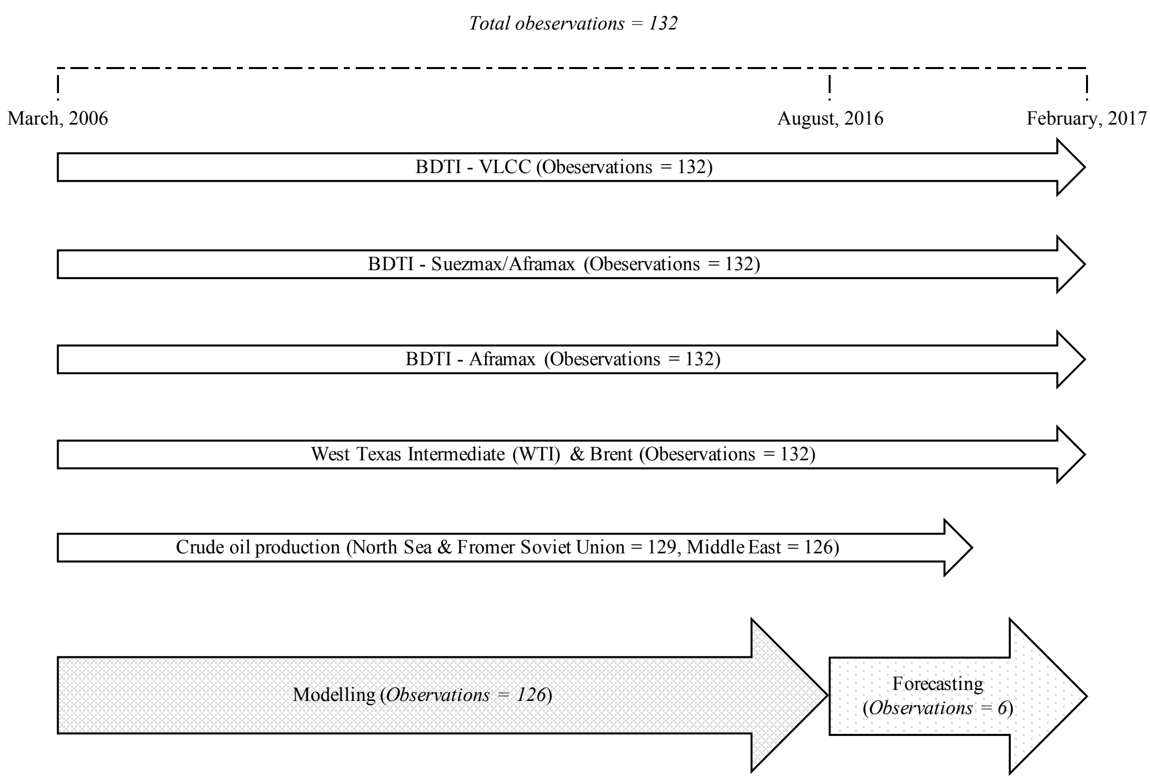


Figure 4.7 Data overview

Source: © Clarkson Research Services Limited 2016, Federal Reserve Bank of St. Louis and U.S. Energy Information Administration

Chapter 5 - Univariate models

Univariate modelling strives to analyse economic time-series to evaluate or predicted processes, based on the assumption that current observations are related to their past, either directly or indirectly (Verbeek, 2004). This approach purely utilises the information contained in previous observations to forecasts its future. In this case, merely the time-series Baltic Dirty Tanker Index routes in Worldscale units for the segments *Very Large Crude Carriers*, *Suezmax* and *Aframax* are independently considered. The application of univariate frameworks has been a focal point of research in the general maritime literature as outlined in *chapter 3*. However, due to high market uncertainty, a defined framework to model crude oil tanker spot freight rates has not been yet achieved. Therefore, this section applies the ARMA based, univariate model to create, in the optimal case a benchmark for the academia.

The outlined framework in this sections is based on the contribution by Box & Jenkins (1976), who developed the Box-Jenkins method for ARMA based models, which comprises three steps;

I. Identification via autocorrelations, partial autocorrelations plots and other information in order to estimate the approximate p and q parameters in the ARMA model.

II. Estimation of the parameters via maximum likelihood techniques or others.

III. Diagnostic testing for inadequacies in relation to the residual series.

The univariate section will only consider the sample from March 2006 through August 2016, which includes 126 observations.

5.1 Stationarity and unit root

Time-series modelling is fundamentally interlinked with the concept of stationarity. Non-stationarity in time-series might lead to spurious regressions, where the persistence of shocks are infinite. Therefore, undermine the validity of standard assumptions for asymptotic analysis. In general terms, a time-series is considered stationary if the conditions of constant mean and constant variance, for the entire $t -$ time are met. Additionally, the autocovariance function Y_{t_1} and Y_{t_2} only depends on the interval t_1 and t_2. A stationary time-series is also referred to as a white noise, which can be illustrated by the analogy of the acoustic power of a cymbal, which is hit to a homogeneous Poisson process. Thus, the acoustic waves would be stationary. According to Verbeek (2004, p. 258), a stochastic process is defined as strictly stationary when it is '*unaffected by a change of time origin*', which means that the statistical properties stay constant along the time axis. In a more technically manner, a strictly stationary process implies that the joint probability distribution is only linked to the interval between the time points and not its place in time (Hamilton, 1994, p. 46). In the usual case, time-series analytics is concerned with weak stationarity, rather than its stricter version. The weaker form of stationarity is referred to as covariance stationarity and implies only a constant mean, constant variance and that the covariances between t_0 and t_1 depend on the distance, rather than their place in time. Therefore, the major difference between strict- and weak stationarity processes, is that in the weaker form '*moments are independent of time, rather than the entire distribution*' (Verbeek, 2004, p. 259). Described in *equation 5.1*, these criteria define a weakly stationary process $\{Y_t\}$.

$$\begin{array}{ll} \text{I.} & E\{Y_t\} = \mu < \infty \\ \text{II.} & V\{Y_t\} = E\{(Y_t - \mu)^2\} = \gamma_0 < \infty \\ \text{III.} & cov\{Y_t, Y_{t-k}\} = E\{(Y_t - \mu)(Y_{t-k} - \mu)\} = \gamma_k \quad k = 1,2,3,\dots \end{array} \tag{5.1}$$

In this case, criteria (I.) relates to a constant finite mean, while criteria (II.) depict a constant finite variance. The last criteria (III.) the autocovariance of Y_t only relates to the distance in time between two observations. Therefore, these criteria are independent of time. Based on the outline of stationary, the figures in *chapter 3* (*4.2, 4.3* and *4.4*), in regards to a graphical inspection might indicate stationarity. Thus confirming the properties of spot freight rates in previous researches (Tvedt, 2003) (Sødal, et al., 2008) (Adland & Cullinane, 2006). Their mean and variance seem relatively stable over time. However, in the following section a formal framework for unit root testing, is proposed. In the case of an unit-root or non-stationarity, the data needs to be integrated to the first order to archive stationarity. Thus the time-series reflects changes, rather than the level.

5.1.1 Dickey-Fuller test

Verbeek (2004, p. 269), approached the Dickey-Fuller test via an autoregressive model with the process $\theta = 1$, also referred to as a random walk model or ARMA (1,0), which is non-stationary due to the rise of variance to infinity. It can is expressed by the *equation 5.2*;

$$Y_t = \delta + \theta Y_{t-1} + \varepsilon_t \tag{5.2}$$

In this model $\theta = 1$, refers to the unit root equal to 1. To test weather this applies, a standard t-statistic is used in *equation 5.3*;

$$DF = \frac{\hat{\theta} - 1}{se(\hat{\theta})} \tag{5.3}$$

The ordinary least square standard error is $se(\hat{\theta})$ and $\hat{\theta}$ the ordinary least square estimator. The hypothesis under the a 5% significance, applies $H_0 : \theta = 1$, which means unit root or non-stationarity and $H_A : \theta < 1$, which means no unit root or stationarity. The test however is not t-distributed. Therefore Dickey & Fuller (1979) suggested to implement the random walk model, AR(1) and to evaluate the null hypothesis via the critical values obtained by Dickey & Fuller. Thus modifying the *equation 5.4*;

$$\Delta Y_t = \delta + (\theta - 1)Y_{t-1} + \varepsilon_t \tag{5.4}$$

Therefore, the null hypothesis of unit root is equal to $(\theta - 1) = 0$ rather than $\theta = 1$, as stated previously. This test can be extended by lags of ΔY_t, to erase potential serial correlation. This extension to a higher order AR processes, refers to a Augmented Dickey-Fuller test (Dickey & Fuller, 1979).

		Intercept only	Trend and intercept	No trend and no intercept
		Test statistics and (MacKinnon one-sided p-value)		
Aframax	South East Asia to East Coast Australia	-3,07	-3,53	-1,26
		(0,0310)	(0,0398)	(0,1887)
	North Sea to Continent	-3,73	-4,41	-1,03
		(0,0047)	(0,0030)	(0,2707)
	Caribbean to US Gulf	-2,43	-2,93	-1,18
		(0,1349)	(0,1565)	(0,2163)
Suezmax / Aframax	Black Sea / Mediterranean	-2,73	-4,20	-1,27
		(0,0711)	(0,0060)	(0,1855)
	Baltic to UK-Continent	-2,20	-3,00	-1,22
		(0,2051)	(0,1357)	(0,2021)
VLCC	Middle East Gulf to US Gulf	-1,67	-4,12	-1,12
		(0,4422)	(0,0077)	(0,2351)
	Middle East Gulf to Singapore	-2,70	-3,81	-0,98
		(0,0769)	(0,0193)	(0,2904)

Table 5.1 Augmented Dickey-Fuller test of level with lags based on AIC

Source: © Clarkson Research Services Limited 2016

The *table 5.1* shows the different models of the Augmented Dickey-Fuller test, which includes lags based on Akaike information criterion (AIC) (Akaike, 1973);

The first model, *Intercept only*, displays a random walk with a constant, the second one is both *a trend and a constant* and the third model with *no trend nor an intercept*, represents the random walk. It is crucial to note that the test is based on observations from the estimation period only, which ranges from March 2006 through August 2016. Based on a significance level α, specified by Verbeek (2004, p. 24) at 5%, the time-series *South East Asia to East Coast Australia* and *North Sea to Continent,* indicate stationarity at level for the a random walk with a constant, while each model accepts the null hypothesis of a present unit root for the random walk model. Due to evidence of unit root, the time-series are differenced. A log-returns transformation in *equation 5.5* is applied;

$$dlog = \ln(y_t) - \ln(y_{t-1}) \tag{5.5}$$

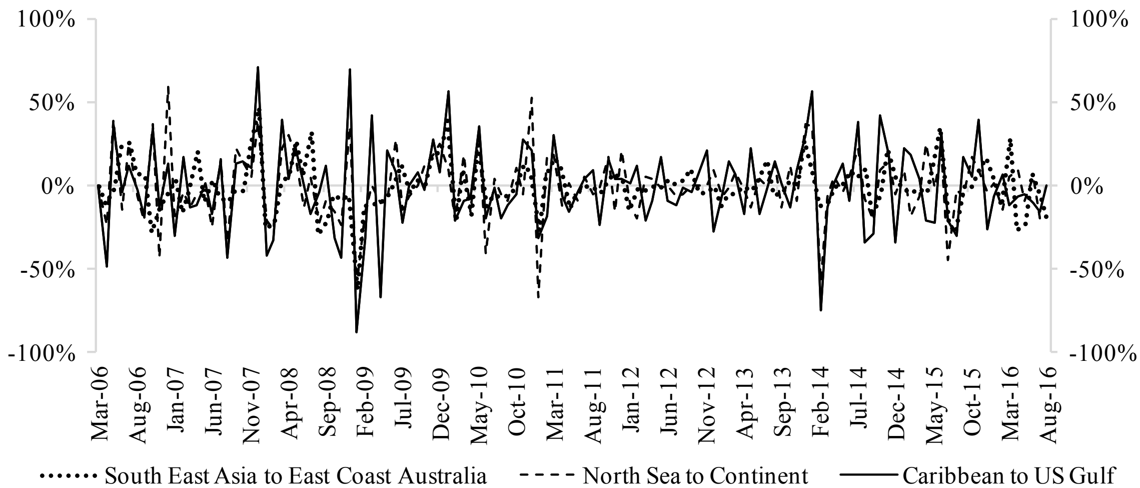
This formula output shows the continuous compounded monthly return (Quigley, 2008). The *table 5.2*, applies the transformed BDTI routes log-returns on the specified Augmented Dickey-Fuller tests.

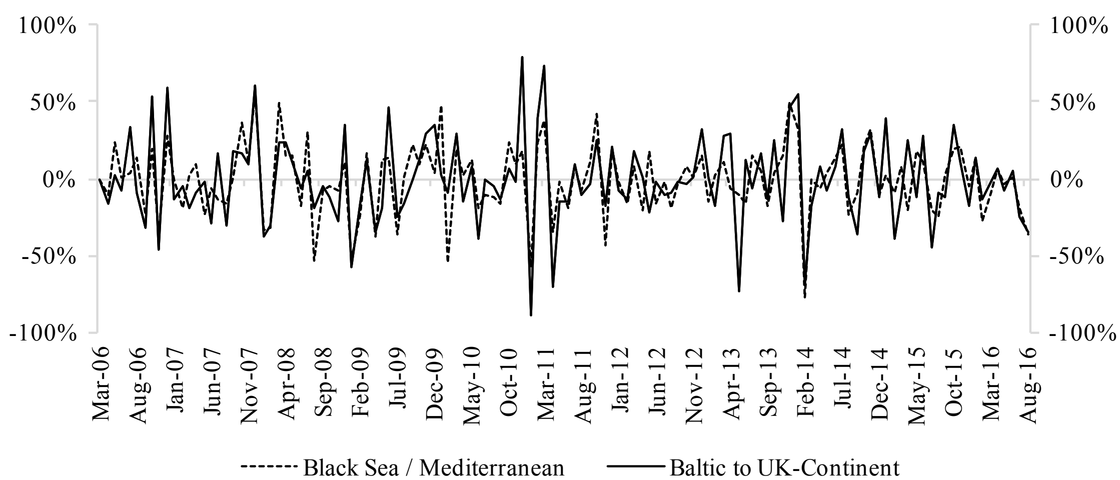
		Intercept only	Trend and intercept	No trend and no intercept
		Test statistics and (MacKinnon one-sided p-value)		
Aframax	South East Asia to East Coast Australia	-10,1	-10,05	-10,13
		(0,0000)	(0,0000)	(0,0000)
	North Sea to Continent	-5,12	-5,11	-5,10
		(0,0000)	(0,0003)	(0,0000)
	Caribbean to US Gulf	-12,21	-12,16	-12,24
		(0,0000)	(0,0000)	(0,0000)
Suezmax / Aframax	Black Sea / Mediterranean	-9,77	-4,70	-9,79
		(0,0000)	(0,0012)	(0,0000)
	Baltic to UK-Continent	-3,76	-3,74	-3,70
		(0,0043)	(0,0232)	(0,0003)
VLCC	Middle East Gulf to US Gulf	-5,08	-5,08	-5,06
		(0,0000)	(0,0003)	(0,0000)
	Middle East Gulf to Singapore	-7,60	-7,58	-7,61
		(0,0000)	(0,0000)	(0,0000)

Table 5.2 Augmented Dickey-Fuller test of log-returns with lags based on AIC

Source: © Clarkson Research Services Limited 2016

The tests accept the alternative hypothesis of stationarity for all routes. Therefore, the univariate section utilises the log-return, rather than the observations on level of the Baltic Dirty Tanker Indexes. In the common case, the usage of differenced time-series, rather than levels affects the ARMA model, which is than transformed to an ARIMA model, abbreviated from Autoregressive integrated moving average model. The ARIMA model, denotes (p, d, q), where p is the order of the autoregressive lags, d the degree of first differencing and q the order of the moving average lags. However, here the applied ARIMA model includes d (0) degree of first differencing, due to the initial usage of log-returns. A sophistic elaboration of such model will be conducted in *section 5.2.* Additionally, to the first log difference, the Baltic Dirty Tanker Index routes are tested for stationarity via Augmented Dickey-Fuller Test on second log difference, confirming stationarity.





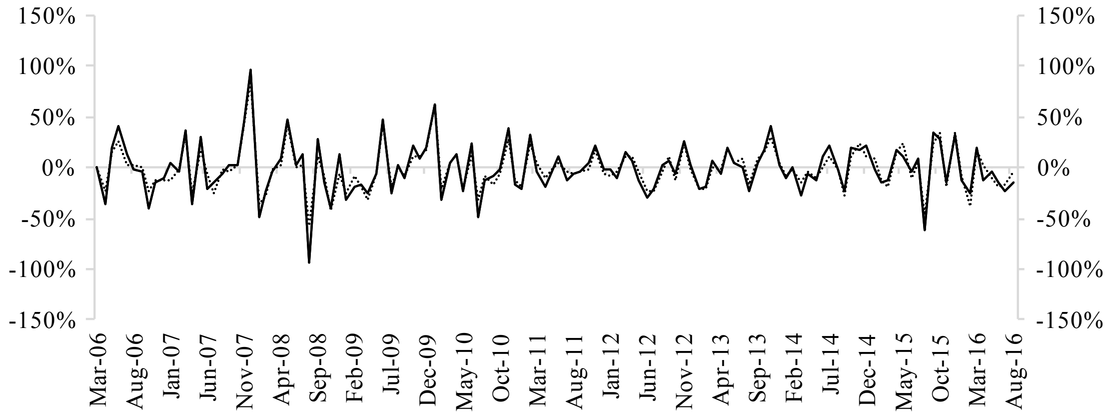


Figure 5.1 BDTI - routes log-returns, monthly, March 2006 - August 2016

Middle East Gulf to US Gulf   Middle East Gulf to Singapore

Source: © Clarkson Research Services Limited 2016

The *figure 5.1,* displays the log-returns, which show the a white noise process; Based on the graphical inspection, the routes depict a constant finite mean and -variance. It is interesting to note that the period between 2007 – 2009, the financial crisis, impacted the BDTI quite substantially, showcased by high volatility. Further, the pattern of volatility differs between the tanker segments; *Very Large Crude Carriers* are significantly more stable. In relation to Kavussanos's (2003) paper, this issue would raise the question of contradiction in regards to the statement that smaller vessels freight rate have lower volatilities than larger vessels on the spot market. However, it needs to be acknowledge that this paper evaluated a different time frame, therefore indicating that the notion of lower volatility for larger vessels is linked to a more recent phenomena.

The *table 5.3*, shows the correlation between log-returns of the selected BDTI routes. The most significant correlation is between the two routes, which depart from the *Middle East Gulf to US Gulf* and *Singapore*. It is quite interesting, due to a substantial nautical mile difference between these two routes. Moreover, other non-VLCC routes show the least correlation.

Additionally, the table displays a geographical linkage between *North Sea to Continent*, *Black Sea / Mediterranean* and *Baltic to UK-Continent*, based on the high positive correlation. The realisation from such correlation analysis is that geographical trade route patterns and vessel size matters.

		Aframax			Suezmax / Aframax		VLCC	
		South East Asia to East Coast Australia	North Sea to Continent	Caribbean to US Gulf	Black Sea / Mediterranean	Baltic to UK-Continent	Middle East Gulf to US Gulf	Middle East Gulf to Singapore
Aframax	South East Asia to East Coast Australia	1,0000	0,4899	0,4295	0,5528	0,4196	0,5366	0,5234
	North Sea to Continent	0,4899	1,0000	0,6508	0,7370	0,8801	0,2702	0,2767
	Caribbean to US Gulf	0,4295	0,6508	1,0000	0,6447	0,5536	0,3387	0,3459
Suezmax / Aframax	Black Sea / Mediterranean	0,5528	0,7370	0,6447	1,0000	0,7015	0,4203	0,4186
	Baltic to UK-Continent	0,4196	0,8801	0,5536	0,7015	1,0000	0,2646	0,2630
VLCC	Middle East Gulf to US Gulf	0,5366	0,2702	0,3387	0,4203	0,2646	1,0000	0,9507
	Middle East Gulf to Singapore	0,5234	0,2767	0,3459	0,4186	0,2630	0,9507	1,0000

Table 5.3 Correlation between log-returns BDTI routes

Source: © Clarkson Research Services Limited 2016

5.2 ARMA

The autoregressive moving average model (ARMA), consists out of two section; The autoregressive (AR) model, which utilises past observations to explain current observations and the moving average (MA) model, which utilises lagged observations of the error term to explain current observations (Verbeek, 2004, p. 261). The AR- and MR models are not significantly different; An AR(1) model can also be formulated as an infinitive MR model.

The non-seasonal ARMA model is denoted as p autoregressive lags, and q moving average lags. As indicated in *section 5.1.1*, the time-series are transformed to log-returns. An ARMA model is fitted for time-series with at least 50 observations, which is in the case of the BDTI routes with 126 observations utilised for the modelling process.

The autoregressive (AR) model, regresses a observation from the time-series y_t on previous observation of the same y_t series. (Verbeek, 2004, p. 261-266). The AR model denotes with p autoregressive lags and is described by the *equation 5.6*;

$$y_t = \beta + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t \tag{5.6}$$

The autoregressive model is summarised in *equation 5.7*;

$$y_t = \beta + \sum_{p=1}^{p} \theta_p y_{t-p} + \varepsilon_t \tag{5.7}$$

The y_t is the modelled Baltic Dirty Tanker Index route at t, while the β is the constant in the model, y_{t-p} symbolises the index until p, the autoregressive lag, θ_p is the parameter for y_{t-p} and ε_t the error term at t. The moving average (MA) model, takes into account the observation value and the previous residuals. It denotes as q moving average lags and is described by the *equation 5.8*;

$$y_t = \varepsilon_t + \emptyset_1 \varepsilon_{t-1} + \emptyset_2 \varepsilon_{t-2} + \cdots + \emptyset_q \varepsilon_{t-q} \tag{5.8}$$

The moving average model is summarised in *equation 5.9*;

$$y_t = \beta + \varepsilon_t + \sum_{q=1}^{q} \emptyset_q \varepsilon_{t-q} \tag{5.9}$$

In regards, to the previous legend; y_t is the modelled Baltic Dirty Tanker Index route at t, while the β is the constant in the model, ε_{t-q} symbolises the error term until p, the moving average lags, $\emptyset_q$ is the parameter for ε_{t-q} and ε_t the error term. The autoregressive moving average model (ARMA), incorporates both AR- and MR models, therefore is illustrated in the *equation 5.10*;

$$y_t = \beta + \sum_{p=1}^{p} \theta_p y_{t-p} + \varepsilon_t + \sum_{q=1}^{q} \emptyset_q \varepsilon_{t-q} \tag{5.10}$$

Due to the usage of log-returns the ARMA models, must not be expanded by the d (1) degree of first differencing, which would alter the ARMA- into the ARIMA model, which is expressed in *equation 5.11*;

$$\Delta\, y_t = \beta + \sum_{p=1}^{p} \theta_p \,\Delta\, y_{t-p} + \varepsilon_t + \sum_{q=1}^{q} \emptyset_q \varepsilon_{t-q} \tag{5.11}$$

5.2.1 Estimation of parameters

Verbeek (2004, p. 281), states that the choice of a specific model, in regards to their parameters is in most cases not necessary. However, an estimation of autocorrelation- and partial autocorrelation coefficients enhances the understanding of the p autoregressive lags, and q moving average lags. In case the autocorrelation function is not capable to offer a distinct picture of the AR- and MA terms, multiple models are constructed and then evaluated by the information criterion. Finally judged by checking whether the residuals depict white noise. The autocorrelation function, commonly abbreviated by ACF, shows the correlation between y_t and its lag y_{t-k}, which is the function of k. The $k - th$ order autocorrelation coefficient is expressed by the *equation 5.12*;

$$y_k = \frac{Cov(y_t, y_{t-k})}{Var(y_t)} \tag{5.12}$$

As a guideline, an AR(1) model might show an exponential decay $y_k = p^k$ and $p > 0$, displaying a direct decay, $p < 0$ oscillating. On the other hand spikes at lag 1 for $\emptyset > 0$ (positive), $\emptyset < 0$ (negative), $y_k = 0$ for $k \geq 2$, describing a MR(1) model.

The partial autocorrelation also referred to as conditional correlation and abbreviated by PACF, is defined as the direct correlation between y_t and its lag y_{t-k} with a linear dependence between the intermediate correlation that has been removed. In the practical case, an AR(1), will display a partial autocorrelation with a spike at $p(1)$ autoregressive lags, while a MA(1) shows a oscillating decay.

Verbeek (2004, p. 284), summarises that an AR(p) process, shows that the autocorrelation function is '*infinite in extent*' and the partial autocorrelation is '*close to zero for lags larger than p*'. A MA(q) process, shows that the autocorrelation function is '*close to zero for lags larger than q*' and partial autocorrelation is '*infinite in extent*'. In the case none of these applies a combination of the AR(p) and MA(q) process, leads to an ARMA process, which may give a more parsimonious representation of the time-series.

Based on the correlogram of log-returns, which depicts the autocorrelation and partial correlation for the sample from March 2006 – August 2016 for the Baltic Dirty Tanker Index routes, an ARMA with a fairly higher order of autoregressive lags, and moving average lags might be appropriate. Verbeek (2004, p. 285), advises to apply additional criteria to choose an appropriate model, rather than singularly inspecting the autocorrelation function. Such criterion provides a '*trade-off between goodness-of-fit and the number of parameters*' used in the ARMA model (Verbeek, 2004, p. 58). One of the in-sample criterion is the likelihood-based Akaike's Information Criterion (AIC), which defined previously the lags order selection in the Augmented Dickey-Fuller tests. (Akaike, 1973). The AIC is expressed by the *equation 5.13*;

$$AIC = log\hat{\sigma}^2 + 2\frac{(p+q+1)}{2} \tag{5.13}$$

The trade-off between goodness fit is determined by the log-likelihood value and based on the regression standard error $\hat{\sigma}^2$. The model with the lowest criterion value is selected. Verbeek, states that the AIC criterion might overparameterized models, however in light of the number of observation this criterion shall be applied.

5.2.2 Estimation

Verbeek (2004, p. 279), advises in regards to the model specifications and distribution assumptions to estimate parameters by the least squares- , or by maximum likelihood method. The approach of the least squares strives to minimize the residual sum of squares in order to determine the parameters. Verbeek, argues that that especially for the autoregressive (AR) model in *equation 5.14*, the estimation is a '*linear regression model with a lagged dependent variable*';

$$y_t = \beta + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t \tag{5.14}$$

The error term is ε_t, which shows that the white noise is uncorrelated with any previous $t-1$ until $t-p$ terms. Therefore, ε_t and explanatory variables are '*contemporaneously uncorrelated*'. The ordinary least square method is applied on the AR model and generates consistent estimators *5.15*;

$$E\{y_{t-j}\varepsilon_t\} = 0 \; for \; j = 0, 1, 2, \ldots, p \tag{5.15}$$

To apply the ordinary least square method to determine the parameters for the moving average (MA) model, bears some struggles. Based on a MR(1) model in *equation 5.16*;

$$y_t = \varepsilon_t + \emptyset_1 \varepsilon_{t-1} + \mu \tag{5.16}$$

The lagged error term ε_{t-1}, is not observed and an application of regression techniques is not possible. Verbeek (2004, p. 280), implies the usage of the conditional maximum likelihood function as an alternative estimator for the MR and ARMA model. The conditional ML function utilises the initial condition $\varepsilon_0 = 0$ for a MA (1) model, resulting estimators are therefore defined as conditional maximum likelihood estimators, which are relatively identical for θ the AR model parameter, $\emptyset$ the MA model parameter and μ the mean to the least squares estimators.

The models are estimated by Eviews 9.5, which incorporates an automatic set up. This framework requires the model specifications in terms of transformation, p is the order of the autoregressive lags, d degree of first differencing and q the order of the moving average lags and the choice of the Information Criterion. For each Baltic Dirty Tanker Index route, models up to autoregressive lags AR(5) and moving average lags MR(5), are considered. Based on the outcome of *section 5.1.1* and the usage of log-returns, rather than observations on level, zero degrees of differencing was added.

In regards to the in-sample criterion, the likelihood-based Akaike Information Criterion was chosen with conscious awareness of possible overparameterization. Additionally, monthly dummy variables, were used to catch potential cyclicality in the route indexes, which also supresses a constant in the model to avoid perfect collinearity.

Eviews settings offer merely the output of the preferred model by the AIC, which is stated in *table 5.4*. The most notable fact is the high order for each time-series, which might be dedicated to either misspecification in regards to the chosen information criterion or the more likely option that adjustments in the tanker market in regards to the BDTI occur approximately every quarter, i.e. four months. Thus reflecting the tanker companies quarterly public investor statement [Link: Frontline Ltd.]. The monthly dummy variables display a persistent pattern throughout all Baltic Dirty Tanker Index routes; In January - February and approximately from July – September, the dummy coefficients turn negative, while being positive in the last quarter of the year. Therefore, indicating a cyclical behaviour of the BDTI.

Based on the automatic setup by Eviews, overfitting has been conducted in regards to $ARMA(p+1, \ldots 5, q)$ and $ARMA(p, q+1, \ldots 5)$, to achieve the most parsimonious representation of the time-series. Additionally, in correspondence to the Box-Jenkins Framework, diagnostic tests based on the residuals are performed to assess the validity of the models, including the Box-Ljung Q-test for serial correlation, Jarque-Bera normality test and the ARCH heteroskedasticity test.

		Aframax			Suezmax / Aframax		VLCC	
		South East Asia to East Coast Australia	North Sea to Continent	Caribbean to US Gulf	Black Sea / Mediterranean	Baltic to UK-Continent	Middle East Gulf to US Gulf	Middle East Gulf to Singapore
		Coefficient and (standard error)						
	Preferred ARMA model	(3,3)	(4,5)	(4,5)	(2,4)	(5,4)	(4,4)	(5,4)
	Observations	125	125	125	125	125	125	125
	Akaike information criterion (AIC)	-0,9278	-0,7699	-0,3309	-0,3309	-0,0663	-0,2996	0,018
ARMA processes	AR(1)	-0,1986 (0,121466)	0,0384 (0,070472)	0,2331 (0,075435)	1,7972 (0,077649)	-1,5733 (0,09341)	-0,0617 (0,14738)	-0,2074 (0,1495)
	AR(2)	0,1678 (0,110757)	1,4687 (0,068379)	1,1216 (0,100396)	-0,8766 (0,072694)	-0,8421 (0,17292)	-0,0990 (0,142403)	-0,0852 (0,152562)
	AR(3)	0,6820 (0,12923)	-0,1657 (0,061116)	0,0622 (0,087086)		0,5913 (0,191847)	0,0318 (0,152562)	-0,0638 (0,144378)
	AR(4)		-0,7944 (0,059653)	-0,7396 (0,087205)		0,9782 (0,15927)	0,5645 (0,120383)	0,5785 (0,12518)
	AR(5)					0,4109 (0,090613)		0,1372 (0,116073)
	MR(1)	0,2231 (80,84404)	-0,4406 (1,091102)	-0,8730 (91,4721)	-2,2616 (4,866558)	1,2437 (156,96)	0,0570 (13828,62)	0,0245 (1812,202)
	MR(2)	-0,2381 (136,7029)	-1,7389 (1,945175)	-1,2696 (141,4698)	1,4828 (6,403531)	0,0000 (1365,496)	0,0000 (0,02109)	0,0000 (0,025822)
	MR(3)	-0,9850 (918,8559)	1,2125 (0,245069)	1,1822 (265,4952)	0,0972 (0,725508)	-1,2437 (258,5121)	-0,0570 (21096,76)	-0,0245 (2755,026)
	MR(4)		0,8796 (2,822092)	0,9516 (221,7473)	-0,3184 (2,792748)	-1,0000 (333,4289)	-1,0000 (612349,8)	-1,0000 (186536,9)
	MR(5)		-0,6313 (0,402863)	-0,9252 (307,8933)				
Monthly dummies	January	-0,0894 (0,037582)	-0,1339 (0,050465)	-0,1186 (0,078091)	-0,0661 (0,044559)	-0,0720 (0,083748)	-0,0715 (0,061551)	-0,0987 (0,094927)
	February	-0,1079 (0,060951)	-0,1610 (0,06062)	-0,0381 (0,083595)	-0,2320 (0,059918)	-0,1888 (0,113631)	-0,1099 (0,079482)	-0,1041 (0,08983)
	March	0,0308 (0,052813)	0,0553 (0,059999)	0,0188 (0,096517)	0,1351 (0,076068)	0,1315 (0,096599)	0,0120 (0,069127)	0,0165 (0,080005)
	April	-0,0299 (0,050296)	0,0038 (0,06019)	-0,1517 (0,088569)	-0,0943 (0,06758)	-0,0298 (0,108275)	-0,0462 (0,056134)	-0,0832 (0,062254)
	May	0,0013 (0,043559)	0,0465 (0,050168)	0,1145 (0,100406)	0,0566 (0,073084)	-0,1326 (0,09366)	0,0578 (0,066576)	0,0574 (0,081784)
	June	0,0738 (0,044969)	-0,0340 (0,05374)	-0,0554 (0,109675)	-0,0496 (0,071251)	-0,0087 (0,094072)	0,0312 (0,066175)	0,0678 (0,08032)
	July	0,0457 (0,044065)	-0,0093 (0,053083)	0,0077 (0,098882)	-0,0194 (0,064782)	0,0001 (0,100162)	-0,0851 (0,058478)	-0,0837 (0,066175)
	August	-0,0838 (0,060916)	-0,0870 (0,056619)	-0,1306 (0,098627)	-0,1555 (0,073587)	-0,1331 (0,099275)	-0,1271 (0,072109)	-0,1887 (0,082421)
	September	-0,0356 (0,073673)	-0,0451 (0,066635)	0,0131 (0,106111)	-0,0307 (0,110217)	-0,1040 (0,141472)	-0,0072 (0,06983)	0,0175 (0,098186)
	October	-0,0357 (0,075305)	0,1100 (0,062066)	0,0214 (0,100242)	0,1781 (0,080276)	0,1978 (0,117089)	0,0269 (0,075542)	0,0379 (0,075516)
	November	0,0620 (0,055062)	-0,0491 (0,052398)	0,1047 (0,089395)	0,0213 (0,058425)	-0,0520 (0,098474)	0,1014 (0,053729)	0,1240 (0,067118)
	December	0,1188 (0,041641)	0,2634 (0,054269)	0,1516 (0,088526)	0,1859 (0,061004)	0,3287 (0,09024)	0,1178 (0,061593)	0,1758 (0,073598)
Diagnostic test	Ljung–Box Q test p-value	0,68	0,05	0,94	0,32	0,25	0,48	0,54
	Jaque-Bera p-value	0,00	0,68	0,00	0,63	0,94	0,00	0,00
	Skewness	0,31	0,03	0,10	0,19	-0,05	0,72	0,63
	Kurtosis	4,8	2,62	4,34	3,12	2,9	4,32	4,31
	ARCH p-value	0,51	0,78	0,91	0,47	0,75	0,33	0,45

Table 5.4 Preferred ARMA model and diagnostic test overview

Source: © Clarkson Research Services Limited 2016

The residual analysis strives to test in the first section if the residuals mirror approximately white noise, which is usually conducted via a Box-Ljung (1978) Q-test statistic for serial correlation. Based on the null hypothesis that $H_0 = p_1, \ldots p_q = 0$, with $q = 36$, which is approximately one-third of the used sample size, the first $q(36)$ correlation in the residuals are equal to zero. In regards, to the latter section of table 5.4 and table 5.5, the p-value each model rejects autocorrelation in the residuals. Hereby, it worth noting that the *North Sea to Continent* route is slightly above the 5% significance level. The Jarque-Bera normality test, which tests if the residuals are normal distributed, displays some problematic issues, in regards to rejecting normality for the routes *South East Asia to East Coast Australia, Caribbean to US Gulf, Middle East Gulf to US Gulf* and *Middle East Gulf to Singapore*, due to high kurtosis. Nonetheless, the maximum likelihood estimators display consistency even when the error term is not normal. Therefore the rejection of normality is not impacting the validity of the models. The ARCH Heteroskedasticity test rejects heteroskedasticity and accepts homoscedasticity for each model. Based on the residual tests the time-series mirror white noise and provide forecasting possibility.

Chapter 6 - Multivariate models

Au contraire to *chapter 5*, the current sections consider multivariate time-series models. According to Verbeek (2004, p. 309), multivariate models strive to enhance knowledge about time-series X_t from Y_t or Y_{t_1}as a lagged second time-series. Thus, enables to model the relationship between these two time-series. In general, testing dynamic time-series model requires in general stationarity. The *figure 6.1*, showcases the applied models in regards to their observation period and multivariate time-series selection.

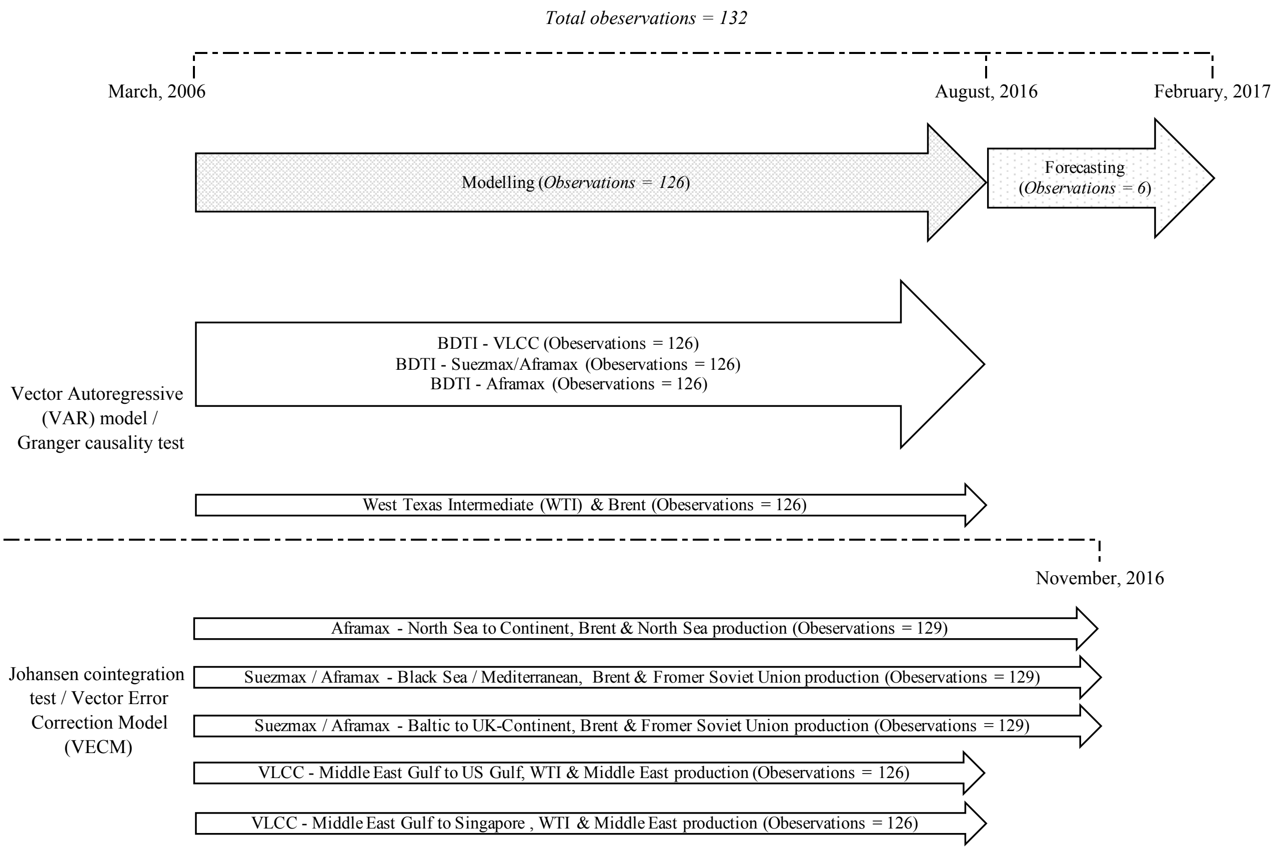


Figure 6.1 Data overview

Source: © Clarkson Research Services Limited 2016, Federal Reserve Bank of St. Louis and U.S. Energy Information Administration

Note: Vector Autoregressive (VAR) model uses the sample and forecast application in *chapter 7*

This section introduces besides the seven Baltic Dirty Tanker Index routes, crude oil prices of the two benchmarks *Brent* and *West Texas Intermediate* and crude oil production in the *North Sea, Former Soviet Union* and the *Middle East*. As discussed in *chapter 4*, previous literature has partially determined the internal factors of the Baltic Dirty

Tanker Indexes, regarding crude oil prices and trade routes. In this paper, a vector autoregressive model (VAR), which includes crude oil prices, evaluates the relationship between the two benchmarks and the BDTI routes. Further, incorporates the Granger Causality test. In the latter part of this section, a possible cointegrating relationship between crude oil prices, - production location and BDTI is analysed.

6.1 Pre-processing data

In regards to *section 5.1.1*, the Augmented Dickey-Fuller test for stationarity is utilised on level and log-returns with lags based on the Akaike Information Criterion (AIC).

		Intercept only	Trend and intercept	No trend and no intercept
		Test statistics and (MacKinnon one-sided p-value)		
Crude oil price benchmark	Brent level	-2,20	-2,25	-0,82
		(0,2072)	(0,4565)	(0,3556)
	Brent log-returns	-7,93	-7,91	-7,95
		(0,0000)	(0,0000)	(0,0000)
	WTI level	-2,93	-3,07	-0,80
		(0,0446)	(0,1157)	(0,3660)
	WTI log-returns	-5,94	-5,94	-5,96
		(0,0000)	(0,0000)	(0,0000)
Crude oil production	North Sea level	-2,35	0,20	-2,55
		(0,1564)	(0,9978)	(0,0109)
	North Sea log-returns	-3,78	-4,33	-2,57
		(0,0041)	(0,0040)	(0,0103)
	Former Soviet Union level	-1,80	-2,77	2,48
		(0,3782)	(0,2100)	(0,9969)
	Former Soviet Union log-returns	-11,42	-11,45	-10,86
		(0,0000)	(0,0000)	(0,0000)
	Middle East level	0,18	-1,48	1,05
		(0,9705)	(0,8305)	(0,9227)
	Middle East log-returns	-11,21	-11,42	-11,16
		(0,0000)	(0,0000)	(0,0000)

Table 6.1 Augmented Dickey-Fuller test of level and log-returns with lags based on AIC

Source: © Clarkson Research Services Limited 2016

The crude oil benchmark, *Brent* and *WTI*, are non-stationary throughout each model while turning stationary after being transformed to log-returns as described in *section 5.1.1*. The time-series *North Sea crude production* at level rejects the hypothesis of non-stationarity at the simple random walk while accepting non-stationarity for the other two models. This issues might indicate misspecification, however the transformation to log-returns makes the variables stationary. The crude oil production in the *Former Soviet Union* and *Middle East* accepts non-stationarity at level while rejecting such at log-return.

The *table 6.2*, showcases the lagged correlation between BDTI routes, crude oil prices and –production. It is interesting to mention that none variable shows significant correlation while being mostly positively correlated. The missing link between crude oil prices is particularly interesting due to the direct influence of bunker fuels, on the BDTIs. On the contrary, the correlation indicates that no serial correlation is present among the variables, neither at $t-1$, $t-2$ nor at higher lags $t-6$ and $t-12$.

		Aframax			Suezmax / Aframax		VLCC	
		South East Asia to East Coast Australia	North Sea to Continent	Caribbean to US Gulf	Black Sea / Mediterranean	Baltic to UK-Continent	Middle East Gulf to US Gulf	Middle East Gulf to Singapore
Crude oil price benchmark	$Brent$	0,0763	0,0802	0,0596	0,0780	0,0254	0,1679	0,1684
	$Brent_{t-1}$	0,2994	0,1528	0,0367	0,1515	0,1063	0,1529	0,1162
	$Brent_{t-2}$	0,1905	0,0878	0,0429	0,0374	0,0615	0,1454	0,1285
	WTI	0,1253	0,1151	0,0849	0,1095	0,0836	0,1844	0,1759
	WTI_{t-1}	0,2757	0,1627	0,0428	0,1145	0,0812	0,1550	0,1233
	WTI_{t-2}	0,2000	0,0516	0,0412	0,0352	0,0266	0,1029	0,0939
Crude oil production	$North\ Sea$	0,1077	0,1789	0,0602	0,2012	0,2381	0,0882	0,1017
	$North\ Sea_{t-1}$	0,0786	-0,0704	0,0470	-0,0135	-0,0771	0,0337	-0,0105
	$North\ Sea_{t-2}$	0,0735	0,1713	0,0870	0,0554	0,1549	0,0288	0,0772
	$Former\ Soviet\ Union$	-0,0282	-0,1249	-0,1004	0,0206	-0,0800	0,0666	0,1601
	$Former\ SovietUnion_{t-1}$	0,1401	0,0115	-0,0118	0,0342	0,0378	0,0622	0,0291
	$Former\ Soviet\ Union_{t-2}$	0,1759	0,2546	0,1406	0,2686	0,2427	0,1198	0,1425
	$Middle\ East$	0,1936	0,0685	0,1353	-0,0062	-0,0033	0,1052	0,1608
	$Middle\ East_{t-1}$	0,0627	-0,0327	-0,1260	-0,0139	-0,0200	0,0817	0,0212
	$Middle\ East_{t-2}$	0,1954	0,0613	0,1106	0,0711	0,0752	0,1038	0,0249

Table 6.2 Correlation of log-return - BDTI routes and lagged crude oil prices and –production

Source: © Clarkson Research Services Limited 2016

The inter-correlation between crude oil prices and –production is shown in *table 6.3*. While crude oil prices are in general positively correlated to production, the *North Sea* makes an exception. Highlighting the possibility that external factors influence this relationship, in the form of depleting reserves or high operating costs, based on the notion that rising oil prices trigger higher production.

		Crude oil price benchmark		Crude oil production		
		Brent	*WTI*	*North Sea*	*Former Soviet Union*	*Middle East*
Crude oil price benchmark	*Brent*	1,0000	0,9259	-0,0209	-0,0121	0,2104
	$Brent_{t-1}$	0,3841	0,4040	-0,0954	-0,0202	0,2695
	$Brent_{t-2}$	0,1735	0,2748	-0,0957	-0,0936	0,2414
	WTI	0,9259	1,0000	-0,0194	-0,0376	0,2488
	WTI_{t-1}	0,3783	0,3939	-0,0811	0,0093	0,2518
	WTI_{t-2}	0,1505	0,2349	-0,1121	-0,1021	0,2857
Crude oil production	*North Sea*	-0,0209	-0,0194	1,0000	0,1004	0,0771
	$North\ Sea_{t-1}$	-0,0511	-0,0582	-0,2280	-0,2251	-0,1626
	$North\ Sea_{t-2}$	-0,0750	-0,0445	-0,2798	-0,0090	0,0536
	Former Soviet Union	-0,0121	-0,0376	0,1004	1,0000	0,0171
	$Former\ SovietUnion_{t-1}$	0,0718	0,0878	-0,0546	-0,0971	-0,0011
	$Former\ Soviet\ Union_{t-2}$	0,0643	0,0290	0,2007	-0,3013	-0,0884
	Middle East	0,2104	0,2488	0,0771	0,0171	1,0000
	$Middle\ East_{t-1}$	0,1118	0,0865	-0,0142	-0,0542	-0,0169
	$Middle\ East_{t-2}$	0,0397	0,0535	-0,0768	-0,2365	0,0263

Table 6.3 Inter - Correlation of log-return of lagged crude oil prices and –production

Source: © Clarkson Research Services Limited 2016

6.2 Vector autoregressive model

The vectorised AR (VAR) model , strives to model the dynamic evolution of multiple time-series. In case of two information sets x_t and y_t the VAR model is illustrated by the *equations 6.1*, in first order (Verbeek, 2004, p. 321);

$$\begin{aligned} y_t &= \delta_1 + \theta_{11} y_{t-1} + \theta_{12} x_{t-1} + \varepsilon_{1t} \\ x_t &= \delta_2 + \theta_{21} y_{t-1} + \theta_{22} x_{t-1} + \varepsilon_{2t} \end{aligned} \tag{6.1}$$

In this case ε_{1t} and ε_{2t} are two white noise processes. VAR models with higher order up to p are expressed by addition terms; $\theta_p y_{t-p} + \theta_p x_{t-p}$. If the θ_p parameter is equal to zero, than the '*history of x helps explaining y*' (Verbeek, 2004, p. 322). The system is than expressed for a VAR(1) via the *equation 6.2*;

$$\begin{pmatrix} y_1 \\ x_t \end{pmatrix} = \begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix} + \begin{pmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{pmatrix} + \begin{pmatrix} y_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{6.2}$$

Zivot & Wang (2003, p. 383), refer to the vector autoregressive (VAR) model as '*a natural extension of the univariate autoregressive model to dynamic multivariate time series*'. The application of such model provides in comparison to univariate time series models often superior descriptions of dynamic behaviour and forecasts, '*because the information set is extended to also include the history of the other variables*' (Verbeek, 2004, p. 322) and fewer lags. The applied VAR model will model the Baltic Dirty Tanker Index routes as well as the crude oil benchmarks simultaneously. Additionally, monthly dummies are added to display any cyclical activities.

The estimation of a VAR model according to Verbeek (2004, p. 323), implies the usage of the ordinary least squares equation by equation, i.e. the ordinary least squares equation is applied to each equation separately. Verbeek advices to estimate multiple VAR model and select the parameters via an Information criterion, rather than an univariate autocorrelation or partial autocorrelation function. Initially, the parameters of the VAR(p) are applied to generate the vector of residual and then utilised to measure the covariance matrix of the residuals, which illustrates the covariance between the residuals. Based on the ordinary least square value matrix the maximum value of the likelihood function is measured.

Maritime research utilises the VAR model as a valuable tool to model and forecast freight rates. In regards to *chapter 4*; Cariou & Wolff (2006) investigated the impact on bunker fuel price, spot freight- and time charter rates. Kavussanos & Nomikos (2003) forecasted Baltic indexes. Veenstra (1999), visualised spot freight- and time charter rate differences. Wright (1999), investigated the relationship between tanker spot freight indexes and one-year time charter rates. Veenstra & Franses (1997), predicted freight rates.

6.2.1 VAR model with BDTI routes and crude oil prices

In regards, to the *figure 6.1* each Baltic Dirty Tanker Index route, is matched with the crude oil price benchmarks, i.e. $VAR(BDTI\,TD1, WTI)$ and $VAR(BDTI\,TD1, Brent)$. The vector autoregressive (VAR) model is applied in *chapter 7* for forecasting purposes. Therefore this setting incorporates 126 observations as a sample. The models are estimated by the ordinary least square equation and include monthly dummy.

Eviews 9.5, utilizes the process of overfitting and selects the appropriate model based on the AIC. The preferred model is displayed in *table 6.4*, in regards to BDTI route, oil benchmark and lags, coefficients and standard errors and residual diagnostic tests. Hereby, it is interesting to note in regards to that the monthly dummy variables that cyclical activity is indicated, i.e. negative coefficients in January - February and approximately from July – September, while being positive in the last quarter.

		Aframax												Suezmax / Aframax	
		South East Asia to East Coast Australia				North Sea to Continent				Caribbean to US Gulf				Black Sea / Mediterranean	
		WTI		Brent		WTI		Brent		WTI		Brent		WTI	
		Coefficient and (standard error)													
Vector autoregressive model	Lag - Akaike information criterion (AIC)	1		1		1		1		2		2		2	
		Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil
	BDTI (-1)	0,0417	-0,0059	0,0484	-0,0048	-0,4675	0,0320	-0,4586	0,0374	-0,4836	-0,0139	-0,4813	0,0060	-0,3077	-0,0212
		(0,0927)	(0,0573)	(0,0915)	(0,0568)	(0,0837)	(0,0448)	(0,0838)	(0,0444)	(0,0891)	(0,0350)	(0,0889)	(0,0348)	(0,0957)	(0,0422)
	BDTI (-2)									-0,3994	-0,0520	-0,4044	-0,0599	-0,2005	-0,0210
										(0,0884)	(0,0347)	(0,0885)	(0,0347)	(0,09561	(0,04220)
	Crude oil price (-1)	0,4333	0,3446	0,4761	0,3360	0,4944	0,3318	0,4604	0,3237	0,3458	0,3058	0,3190	0,3324	0,3902	0,3033
		(0,1465)	(0,0905)	(0,1454)	(0,0902)	(0,1693)	(0,0906)	(0,1704)	(0,0903)	(0,2438)	(0,0958)	(0,2460)	(0,0963)	(0,2192)	(0,0967)
	Crude oil price (-2)									0,2782	0,1530	0,3332	0,0740	0,2147	0,1478
										(0,2445)	(0,0960)	(0,2432)	(0,09531	(0,2226)	(0,0982)
Diagnostic test	Portmanteau test p-value	0,75		0,85		0,23		0,46		0,27		0,44		0,23	
	Jaque-Bera p-value	0,14		0,17		0,90		0,89		0,02		0,04		0,89	
	ARCH p-value	0,17		0,17		0,40		0,26		0,68		0,56		0,10	

		Suezmax / Aframax						VLCC							
		Black Sea / Mediterranean		Baltic to UK-Continent				Middle East Gulf to US Gulf				Middle East Gulf to Singapore			
		Brent		WTI		Brent		WTI		Brent		WTI		Brent	
		Coefficient and (standard error)													
Vector autoregressive model	Lag - Akaike information criterion (AIC)	1		3		3		1		1		1		1	
		Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil	Eq. route	Eq. oil
	BDTI (-1)	-0,2594	-0,023	-0,6024	-0,019	-0,5707	-0,013	-0,0918	-0,039	-0,0914	-0,035	-0,2055	-0,021	-0,2064	-0,022
		(0,0926)	(0,0404)	(0,1003)	(0,0382)	(0,0987)	(0,0365)	(0,0955)	(0,0414)	(0,0956)	(0,0412)	(0,0939)	(0,0353)	(0,0943)	(0,0352)
	BDTI (-2)			-0,5393	0,0983	-0,4034	-0,0964								
				(0,1179)	(0,0449)	(0,1067)	(0,0395)								
	BDTI (-3)			-0,2218	-0,1123	-0,0986	-0,0955								
				(0,1270)	(0,0484)	(0,0985)	(0,0364)								
	Crude oil price (-1)	0,5054	0,3447	0,6903	0,2890	0,4772	0,3069	0,4416	0,3624	-0,4358	-0,353	0,5366	0,355	0,5227	0,3486
		(0,2086)	(0,0909)	(0,2682)	(0,1022)	(0,2578)	(0,0955)	(0,2110)	(0,0914)	(0,2124)	(0,0917)	(0,2435)	(0,0916)	(0,2459)	(0,0920)
	Crude oil price (-2)			0,5816	0,2463	0,6158	0,1412								
				(0,2746)	(0,1047)	(0,2745)	(0,1017)								
	Crude oil price (-3)			-0,079	-0,16	0,1029	0,0077								
				(0,2879)	(0,1098)	(0,2618)	(0,0970)								
Diagnostic test	Portmanteau test p-value	0,54		0,44		0,77		0,28		0,84		0,34		0,85	
	Jaque-Bera p-value	0,90		0,54		0,62		0,00		0,00		0,01		0,01	
	ARCH p-value	0,06		0,62		0,75		0,96		0,84		0,93		0,94	

Table 6.4 Vector autoregressive model and diagnostic test

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In regards to the *section 5.2.2*, the VAR model includes the white noise assumption of the residuals in the model. The residual diagnostic tests include the Portmanteau serial correlation test, Jarque-Bera normality test and the ARCH heteroskedasticity test. The Portmanteau test is based on the null hypothesis of no serial correlation in the first number of lag in the residuals (Verbeek, 2004, p. 285), which all applied VAR models accept in in regards to no serial correlation. Thus, indicating the appropriate model choice by the information criterion. The Jarque-

Bera normality test is rejected in the models; (*Caribbean to US Gulf, WTI*), (*Caribbean to US Gulf, Brent*), (*Middle East Gulf to US Gulf, WTI*), (*Middle East Gulf to US Gulf, Brent*) and (*Middle East Gulf to Singapore ,WTI*). Based on the fairly large sample $N > 100$, the rejection of normality is not influencing the consistency of the models' estimates. The ARCH heteroskedasticity test, accepted the null hypothesis of no heteroskedasticity across all models.

The following *section 6.2.2*, further evaluates the relationship between Baltic Dirty Tanker Index routes and the crude oil price benchmarks, based on Granger causality test.

6.2.2 VAR based Granger causality test

The VAR model estimations in the preceding section, are further discussed in regards to the Granger causality test (Granger, 1969). The application in the maritime context, has already been conducted by Cariou & Wolff (2006), in regards to the impact on bunker fuel price, spot freight- and time charter rates and by Poulakidas & Joutz (2009), who successfully determined that spot freight rates and oil price surges are interlinked.

This test measures the predictive causality between the Baltic Dirty Tanker Index rates and crude oil benchmarks, i.e. whether x_t causes y_t and which information of the current y_t is explained by past observations of y_{t-p} and whether additionally lagged x_t improve the causality. The tests outcome shows a two-way causation, in regards x_t causes y_t and y_t causes x_t. These cases apply in a VAR (1) model in *equation 6.2*, if $\theta_{12} \neq 0$. The estimation of the Granger causality test is based on the hypothesis $H_0 = \theta_{12} = 0$, in such case x_t does not causes y_t. A higher order VAR(p) model extends the null hypothesis $H_0 = \theta_{12t-1} = \theta_{12t-2} = \cdots = \theta_{12t-p} = 0$.

In regards to *section 4.1* the BDTI is impacted by voyage expenses, such as crude oil prices, which have a significant impact on the operational vessel expenses in the form of bunker fuel costs. Under this notion, crude oil prices should have predictive causality on BDTI rates. The *table 6.5,* justifies this, in regards to the p-values for all routes under the 10% significance level. Appling a more conventional 5% level, WTI causes five- and Brent causes six BDTI routes. Even at a 1% level, this applies for three WTI- and Brent-related routes. In practice, this means that past crude oil price observations contain information about current observation in the BDTI rates.

		$H_0 =$ *WTI crude oil prices do not granger cause BDTI route*	$H_0 =$ *Brent crude oil prices do not granger cause BDTI route*	$H_0 =$ *BDTI routes do not granger cause WTI crude oil price*	$H_0 =$ *BDTI routes do not granger cause Brent crude oil price*
		p-value	p-value	p-value	p-value
Aframax	South East Asia to East Coast Australia	0,0030	0,0011	0,9173	0,9326
	North Sea to Continent	0,0035	0,0069	0,4745	0,3993
	Caribbean to US Gulf	0,0861	0,0762	0,3094	0,1568
Suezmax / Aframax	Black Sea / Mediterranean	0,0547	0,0154	0,8188	0,5643
	Baltic to UK-Continent	0,0010	0,0032	0,0204	0,0174
VLCC	Middle East Gulf to US Gulf	0,0364	0,0402	0,3504	0,3946
	Middle East Gulf to Singapore	0,0276	0,0336	0,5612	0,5332

Table 6.5 Granger causality test

Source: © Clarkson Research Services Limited 2016

The significant WTI-related routes are BDTI routes are*; South East Asia to East Coast Australia, North Sea to Continent, Black Sea / Mediterranean, Baltic to UK-Continent, Middle East Gulf to US Gulf, Middle East Gulf to Singapore*. While the Brent-related routes include additionally, *Black Sea / Mediterranean*. In contrast, only the *Baltic to UK-Continent* route granger causes crude oil prices at a significance level of 5%. The fact that this Suezmax / Aframax route, which operates in a confined trade zone in Europe, rejects the null hypothesis of the Granger causality test, might reflect the geographical dependency of seaborne transportation. At last, the *Caribbean to US Gulf* route accepts the H_0, which also incorporates on average smallest Aframax tanker vessel with 70,000 DWT. The missing link between crude oil prices and this particular route might stem from the influence of mixed clean- and dirty oil product trade. Therefore, skewing the causality.

6.3 VECM model and Johansen cointegration test

Prior models, demand that non-stationary time-series are transformed in order to avoid spurious regressions (Verbeek, 2004, p. 313). The log-returns transformation has been so far enforced throughout the ARMA- and VAR models. In terms of cointegrated time-series, i.e. multiple non-stationary obtain stationarity when combined, builds the exception. The Johansen cointegration test (Johansen, 1988), which is a '*multivariate generalization of the Augmented Dickey-Fuller test'* (Dwyer, 2015, p. 1), provides an option to test for cointegration via the maximum likelihood method and measures the estimates for the cointegrating vectors. The test utilizes a VAR(p) model as written in the *equation 6.4*;

$$\Delta y_t = \delta + II y_{t-1} + \theta_1 y_{t-1} + \cdots + \theta_{t-p+1} + \Delta y_{t-p+1} + \varepsilon_t \tag{6.4}$$

The *equation 6.4*, refers to a Vector Error Correction Model (VECM), where y_t is the vector of non-stationary variables, II the coefficient matrix and ε_t the vector of innovations. The coefficient matrix $\mathrm{n} \times \mathrm{r}$, illustrates the number of variables, while r specifies the rank of the II. This matrix can be expressed as $II = \gamma\beta$, where the matrix γ includes the weights and the matrix β contains the cointegration vectors. The equations are than evaluated by the maximum likelihood in regards to different rank values. The outcome the log-likelihood function than depends on such rank value, in regards to this the standard likelihood ratio test is applied. In case the rank is 0, than it indicates no cointegration and the combination of time-series in non-stationary, while the same rank as variable numbers shows stationarity. In the residual case, i.e. rank higher than 0 but not the same as variable numbers, than it is evident that there are a number of cointegration relationships given (Dwyer, 2015). Therefore, the null hypothesis for the Johansen cointegration test is $H_0 : r = 0$, while $r \geq 1$ indicates the alternative hypothesis, which means that there is at least one cointegration relationship. The table 6.6, displays that cointegration is rejected for each model, with the exception of the BDTI routes *Black Sea / Mediterranean* and *Baltic to UK-Continent*.

		Aframax	Suezmax / Aframax		VLCC	
Route		North Sea to Continent	Black Sea / Mediterranean	Baltic to UK-Continent	Middle East Gulf to US Gulf	Middle East Gulf to Singapore
Crude oil benchmark		Brent	Brent	Brent	WTI	WTI
Crude oil production		North Sea	Former Soviet Union	Former Soviet Union	Middle East	Middle East
	Observations	125	125	125	122	122
	Lag - Akaike information criterion (AIC)	3	3	3	2	2
Johansen co-integration test	Trace statistic	23,13	42,99	45,38	24,23	27,01
	Critical value (0,05)	29,79	29,79	29,79	29,79	29,79
	p-value	0,2396	0,0009	0,0004	0,1906	0,1012
Vector Error Correction model equation	R-squared		0,2479	0,3179		
	Prob. (F-statistic)		0,0002	0,0000		
	Coefficent (1)		-0,0084	-0,2058		
	Coefficent (1) p-value		0,2407	0,0416		
	Wald test (F-statistic) - Crude oil production		0,0220	0,0887		
	Wald test (F-statistic) - Crude oil price		0,1004	0,2823		
Diagnostic test	Breusch-Godfrey serial correlation LM test		0,3188	0,5163		
	Jaque-Bera p-value		0,0000	0,3149		
	Breusch Pagan heteroscedasticity test		0,0085	0,0000		

Table 6.6 Johansen co-integration test vector error correction model

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The *Black Sea / Mediterranean*'s vector error correction equation, calculated via the least square method, rejects the hypothesis of an existing long-run relationship based on the error corrective term. However, the parametric statistical Wald test, shows a short-run relationship running from *Former Soviet Union crude oil production* to the BDTI route *Black Sea / Mediterranean*. In regards to the latter section, residual diagnostic tests, in the form of the Breusch-Godfrey serial correlation LM test, Jaque-Bera normality test and Breusch Pagan heteroscedasticity test are performed. The model rejects the alternative hypothesis of present serial correlation while showing non-normality based on the Jaque-Bera p-value and a kurtosis ≥ 3. The heteroscedasticity test accepts the alternative hypothesis of present heteroscedasticity.

The BDTI route *Baltic to UK-Continent*, also accepted the hypothesis on an existing long-run relationship based on the error corrective term, while rejecting a short-run relationship between crude oil production and –price. Serial correlation is rejected, while normality and heteroscedasticity are accepted.

Both models indicate a relatively low R^2, which means only a fraction of the variability of the response data is around its mean. In conclusion, based on the diagnostic tests both accepted models, indicate flaws, which may lead to the rejection of such.

Chapter 7 - Forecasting

Based on the research question, which strives to answer whether econometric models are capable of forecasting crude oil tanker spot freight rates, the ARMA- and VAR model, have been presented in *chapter 5* and *chapter 6*. As showcased in *table 4.7* and *table 6.1* the forecast period consists of six months, i.e. September 2016 – February 2017, which is the forecast horizon h. This chapter utilises static and dynamic forecasting based on the seven ARMA route models and fourteen VAR models and benchmark them to a random walk model, applying common performance criteria. The random walk, referred to a first order autoregressive process AR(1) (Verbeek, 2004, p. 266) and predicts simple that there is zero change from the current level. A static forecast uses a one-step ahead forecast, i.e. each step t_1 contains the information pervious step t_0. The forecast is conduct step by step until the end of the forecast period. A dynamic forecast uses a multi-step forecast, i.e. the forecasted period is based on the pervious period while being not updated.

The *forecasting section* incorporates a critical evaluation of the performance criteria, an outline of ARMA- and VAR model forecasting and the results.

7.1 Performance criteria

Based on Chai and Draxler (2014, p. 1274), econometric literature relays on the root mean square error (RMSE) as a '*standard statistical metric to measure model performance in meteorology, air quality, and climate research studies*', while the mean absolute error (MAE) is commonly applied in model evaluations. Both performance criteria evaluate a forecast in regards to the economics loss of an incorrect prediction, i.e. the actual value y_{T+h} is subtracted from the forecasted value $\hat{y}_{T+h}$. The MAE summarises the absolute value of the prediction error and expressed by the *equation 7.1*;

$$MAE = \frac{1}{n}\sum_{h=1}^{n}(y_{T+h} - \hat{y}_{T+h}) \tag{7.1}$$

In the *equation 7.1*, n observations in the forecasted period, while h is the forecast horizon of six months. The RMSE, illustrates the square root of the quadratic errors and associates a relatively high weight to large errors in comparisons to smaller errors. Therefore, the loss functions' value rises at an increasing rate in regards to the error. The RMSE is of use when large prediction error are undesirable.

The RMSE is expressed by the *equation 7.2*;

$$RMSE = \sqrt{\frac{1}{n}\sum_{h=1}^{n}(y_{T+H} - \hat{y}_{T+H})^2} \qquad (7.2)$$

The MAE and RMSE can be used to express an average model prediction error in the units of the Baltic Dirty Tanker Index. The error direction is indifferent for both and metrics range from zero to infinity. The main difference lies in the interpretation, i.e. if missing by 2 is more than twice as worse as missing by 1, than the RMSE is favoured, while is missing by 2 is just twice as worse as missing by 1, than the MAE is appropriate.

Therefore in the context of the Baltic Dirty Tanker Index, companies might favour in recessions the RMSE, based on the notion that it depicts the business environment more accurate the MSE. If expectations are more than worse, than risk mitigation strategies might be more effective, while if expectations are more than good, than overestimation might have an negative affect. Due to this intrinsic problem, the root mean square error as well as the mean absolute error are allocated to evaluate the performance of the forecasts.

7.2 ARMA

Verbeek (2004, p. 288 – 291), suggests that the information set I_T includes at any t the value of y_T with its lags and is expressed as $I_T = [y_1, y_2, \dots, y_T]$, referring to the information set, while the optimal prediction y_{T+h} is equal to the conditional expectation y_{T+h}. Therefore, the optimal prediction is illustrated as $E(y_{T+h}| \, y_1, y_2, \dots, y_T)$. Verbeek approaches the ARMA forecast by analysing the AR- and MR processes separately before merging. In an AR(1) model, which includes no constant, the conditional expectation in an one-step ahead forecast is illustrated in *equation 7.3*;

$$y_{T+1} = \theta_1 y_T + \varepsilon_{T+1} \qquad (7.3)$$

As the expected value of $\varepsilon_{T+1} = 0$, than the one-step ahead forecast turns to $\theta_1 y_T$, under the premises that $|\theta| < 1$. In an h-step ahead forecast the same notion applies, therefore is expressed as $\theta_1^h y_T$. The error term converge to zero in case the process has no constant and is stationary. In a MA (1), which includes no constant, the conditional expectation for a one-step ahead forecast is expressed as $\emptyset_1 \varepsilon_T$, while ε_T is contained in the realizations of y. For a h-step ahead forecast the conditional expectation turns to 0. The one-step prediction of an ARMA model with $\hat{y}_{T+1}$ as the predictor and the unobserved error term $\varepsilon_T = y_T - \hat{y}_{T|T-1}$ the model is illustrated in the *equation 7.4*;

$$\hat{y}_{T+1|\,I_T} = \theta_1 y_T + \theta_2 y_{T-1} + \cdots + \theta_p y_{T-p+1} + \emptyset_1 \hat{\varepsilon}_T + \emptyset_2 \hat{\varepsilon}_{T-1} + \cdots + \emptyset_q \varepsilon_{T-q+1} \tag{7.4}$$

The h-step prediction of an ARMA model turns to an AR(p) model, based on the issue that MA(q) parameters become irrelevant after $h > q$. The h-step forecast is expressed in the *equation 7.5*;

$$\hat{y}_{T+h|\,I_T} = \theta_1 \hat{y}_{T+h-1|I_T} + \cdots + \theta_p \hat{y}_{T+h-p|I_T} + \emptyset_1 \hat{\varepsilon}_{T+h-1|I_T} + \cdots + \emptyset_q \hat{\varepsilon}_{T-h-p|I_T} \tag{7.5}$$

7.4 VAR

A one-step ahead forecast for a VAR(2) model estimates the AR matrix θ_1 and the second matrix θ_2, based on the given observations. The prediction of $\hat{y}_{n+1|\,I_T}$ can than be illustrated by the *equation 7.6*;

$$\hat{y}_{n+1|\,I_T} = \delta + \theta_1 y_T + \theta_2 y_T \tag{7.6}$$

A dynamic forecast for a VAR(2) model updates the given time-series with the forecasts and based on this it predicts the next h-steps ahead as show in *equation 7.7*;

$$\hat{y}_{n+h|\,I_T} = \delta + \theta_1 \hat{y}_{T+h-1} + \theta_2 \hat{y}_{T+h-2}. \tag{7.7}$$

7.5 Results

This section summarises the ARMA-, VAR- and random walk model's static and dynamic forecasts. The performance criteria, MAE and RMSE, and the benchmarked random walk ratio in percentage is displayed for each Baltic Dirty Tanker Index route in *table 7.1* and *table 7.2*. The first paragraph illustrates some general consideration, while the latter ones evaluated each BDTI route separately; The *static forecast* shows that the WTI-related VAR model performs better than the random walk model, while the Brent-related VAR- and the ARMA model are only marginally better than the random walk model. The *dynamic forecast,* underlines that the WTI-related VAR model has better forecasting abilities than the random walk model, while the other two models underperform. The performance of the VAR model, confirms the usefulness of the crude oil benchmark WTI in predicting the progression of the BDTI routes. Further, emphasising that the Granger causality test has determined this in *section 6.2.2*. The RMSE and MAE prediction error, showcase that the forecast is on average between 10% - 25% off the actual time-series. Therefore, highlighting that the none of these models are on average particular useful to forecast the BDTI routes.

South East Asia to East Coast Australia, illustrates that the WTI-related VAR model performs better than the random walk, while the other two model perform either worse or nearly the same as worse as the random walk, both in the *static*- and *dynamic forecast*. The RMSE and MAE, showcase that the forecast is off by 10% - 13%. *North Sea to Continent,* suggests in the *static*- and *dynamic forecast* the WTI-related VAR- and the ARMA model outperform the random walk while being in regards to the performance criteria between 12% - 17% off the actual time-series. *Caribbean to US Gulf,* each model in the *static forecast,* performs better than the random walk while displaying such in the *dynamic forecast* only for the WTI-related VAR model. The RMSE and MAE, show that the models are on average off by 14% - 24%. *Black Sea / Mediterranean* and *Baltic to UK-Continent*, both routes display the same patterns in terms of model performance, the WTI-related VAR- and the ARMA model outperform the random walk in the *static forecast*, while only WTI-related VAR-model achieves such in the *dynamic forecast*. The performance criteria suggest that both time-series forecasts are off by 15% - 25%. *Middle East Gulf to US Gulf*, indicates that WTI-related VAR- and the ARMA model beat the random walk in the *static forecast,* while only WTI-related VAR-model achieves such in the *dynamic forecast.* The models are on average by 13% -19% off the actual values. *Middle East Gulf to Singapore*, showcases the same patterns in regards to the previous route. However, the performance criteria suggest that these models are off by 15% - 24%.

In conclusion, it can be stated that the WTI-related VAR model outperforms across all BDTI route the other forecasting models. The ARMA models are doing slightly better than the random walk in most cases, while still underachieving. The route *South East Asia to East Coast Australia,* in particular, seems to perform better than all other routes. It is surprising to note that the Brent-related VAR model is even beaten by random walk for Intra-European routes, based on the notion that the benchmark Brent should reflect better the crude oil market in Europe. Regarding the average RMSE prediction error of 18% in the *static forecast* and 20% in the *dynamic forecast*, and a MAE error of 14% and 15%, in the respective order, might be explainable by the volatile period between 2007 – 2009, which the time-series incorporates. It is worth noting that pervious literature such as Steen (2013), attempted to beat the random walk and failed. The notion that simplistic models outperform more complicated once is therefore nothing new.

			Random Walk	VAR - WTI benchmark	VAR - Brent benchmark	ARMA
Aframax	South East Asia to East Coast Australia	RMSE	0,208442	0,133354	0,132279	0,131741
		Ratio %		64,0%	99,2%	99,6%
		MAE	0,146101	0,101404	0,100722	0,100862
		Ratio %		69,4%	99,3%	100,1%
	North Sea to Continent	RMSE	0,34629	0,153524	0,154326	0,135797
		Ratio %		44,3%	100,5%	88,0%
		MAE	0,249755	0,120759	0,121668	0,109246
		Ratio %		48,4%	100,8%	89,8%
	Caribbean to US Gulf	RMSE	0,419235	0,206344	0,206029	0,189212
		Ratio %		49,2%	99,8%	91,8%
		MAE	0,307755	0,155122	0,154999	0,143168
		Ratio %		50,4%	99,9%	92,4%
Suezmax / Aframax	Black Sea / Mediterranean	RMSE	0,361938	0,185295	0,18785	0,177019
		Ratio %		51,2%	101,4%	94,2%
		MAE	0,279042	0,14498	0,148773	0,13866
		Ratio %		52,0%	102,6%	93,2%
	Baltic to UK-Continent	RMSE	0,469217	0,193674	0,212077	0,196131
		Ratio %		41,3%	109,5%	92,5%
		MAE	0,349576	0,154918	0,168661	0,158041
		Ratio %		44,3%	108,9%	93,7%
VLCC	Middle East Gulf to US Gulf	RMSE	0,295446	0,189347	0,18949	0,177294
		Ratio %		64,1%	100,1%	93,6%
		MAE	0,221375	0,149195	0,149513	0,138117
		Ratio %		67,4%	100,2%	92,4%
	Middle East Gulf to Singapore	RMSE	0,369305	0,218633	0,218955	0,204828
		Ratio %		59,2%	100,1%	93,5%
		MAE	0,271915	0,168955	0,170237	0,153511
		Ratio %		62,1%	100,8%	90,2%

Table 7.1 Static forecast

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			Random Walk	VAR - WTI benchmark	VAR - Brent benchmark	ARMA
Aframax	South East Asia to East Coast Australia	RMSE	0,223698	0,133325	0,132256	0,139326
		Ratio %		59,6%	99,2%	105,3%
		MAE	0,18426	0,101479	0,100689	0,104134
		Ratio %		55,1%	99,2%	103,4%
	North Sea to Continent	RMSE	0,287823	0,174209	0,174949	0,169694
		Ratio %		60,5%	100,4%	97,0%
		MAE	0,2327	0,131281	0,131864	0,125669
		Ratio %		56,4%	100,4%	95,3%
	Caribbean to US Gulf	RMSE	0,375104	0,241307	0,241423	0,245137
		Ratio %		64,3%	100,0%	101,5%
		MAE	0,296448	0,185615	0,187129	0,187069
		Ratio %		62,6%	100,8%	100,0%
Suezmax / Aframax	Black Sea / Mediterranean	RMSE	0,330419	0,195909	0,195229	0,197524
		Ratio %		59,3%	99,7%	101,2%
		MAE	0,282745	0,152473	0,152801	0,153861
		Ratio %		53,9%	100,2%	100,7%
	Baltic to UK-Continent	RMSE	0,379999	0,236976	0,246629	0,249359
		Ratio %		62,4%	104,1%	101,1%
		MAE	0,307915	0,176767	0,183951	0,18273
		Ratio %		57,4%	104,1%	99,3%
VLCC	Middle East Gulf to US Gulf	RMSE	0,251949	0,190293	0,190668	0,193756
		Ratio %		75,5%	100,2%	101,6%
		MAE	0,189787	0,150573	0,150845	0,148462
		Ratio %		79,3%	100,2%	98,4%
	Middle East Gulf to Singapore	RMSE	0,356284	0,223905	0,224902	0,225389
		Ratio %		62,8%	100,4%	100,2%
		MAE	0,280281	0,176835	0,178547	0,171208
		Ratio %		63,1%	101,0%	95,9%

Table 7.2 Dynamic forecast

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Chapter 8 - Critique and perspective

The previous chapter laid the fundament in regards to the question whether economics models are able to model and forecast crude oil spot freight rates, while this chapter is dedicated to enhance the critical understanding of the applied models. *First*, a structured recap of residual diagnostic tests is outlined to understand the potential limitations. *Second*, a nuanced observation of implication this paper might have on various stakeholders is illustrated. *Third*, the general application of forecasts in the tanker market is discussed, in regards to the efficient market hypothesis and random shocks. *Fourth*, the appropriate application of univariate- versus multivariate models in the maritime context is showcased, concerning hybrid models and a new perspective on market fundamentals.

8.1 Econometrical issues

The residual analysis tests have been conducted for each proposed model, in order to validate their outcome and potential application. The ARMA-, VAR model and VECM is based on the assumption of no serial correlation, which was tested either via Box- Ljung test, Portmanteau test or Breusch-Godfrey serial correlation LM test. Further, the residuals were tested via the Jarque-Bera test for normal distribution. Finally, the assumption of no heteroskedasticity was evaluated via the ARCH Heteroskedasticity test or Breusch Pagan heteroscedasticity test.

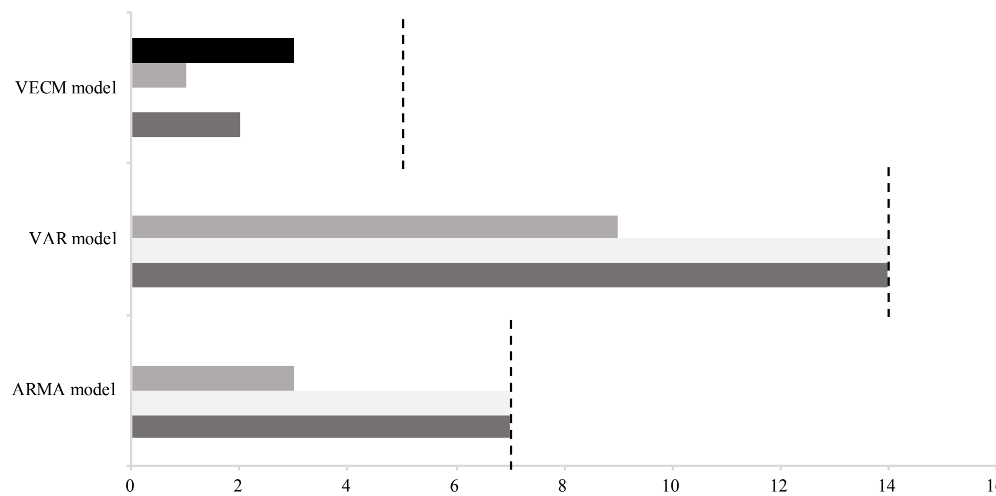

Figure 8.1 Residual analysis

■N/A ■Normality ■No heteroskedasticity ■No serial correlation

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The ARMA- and VAR model fulfilled both the assumption of no heteroskedasticity and no serial correlation while displaying problematic issue in regards to normality. In particular, the ARMA models only confirmed normality for residuals in $3\ out\ of\ 7$ models and the VAR models $9\ out\ of\ 14$ estimations. However, based on the fairly large sample of $126\ observations$, a rejection of normality is not influencing the consistency of the model estimates. Therefore, both models are validated in terms of appropriate application.

On the other hand, the VECM displayed major misspecification error, in terms of present heteroskedasticity for each model and rejection of normality. Thus demands further research and a re-evaluation of applied time-series.

8.2 Implications

This paper illustrated an approach via econometric models to evaluate and forecast crude oil tanker spot freight, to enhance the practical application, this section addresses directly the stakeholders in the global supply chains. Based on *chapter 2*, foresight in the freight market raises the positive cash flow of charterers and ship-owners, it mitigates the operational cost risks and improves the productivity of the tanker fleet. Due to the various impacts on the stakeholders, a nuanced observation of implication is demanded.

Ship-owner's or leasing charterer's bottom line result highly depend on the spot freight level, to estimate their financial performance, which includes the level of cash flow, available investment capital and market value of assets. Therefore, forecasting crude oil tanker spot freight enhances their financial decision-making process. Another aspect is the impact on strategic directions, including the order or demolition of vessels. In case freight rates are below-average, while predictions indicate an upswing, these stakeholders might hold out with the anticipation of a recovery. This point also includes routing decisions, the evaluation of multiple Baltic Dirty Tanker Index routes, enhances the understanding of the market environment, while offering potential prospects regarding fleet deployment.

Other stakeholder, such as *port operators*, *banks* and *shipyards*, have an intrinsic interest to understand freight rates. *Port operators*, which facilitate the onshore infrastructure at one of the load- or discharging ports of the BDTI routes, relay heavily on the demand of their services. The oil production in the respective geographical location enables seaborne transportation- and port service demand. As showcased, the *North Sea oil production* experienced a decline since a decade, therefore decreasing also the demand for onshore infrastructure. Another aspect are port fees, which are an integral part of the BDTI, high-level charges, decreases the attractiveness of a respective route. Moreover, the spot freight activity indicates the demand or supply for seaborne transportation services, port operators must expect that shifts in the freight market will affect their service demand directly. *Banks*, due to high capital costs in the maritime industry, financial investors are a necessity in this sector. These entities base their investments on freight rate predictions to assess the defaulting risk of such loan, underlining the potential of econometric forecasting models. *Shipyards*, depend on continuous ship investments, which are connected to a profitable freight market. Therefore, it is obvious that ship builders relay on the future outlook of the freight rates to adjust their capacity and order expectations in regards to the market environment.

Based on the outline of this paper, reliable freight rate forecasting in the tanker market and the whole maritime industry is crucial to mitigate risks and enhance profitability. Thus emphasising the necessity for an appropriate forecasting methodology, while this paper could not offer a defined superiority of econometric models it paves the path for further research.

8.3 Philosophical forecasting

'*It is not primarily in the present nor in the past that we live. Our life is an activity directed towards what is to come. The significance of the present or the past only becomes clear afterwards, in relation to this future'* (Lewis & Nakagawa, 1995, p. 2)

The Spanish philosopher, José Ortega Y Gasset, referred in his quote to the paradox of the human experience in regards to the future. This paper illustrated this strive to predict the market environment, based on the notion the knowledge about such enhances the present decision-making process.

The applied econometric models incorporated the assumptions that current observations of univariate time-series are related to their past, either directly or indirectly and that multivariate models enhance the understanding of multiple time-series, with the central argument that these models are capable of predicting the future. This argument would only hold, if efficient market hypothesis by the American Professor Eugene Fama did not apply to the Baltic Dirty Tanker Indexes, i.e. that all relevant information are already included in the index. If this hypothesis applies then there is no possibility given to beat the market and questions the idea of predicting future movements. However, some might argue that irrationality by the stakeholders skew the market and econometric models, which only utilise fundamentals are able to disregard these psychological factors, than forecasting methodologies would be beneficial. In *figure 5.1*, high volatility in the BDTI routes was visible in the time frame 2007 – 2009, showcasing to a certain degree this irrationality in the market. Therefore, providing an argument that the efficient market hypothesis does not apply to the Baltic Dirty Tanker Indexes. Moreover, the notion by Fama is coined on the properties of the stock market, rather than shipping indexes, which are non-tradable or -storable. Concluding, that the BDTI does not fall under the efficient market hypothesis, which means that econometric models are theoretically capable in this specific market to reach valid forecasts.

In regards to the applied ARMA- and VAR models, which are guided by the assumption of normal distribution, are not capable of taking into account random shocks, which might stem from onshore infrastructure projects, such as pipelines and canals or geopolitical disruptions, such as wars, labour strikes or environmental policies. Additionally, the deterministic seasonality validated by Kavussanosa & Alizadeh-M (2002) has not been considered. Based on the notion that the BDTI is influenced by unpredictable events and / or seasonality, it questions the validity of the previous forecasts. Further, *table 7.1* and *table 7.2*, showcased that only the WTI-related VAR model was able to beat a simple random walk model with a certain kind of consistency. Despite the arguments presented in favour or against the validity and reliability of forecasting frameworks, it is obvious that these can only act as a mosaic stone when implementing strategic decisions.

8.4 Further research

The theoretical foundation of the applied model in this paper is based on the book '*Modern Econometrics'* by Verbeek (2004), which separated univariate- from multivariate time-series models. Univariate models, which assume that current realisations are linked to the past ones, bear the intrinsic problematic that information sets are not extended to the history of other variables, leading to underperformance as showcased in *chapter 7*. Researchers critically argue about the appropriate application of univariate versus multivariate in the maritime context. Kavussanos & Nomikos (2003), who strived to forecast Baltic indexes and concluded that ARMA models underachieve, while a VECM performs well, while Batchelora, et al. (2007) found evidence that ARIMA models outperforms VECM. Based on this notion, maritime research strives to tackle the lacking performances, with hybrid models, which include variance models such as ARCH or the generalized ARCH. A particularly interesting example of such hybrid application was conducted by Haque Munim & Schramm (2016), who investigated container freight rates for the Far East to Northern Europe trade lane and provided evidence for the superiority of an *ARIMA-ARCH model* in comparison to a pure ARIMA model. On the other hand, Steen (2013) showcased while utilising a BDTI route that a simple random walk model could outperform an ARMA-GARCH model.

In regards to multivariate time-series models, this paper took the approach to base the fundamental factors on previous literature, rather than data mining. It introduced crude oil prices and –geographical production locations.

Therefore, consciously accepted delimitations in variable choice, which might have been interlinked with the BDTI routes. The book '*Ships and Shipping*' by Nersesian (1981), provides options to enhance the multivariate model, concerning total energy demand, seaborne fossil fuel trade and patterns, global crude oil trade patterns, transportation demand in tonne-mile and future vessel demand. The *section 2.2* and *section 2.3.1*, additionally offer a base to construct a more cohesive model in regards to demand- and supply in the tanker market.

Regarding the Baltic Dirty Tanker Index routes selection, which aimed to mirror the tanker market environment, rather than specific circumstances, might raise critique. Therefore, further research might investigate specific routes, potentially in combination with geographically linked fundamentals. In practical terms suggesting, e.g. research in regards to the VLCC route *Middle East Gulf to US Gulf* and U.S. energy demand, respective crude oil price benchmark, economics growth and onshore U.S. shale oil production.

Lastly, the appliance of WTI-related as well as Brent-related VAR model, has not been to discussion. Additional research might look into the fundamental difference of these two benchmarks in regards to the BDTI routes. Moreover, the allocation of WTI and Brent to specific routes might pose room for other econometric models.

Chapter 9 - Conclusion

This paper dedicates itself to the question whether econometric models are able to model and forecast crude oil carriers spot freight rates. The particular tanker segment accounts for approximately one-quarter of the merchant fleet in DWT, underlining the necessity to conduct research in this area. Econometric modelling and forecasting is relatively scarce and unreliable, while bearing potential to enhance the common understanding of certain economic variables.

The tanker market model acted as a solid introduction into the freight rate mechanism, illustrating the spot freight rates fundamentals, in regards to supply and demand. In the literature review, decisive studies presented the complexity of the crude oil tanker market. With partially contradicting results, econometric models have been applied to quantify the linkage between spot freight rates and new-build- and second-hand prices, time charter rates, environmental policies and bunker fuel prices.

The paper allocated seven Baltic Exchange Dirty Tanker Index (BDTI) routes for evaluation; *Middle East Gulf to Singapore, Middle East Gulf to US, Black Sea/Mediterranean, Baltic to UK-Continent, North Sea to Continent, Caribbean to US Gulf* and *South East Asia to East Coast Australia*. The time-series incorporated monthly observations from March 2006 through February 2017. The evidence of unit root made the transformation to log-returns necessary in order to achieve consistent stationarity. The correlation analysis showcased a significant positive linkage between the routes departing from the *Middle East Gulf,* additionally to a correlation between *Intra-European* routes.

The *univariate chapter* outlined the ARMA model, based on the framework by Box & Jenkins (1976). The likelihood-based Akaike Information Criterion selected the most fitting models. The estimates parameters, indicated high order models with up to AR(5)- and MA (5) terms, showing the adjustments in the tanker market of approximately one quarter. The monthly dummy variables visualised the cyclical BDTI behaviour. The residual diagnostic tests confirmed that the ARMA models are capable of fitting the time-series. Autocorrelation and heteroscedasticity were rejected, while showcasing problematic issues in regards to normal distributed residuals.

The *multivariate chapter* introduced the major crude oil benchmark prices, *West Texas Intermediate* and *Brent*, as a reference to the global crude oil market and the crude oil production in *Middle East, Former Soviet Unions* and *North Sea,* as a seaborne transportation demand indicator. Present unit root in these time-series, required the transformation to log-returns, to achieve stationarity. The correlation analysis shows no significant relationship between the BDTI routes and the explanatory variables, while indicating a mostly positive linkage. Thus illustrating no serial correlation among the time-series. The vectorised AR (VAR) model was utilised to model the dynamic evolution of the BDTI routes and crude oil price benchmarks. With this, monthly dummies confirmed cyclical activity. The residual diagnostic tests showcased no serial correlation, no heteroskedasticity and pointed out problems for some model in regards to normality. The VAR based causality test by Granger (1969), justified the notion that crude oil prices have predictive causality on BDTI rates. This applied at a conventional significance level to five WTI-related routes and six Brent-related routes. At last the VECM model rejected cointegration in each model, with the exception of the BDTI routes *Black Sea / Mediterranean* and *Baltic to UK-Continent*, while displaying major misspecification errors, in regards to heteroscedasticity.

The *forecasting chapter* utilised static and dynamic forecasting based on the ARMA- and VAR models and benchmarked them to a random walk model, applying the MAE- and RMSE performance criteria. The criteria indicated that the predictions were off by 10% - 25% from the actual monthly observations. The VAR model forecast highlighted the outcome of the Granger causality test, confirming that crude oil prices are usefulness when predicting the progression of the BDTI routes. The ARMA and Brent-related VAR model, performed close to the random walk model, while the WTI-related VAR model proved on average to be superior. The static WTI-related VAR model forecast, showcased a reliable prediction performance for the *South East Asia to East Coast Australia* route.

In the latter chapter, econometrical issues in regards to the residual tests of the ARMA-, VAR model and VECM were illustrated. Additionally, stakeholders in the global crude oil supply chain were directly addressed, providing nuanced implications, in regards to ship-owners, port operators, banks and shipyards. Further, the strive to predict market environments was discussed via the efficient market hypothesis and the shortcomings of the applied econometric models.

Finally, options to enhance the *univariate section,* in regards to more comprehensive hybrid models and a re-evaluation of *multivariate model* variable selection, were proposed. In particular, suggestions for further investigation in regards to specific routes in combination with geographically linked fundamentals, aimed to offer a new perspective.

Regarding the aspiration to model and forecast crude oil tanker spot freight via econometric models, it can be concluded that an ARMA model is capable of enhancing the common understanding of freight rates, while underperforming in forecasts. The vector autoregressive (VAR) model and Granger causality test in connection with crude oil prices and BDTI routes, proved to generate a superior description of dynamic behaviour and forecasts. Thus, providing evidence for crude oil prices' predictive causality on BDTI routes.

'*Correlation is not causation but it sure is a hint'*

Chapter 10 - Bibliography

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