Implementing the New Science of Risk Management to Tanker Freight Markets

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This thesis is dedicated to my father,

Mohamed Taher, Abouarghoub

He was and remains my inspiration and best role model in life.

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Abstract

Studies in the area of shipping freight risk measurement and management are limited and the understandings of the impact of freight volatility dynamics on the freight market remain insufficient and under-researched. The few studies that explore different approaches to measuring freight risk disagree on the most suitable measures and this is down to different interpretation of the underlying conditional variance for freight rates. Thus, the intention of this study is to contribute to the literature in the field of shipping freight risk studies. In this thesis tanker freight risk is measured using univariate and multivariate value-at-risk measures that are structured on a variety of single- and multi-state conditional variance models. Moreover, uncorrelated freight risk factors and conditional freight-beta are estimated through an orthogonal conditional variance and a dynamic freight-beta approach for a portfolio of freight returns, respectively. This thesis also investigates the hypothesis of the state dependency of freight dynamics through a conditional freight limitation framework, which distinguishes between 'ship-owner' and 'cargo-owner' markets, in particular pre- and during the most recent financial crisis. Furthermore, the short and long term effect of the financial crisis on freight markets are examined through a multi-state Markov switching-regime framework that provides thresholds indicating different freight bands for distinct market conditions. Thus, the hypothesis of variation in the freight-return relation is investigated on the basis that up and down market movements are defined as shipping agent controlled. Additionally, specific and systematic risks for the tanker market are extracted and compared across distinct tanker segments. Finally, a practical insight into shipping practitioners' measurement and management of freight risk for different shipping segments is examined, where the directional accuracy and volatility of short- and long-term forward curves are assessed and compared against a general perception in the literature.

Chapter one

1. Introduction

1.1. Background and structure

Perfect conditions prevail in shipping spot freight markets. These markets are usually held as textbook examples of perfectly competitive markets, Norman (1979), and Stopford (2009). Freight rates are considered to revert to a long-run mean and are determined by the interaction of demand and supply that are subject to random spikes. The continuous adjustment to equilibrium under these conditions ensures the unsustainability of extreme low and high freight prices, for more details see Koekebakker *et al* (2006). Therefore, these markets are known to be extreme volatile, asymmetric, seasonal and clustered in returns, and feature non-zero and higher levels of skewness and kurtosis, respectively. The implications of such conditions are profound on freight risk management strategies for ship-owners, charterers and other shipping participants. Consequently, Koopmans (1939) among other maritime economists, and most recently Strandenes (2012), explain that these characteristics shape the freight supply curve, as the level of fleet utilization increases, the freight supply curve goes from being price-elastic to price inelastic. Furthermore, the literature associate lower and higher volatility levels periods with low and high freight price-levels, respectively. These distinctive conditions are linked to down and upper market movement influenced by numerous external and internal factors, which are difficult to estimate and model. Thus, a more conditional limited structure that is easier to estimate is desirable. Tvedt (2011) proposes a theoretical framework to derive the short-run freight equilibrium through limited market indicators that is based on market agents and by restricting freight rates to a maximum upper and minimum lower freight price-level, creating a gap in the literature worth exploring. In addition to the variety of quantitative techniques proposed in the literature to estimate the underlying asset for managing freight risk, it is useful to explore current practices in freight markets to neutralise and exploit freight risk. This insight into practical techniques used by market practitioners should improve the understanding of freight risk. Furthermore, Stevens (2005) argues that strengths in oil prices are better explained by a structural change based method, postulating that the most recent prolonged strength in oil prices is attributed to a structural change in price levels. As the link between oil markets and tanker markets are well documented in the literature, it is interesting to study freight markets following the structural school of thought. Finally, the most recent financial crisis had a profound impact on global international trade, most importantly for interlinked markets such as energy, commodities and shipping services. Therefore, empirical work that investigates the exogenous/endogenous of structural breaks within freight dynamics pre and during the financial crisis is most needed.

This thesis consists of nine chapters in total. The first and last chapters are the introduction and conclusion of the thesis, respectively. The second chapter provides a brief overview and discussion of related topics from maritime literature. The third chapter describes the general framework implemented in the thesis; this is a birds-eye view of the empirical methods used within this study. Furthermore, the contribution and empirical work of this thesis is presented in five working chapters. It is important to point out that each one of the working chapters includes subsequent sections that discuss the relevant literature and methodology. Thus, the empirical work is of three clusters. First, a measure of tanker freight risk based on distinctive conditional volatility models and conditional freight-beta is proposed. Second, a practical insight into market practitioners' use of derivatives to manage freight risk is investigated and compared against an improved freight risk framework that is proposed in this thesis. Finally, an investigation into the existence of structural breaks within tanker freight earning-levels and returns is conducted, to study freight dynamics during different market conditions and most importantly their implications on risk management from the perspective of shipping agents, in particular pre and during the most recent financial crisis.

Therefore, this study expands on previous empirical attempts in the literature to explore volatility dynamics within freight price-levels and returns through several frameworks. First, freight risk for distinct tanker segments is measured using single/multi state univariate/multivariate conditional variance models. Therefore, the volatility dynamics within the elastic and inelastic parts of the freight supply curve is modelled through a two-state Markov regime-switching and distinctive conditional variance process. Furthermore, uncorrelated risk factors and conditional freight-beta are extracted and estimated for a portfolio of freight returns, respectively. Thus, in chapters 4 and 5 freight risk for single tanker routes and a portfolio of returns are measured using a value-at-risk method, respectively. Furthermore, single and multi-state conditional variance models that are proposed in chapter 4, to construct different risk measures to assess freight risk for the tanker market are compared against uncorrelated risk factors and conditional freight-beta to improve our understanding of management of freight risk within a portfolio of returns, in chapter 5.

Second, volatility directional accuracy of short- and long-term freight forward curves are measured for different tanker segments and compared against a general perception in maritime literature and the empirical wok proposed in this thesis. Therefore, in chapter 6 we provide an insight into the practical techniques used by shipping practitioners to mitigate freight risk and profit from extreme volatility through the use of freight derivatives and investigate the ability of the proposed freight risk measure in this thesis to improve freight market information.

Third, the hypothesis of a significant homogenous structural shift within freight tanker earnings that is caused by a significant structural change in oil price levels is tested, in chapter 7. The importance of such an investigation is that this phenomenon triggered the most recent prolonged period of shipping expansion. Fifth, a framework for conditional freight limitation is proposed to distinguish between two distinctive market conditions that are largely controlled by either ship-owners or cargo-owners, in particular pre and during the financial crisis, in chapter 7. Finally, the freight risk-return relation is investigated on the bases that up and down market movements are defined as ‘shipping-agent controlled’, in chapter 8.

In summary, this study attempts to improve measurements and management of freight risk by proposing a framework that accounts for state dependency and the influence of main market agents on freight volatility dynamics within the tanker market.

1.2. The thesis objectives and contributions

In this section we present the objectives and contributions of this thesis. The main aim of this study is to investigate empirically different methods of measuring and managing freight risk in tanker shipping markets and then to propose an improved risk framework, which can adapt to changes in volatility and uncertainty that are associated with the shipping industry. Furthermore, it is paramount that the ability of the proposed risk framework to improve market information is investigated and assessed. Therefore, this thesis aims to explore current market practices in exploiting and mitigating fright risk and the suitability of the new framework to improve market information.

The few papers that explore different ways of measuring shipping freight dynamics have differed in their interpretation of the most suitable measure for conditional freight volatility and consequently for the most appropriate freight risk measure. Furthermore, recent empirical work in maritime studies suggests the possibility of conditional freight volatility switching between different regime states that are dynamically distinct. This study attributes these dissimilarities in findings within the maritime literature to the possibility of freight returns switching between distinctive volatility structures and proposes an empirical framework that is capable of capturing these distinctive dynamics. Thus, the main aim of this study is to attempt to explain the dissimilarities within the maritime literature in measuring freight risk by improving our understanding of the changes in volatility dynamics of the freight supply curve.

Therefore, this thesis aims to address the following main research questions that are related to the topic of shipping risk measurement and management: a) Which framework from the existing financial literature is most suitable for measuring conditional freight volatility? b) How suitable is a developed value-at-risk framework, for capturing the changes in volatility dynamics of the freight supply curve, and in assessing freight risk in comparisons to other proposed models in the literature and current market practices? c) Are freight earnings (level-prices) stationary? d) Are structural breaks present in tanker freight markets and are they caused endogenously or exogenously? and e) Is freight sensitivity consistent across different market conditions for different tanker segments? To answer these research questions, we consider the following question and hypotheses'. i) The suitability of parametric, non-parametric and semi-parametric approaches to measure value-at-risk for tanker freight markets. ii) That shipping tanker freight returns do shift between two regimes, a lower freight volatility regime state and a higher freight volatility regime state, that are associated with the elastic and inelastic part of the supply curve, respectively. iii) That a significant homogenous structural shift within freight tanker earnings is influenced by a structural change in the underline transported commodity. iv) That the suitability of a conditional freight limitation framework in distinguishing between a ship-owner market and cargo-owner market and v) That a conditional five-beta freight-return framework is suitable for measuring and comparing total risk across tanker segments.

Thus, this thesis makes several contributions to the theoretical and empirical aspects of maritime economics, in an attempt to fill a gap in the literature related to the study of shipping freight risk measurement and management. From a theoretical perspective, this study proposes a new concept of defining market conditions as shipping agent controlled. From an empirical perspective, this study proposes a new framework that is capable of capturing the distinctive nature of freight dynamics and is associated with returns shifting between the elastic and inelastic parts of the supply freight curve.

In general, this thesis attempts to contribute to the existing body of knowledge as follows. First, an attempt is made to explain the dissimilarities within the maritime literature in measuring freight risk by improving our understanding of the changes in volatility dynamics of the freight supply curve. These dissimilarities are due to the disagreement on the most suitable underlying conditional variance model that best captures volatility dynamics within freight markets. Thus, this study postulates that volatility dynamics within freight rates are distinct and conditional on the freight volatility regime state that prevails at the time. Therefore, this hypothesis is tested and distinctive volatility dynamics within these state regimes are captured by a two-state Markov regime-switching distinctive conditional variance framework to measure freight risk for univariate and multivariate structures. This provides a better insight into the dynamics of shipping freight rates for the elastic and inelastic part of the freight supply curve. Furthermore, in addition to measuring univariate and multivariate freight risk, uncorrelated freight risk factors and conditional freight-beta are extracted and estimated, respectively, from a portfolio of freight returns to provide a better platform to extract market information for ship-owners and cargo-owners to optimise operations and reduce financial risk exposure, thus, improving profit margins.

Second, we investigate the extent of the effect of structural change in the underlying transported commodity by tanker vessels on freight earnings. In other words, we test the hypothesis of a significant homogenous structural shift within tanker freight earning, which is caused by a significant structural change in oil price levels, which this study claims to have triggered the most recent prolonged period of shipping expansion. Thus, this study postulates that post-2000 freight earnings have exhibited an exogenous and homogenous upward shift in mean and volatility levels with no empirical evidence of this ending up until 2010. Furthermore, a conditional freight limitation framework is proposed to distinguish between two periods of freight earnings-levels that are largely controlled by either ship-owners or cargo-owners. Thus, this study claims that by defining ‘up’ and ‘down’ market movements as shipping agent controlled, risk management techniques for shipping practitioners is improved.

Third, motivated by the above assumptions and findings, this study investigates variations in freight risk-return relation by adopting a conditional five-beta freight-return model. Thus, testing the consistency of freight sensitivity measure across different market conditions that are asymmetric pre- and post-2000, a significant structural shift in freight earning levels. Furthermore, a framework is proposed to estimate total freight risk through its components, specific and systematic risks. That can be used to analyse risks across different tanker segments, to improve techniques of portfolio diversifications.

Fourth, for the first time the stationarity of freight earning level-price is investigated by testing time series’ of daily earnings for distinctive tanker segments for unit-root. Thus, providing empirical evidence that freight earnings are stationary and in alignment with maritime economic theory.

Finally, a practical insight into current practices in freight markets to neutralise and exploit freight risk, through the use of derivatives is provided, by attending a tanker freight derivatives professional trading course, set by Imarex Academy part of the Imarex group. Therefore, directional accuracy and volatility of short- and long-term forward curves are measured across different tanker segments and compared against a general perception in the literature. Furthermore, the empirical framework proposed in this thesis is compared against current market practices to assess its suitability for measuring shipping freight risk and thus, improving market information.

Chapter two

2. An overview of maritime economic literature

2.1. Introduction

This chapter reviews selected topics from maritime economic literature that are relevant to the scope of this thesis. Each of the working chapters includes subsequent sections of the relevant literature that is related to the work conducted in that particular chapter. Thus, this chapter attempts to review the ideas implemented in this thesis in relation to maritime literature.

The rest of the chapter is organised as follows. Section 2.2 discusses the importance of oil markets relevant to tanker markets. Section 2.3 discusses the thesis's proposed concept of conditional freight limitations from the literature perspective. Section 2.4 reviews classic maritime theory. Section 2.5 describes the data within this thesis relevant to data used in other empirical maritime studies. Section 2.6 discuses the stationarity of freight rates in the literature. Section 2.7 reviews value-at-risk in the literature. Section 2.8 concludes the chapter.

2.2. The effect of oil prices on tanker freight markets

It is widely accepted among maritime economists that shipping services are demand driven (see Stopford (2009) and references within). Thus, the importance of the underlying transported commodity for shipping tankers has been thoroughly investigated in maritime literature. For example Koopmans (1939), Stevens (1958), Zannetos (1966), Devanney (1971), Hawdon (1978), Wergerland (1981) Evans and Marlow (1990), Beenstock (1985), Kumar (1995), Li and Parsons (1997), Kavussanos and Alizadeh (2002a, 2002b), Lyridis *et al* (2004) and Poulakidas and Joutz (2009). Examine the determinations of tanker prices and their relationship with oil prices.

Poulakidas and Joutz (2009) investigate the link between oil prices and freight rates by examining the relationship between weekly spot tanker prices and the oil market over a period from 1998 to 2006 for the West African and US Gulf Coast tanker market. They find that the spot tanker market is related to the intertemporal relationship between current and future crude oil prices, where a relatively high expected oil price puts upward pressure on spot tanker rates. Thus, they suggest that demand for tankers is a derivative of the demand for crude oil. They conclude that spot and future crude oil prices, crude oil inventories and freight rates are interlinked and that this relationship should be further investigated to better understand the relationship between freight rates and crude oil prices. From a practical point of view, market reports provide evidence of the effect of high oil prices in larger tanker segments where increases in oil prices and freight rates are consistent, Poulakidas and Joutz (2009). Furthermore, the recent prolonged strength in oil prices from 2003 to 2007 can be attributed to either a structural or cyclical change, creating an interesting debate between two schools of thoughts, the cyclical school and the structural school. Stevens (2005) recognises the importance of such a study by investigating the particulars of the oil markets and its influence over policy structure. He finds that recent strengths in oil prices are better explained by the structural school of thought and that the oil markets have exhibited an upward shift that will last up until 2014. The implication of this to tanker markets should be further investigated in particular pre and during the most recent financial crisis. Therefore, the importance of shipping services being demand driven is further reviewed and discussed in section 7.2.1.

2.3. Conditional freight limitations

Tvedt (2011) suggests that traditional modelling of shipping markets in the short-run by specifying aggregated supply and demand functions is limited due to abrupt shifts in freight rates and agent behaviours. Furthermore he argues that Stopford (2009) description, that psychology is just as important as fundamentals for the formation of freight rates, is an accurate one. Tvedt suggests that the term ‘psychology of the market’ is inappropriately defined and that for shipping markets it is down to a description of real and perceived strengths and weaknesses of the market agents and the bargaining game between these players, Tvedt (2011). Therefore, he derives a theoretical framework for short-run freight rate equilibrium in the VLCC market based on a limited number of market characteristics, focusing on the microcosmic level of matching individual cargoes and vessels. The proposed simple model is market-agent influenced and capable of identifying a unique freight rate to a stable match of cargo and tonnage. Most importantly, he claims that the compromises between the two parties are restricted by assuming an upper and a lower freight rate limit, these upper and lower freight rates are a result of either the ship-owner solely or the charterer solely setting freight price levels, respectively.

2.4. Classic maritime theory

Shipping freight spot markets are referred to as textbook examples of perfectly competitive markets (see Norman (1979), Kumar, (1995) and Stopford (2009)). These markets satisfy the required conditions of perfect competition. Features such as the freedom of entry and exit, a large number of ship-owners and cargo-owners negotiating a homogenous freight service, characterise shipping markets. Furthermore, the agreement of a freight price is established through mediators that provide perfect information for all participants for freight prices and transportation services available at any time with no cost.

In the classic maritime literature, Tinbergen (1934) and Koopmans (1939) characterise the supply curve in tramp shipping by two distinct regimes depending on whether or not the fleet is fully employed. This definition holds ground to date because when demand exceeds supply the current fleet is fully employed and aggregate supply is inelastic causing high freight rates. In contrast, aggregated supply is nearly perfect elastic when supply exceeds demand causing low freight rates with most vessels operating near or below breakeven point. Thus, in depressed markets the current fleet will be partially employed with the rest either laid up or scrapped. There is general agreement within maritime researchers that the formal leads to the latter. In other words, when freight rates are attractive, this is an incentive for investors (ship-owners) to order new vessels, even though they lack any indications of increases in seaborne trade. Eventually this rational uncoordinated behaviour will lead to excess of freight supply over demand, leading to lower freight rates and causing depressed markets. For more details see Sødal *et al* (2009) and references within. Historically, booming freight markets are followed by depressed periods characterising freight markets as being clustered, this is simply caused by the strong response of the supply side in booming periods through the new-building market. Sødal *et al* (2009) explore the usefulness of switching between freight market segments based on the freight rate differential and relative ship value, arguing that if arbitrage opportunities exist in freight markets through asset play or market segment, switching to the second-hand market for vessels is inefficient. Therefore, it seems that there is a gap in the literature for a framework that provides a better insight of market information for the elastic and inelastic part of the supply curve.

Furthermore, the methodology of ship valuation in maritime literature is no different to asset valuation in financial economics, where the present value of a ship is the discounted value of its prospective earnings. Aaccording to Sødal *et al* (2009) this concept was first introduced by Strandenes (1984) and Beenstock (1985) and highlights the importance of accurate freight rate estimation for shipping valuation, which is relevant to our work in this thesis. Furthermore, Sødal *et al* (2009) suggest that the early work of Strandenes (1986) and Beenstock (1985) on market efficiency triggered a wide range of empirical work on the topic. For example Kavussanos and Alizadeh (2002a), Adland and Koekebakker (2004), Alizadeh and Nomikos (2011) and Nomikos and Alizadeh (2011). These investigations provide mixed results, simply because the difficulty of estimating the appropriate freight revenues relevant to a specific price level of an asset (ship) in a specific time. Therefore, an appropriate framework to accurately estimate freight earnings is paramount for shipping valuation.

Moreover, the prospective cash flow for any business has been and still is the basis for valuing any business adventure by prospective investors. The shipping industry is no different. The main challenge for any prospective investors that are willing to invest capital in buying a particular type of a vessel is the timing of the investment. This is a difficult management decision that is affected by unpredictable changes in levels of earnings (freight rates), for example the clusters within freight rates mean that freight rates can be extremely high for a long period creating an incentive to invest in that particular trade and can be below breakeven levels for a long period as well, tempting investors to treat their investment as a sunk cost. Recognizing that timing of investment is crucial in shipping, many researchers have postulated different frameworks to assess practitioners in making such a decision. Sødal *et al* (2009) use a real option valuation model to investigate freight market efficiency and the economics of switching between a dry bulk vessel and a tanker vessel when the net present value of such a switch is optimal from a real option based decision rule.

On similar grounds, an argument can be made for a framework that can help practitioners in making a management decision to switch between different sectors within the tanker trade market. Furthermore, most importantly, for shipping companies that operates a large fleet, this is useful to assess their entry/exit timing to/from spot (voyage-charter contract) and forward (time-charter contract) markets.

2.5. Freight data in the literature

In general there are three different measures of freight rates. The two main ways to quote dry cargo freight rates are US dollars per ton and US dollars per day, which are two contrasting measures with different implications for freight risk and are associated with voyage-charter and time-charter contracts, respectively. Even though recently freight information providers started calculating tanker freight rates in similar ways, tanker freight rates are normally quoted in a more complex measure known as WorldScale points.

The tanker industry uses this freight rate index as a more convenient way of negotiating the freight rate per barrel of oil transported on many different routes. This system is used to compare tanker freight rates all over the world irrespective of the length of the voyage and its geographical location. Hence, the corresponding flat-rate (WS100) is quoted in dollars per cargo tonne where ship-owners and charterers negotiate a fraction or a higher value of the flat-rate. For a detailed analysis of the WorldScale point system as a useful measure of tanker hire see Laulajainen (2007 and 2008). This is discussed in more detail in section 6.2.5.

Therefore, empirical work in maritime literature that investigates volatility dynamics within the tanker spot freight markets, uses one of two estimations, tanker freight rates that are either quoted in WorldScale (WS) points or time charter equivalent (TCE). First, a daily frequency of freight rates reported in WorldScale points for different tanker routes are examined in the literature, where there is general consent that freight-returns for all tanker routes are first difference stationary, the unconditional means are statistically zero, exhibit significant positive skewness, exhibit high kurtosis and that the distribution of returns are non-normal and fat-tailed.

For example Kavussanos and Dimitrakopoulos (2011) in their investigation of medium-term risk from limited historical data, study six freight indices, two of which are imitations of portfolios of freight rate positions, the Baltic Clean Tanker Index (BCTI) and the Baltic Dirty Tanker Index (BDTI). The other four are single routes that constitute part of the BDTI; these indices correspond to the most active routes within the dirty tanker market and cover different vessel sizes in the tanker market that transport crude oil and oil products. These are routes TD3, TD5, TD7 and TD9 that correspond to VLCC, Suezmax, Aframax and Panamax, tanker segments respectively. Angelidis and Skiadopolous (2008) investigate only one tanker route that represent daily freight rates for a VLCC on a round voyage from the Mediterranean Gulf (Ras Tanura) to Japan (Chiba) with a maximum capacity of 260,000 metric tonnes. Abouarghoub and Biefang-Frisancho Mariscal (2011) in their investigation of short-term risk exposure in tanker markets, study five distinctive single tanker routes that represent different segments within the tanker market. These are TD3, TD4, TD5, TD7 and TD9 routes that correspond to VLCC, Suezmax, Aframax and Panamax tanker segments, respectively. Therefore, all the above studies analyse tanker freight rates that are reported in WS points and agree that freight-returns are stationarity and non-normal.

Second, freight earnings reported in dollars per day for different tanker segments known as TCE that represent a daily hire for a specific tanker vessel on a specific operating route are analysed in the literature and are limited for tanker markets. For example Alizadeh and Nomikos (2011) analyse 560 weekly observations of freight earnings for three tanker segments; VLCC, Suezmax and Aframax to investigate the relationship between the dynamics of the term structure and time-varying volatility of shipping freight rates. In there empirical works they assume that freight earning returns are stationary. Adland and Cullinane (2006) analyse three series of weekly TCE spot freight rate for the VLCC, Suezmax and Aframax sectors. There sample corresponds to 770 observations and basic statistics indicate the non-normality of freight earning level-price and returns and are positively skewed and fat-tailed. Therefore, there is a general consent that freight-returns for all tanker segments are first difference stationary, the unconditional means are statistically zero, exhibit significant positive skewness, exhibit high kurtosis and that the distribution of returns are non-normal and fat-tailed.

The empirical work within this thesis can be distinguished on the basis of the type of freight rate measure under investigation. On the one hand, tanker freight rates quoted in WorldScale points refer to the revenue/cost of transporting one tonnage of cargo for ship-owner/charterer on a round voyage in US dollars. This type of measure includes variable voyage costs such as bunker cost, port cost and canal dues. On the other hand, tanker freight earnings quoted in time-charter-equivalent (TCE) refer to the daily earnings/costs for ship-owners/charterers in US dollars exclusion of variable voyage costs such as daily bunker costs, port costs and canal dues. Therefore, in this thesis we use freight rate returns measured in WS points for numerous tanker routes to investigate the usefulness of value-at-risk, uncorrelated risk factors and conditional freight-beta to measure and estimate tanker freight risk. This is employed in chapters four and five. Furthermore, freight earnings level-price and returns measured in dollars per day for distinct tanker segments are investigated in chapters seven and eight, respectively.

2.6. Stationarity of freight rates

The empirical work within this thesis is carried out on sixteen different time-series that represent tanker freights and belong to two distinguish freight measures. First, ten time-series that represent freight rates for different tanker routes that are measured in WorldScale points. These routes specifications and basic statistics are described and reported in Tables 5.1 and 5.2, respectively. Second, six time-series that represent freight earnings for distinct tanker segments that are measured in dollars per day. Basic statistics of freight earnings for different tanker segments are reported in Table 7.2. All of these data sets are investigated for unit-root and found to be first difference stationary using the ADF test described in relevant methodology sections along with reported empirical results. This is similar to other empirical research that found freight-returns to be stationary. For example Kavussanos and Dimitrakopoulos (2007 and 2011), Angelidis and Skiadopolous (2008), Alizadeh and Nomikos (2011) and Abouarghoub and Biefang-Frisancho Mariscal (2011). Furthermore, Adland and Cullinane (2006) propose a drift function to investigate the dynamics of tanker freight earning returns and as their estimators are based on the assumption of stationarity, they perform the conventional Augmented Dickey Fuller (ADF) test with both a constant and a trend, Dickey and Fuller (1981) and the Kwiatkowski *et al* (1992) unit-root tests. Their results support the strong stationarity of tanker spot freight earning-returns. Moreover, Alizadeh and Nomikos (2011) investigate the relationship between the dynamics of the term structure and time-varying volatility of shipping freight rates for three tanker segments, where they assume that freight earning returns are stationary.

In chapter seven we investigate for the first time structural-breaks within freight earnings price-levels for distinct tanker segments using a Markov regime-switching framework. Therefore, it is paramount that freight earnings price-levels are tested for unit-root and structural-breaks. The relevant literature for unit-root and structural break tests are discussed in sections 7.2.4 and 7.2.5, respectively. The relevant methods for these tests are described in sections 7.3.1 and 7.3.3, respectively. Finally, the relevant empirical results are reported in section 7.4.5 in Table 7.3. On the one hand, maritime empirical results suggest the non-stationary of freight rate price-levels in contrast to classic maritime literature. On the other hand, a general consent of stationarity of freight-returns prevails in empirical results of maritime literature. In particular it is found that freight earnings-returns are strongly stationary, while in the literature, even slight rejections are interpreted as strong evidence in favour of stationary due to the lower power of the ADF test, see Adland and Cullinane (2006) and references within. Therefore, the challenge is to validate the assumption made in chapter seven that freight earning price-levels are stationary.

2.7. Value at risk

Value-at-risk is a powerful method used to assess the overall market risk for an asset or a portfolio of assets over a short horizon, such as one-day and ten-day periods, and under normal market conditions. The applied methodology captures in a single number the multiple components of market risk, such as curve risk, basis risk and volatility risk. However, value-at-risk measure is unreliable over longer periods and abnormal market conditions, Crouhy *et al* (2006). They argue that during crisis periods financial institution tend to sell assets in the affected classes to reduce their risk exposure and keep within the required value-at-risk limit set by the risk management team. This further depresses the market and increase’s volatilities and correlations of the risk factors for these assets.

Value-at-risk is defined as the worst loss that is expected from holding an asset or a portfolio of assets for a defined period of time and with a specified level of probability. Thus, offering a probability statement of a potential change in the value of a portfolio resulting from a possible change in market factors over a specified period of time. Most value-at-risk models are designed to measure risk over a short period of time and with a high level of confidence and is in aligned with the requirement of the Basel Committee (BIS, 1998)[1], ten-day period and 99 per cent confidence level, respectively. For more details see Crouhy *et al* (2006).

Value-at-risk methods for traditional financial markets are well documented in Dowd (1998), Jorion (2006) and most recently in Alexander (2008b). A comprehensive introduction to VaR for shipping markets can be found in Alizadeh and Nomikos (2009). VaR main criticism seems to be twofold. Firstly, VaR measures do not provide any information regarding the loss beyond the estimated VaR level. Secondly, VaR is not a coherent risk measure, as it fails to fulfil the sub-additivity condition, which requires the risk of the total positions to be less than or equal to the sum of the risk of the individual positions, Artzner *et al* (1997). These defects are overcome by the introduction of the expected tail loss (ETL) that expresses the loss beyond the VaR and fulfils the coherent condition, Artzner *et al* (1999). Yamai and Yoshiba, (2005) find that expected shortfall is a better risk measure than value-at-risk and that the latter should be complemented with the former to produce more comprehensive risk monitoring.

The recent financial crisis caused concerns regarding the way banks calculate value-at-risk and raised the need to modify VaR methods, in particular adjustments that incorporate extreme and clustering downside risk (Huang, 2010). Kuester *et al* (2006) suggest that there is no consensus among researchers in regards to the most appropriate method of measuring risk and that it is simply a matter of empirical investigation that differs from one researcher to another. Thus, value-at-risk is a common tool for risk measurement that is widely used by financial institutions. This motivated researchers to propose different methods to modify the basic approach of Morgan (1994) to generate reliable VaR measures, despite the increase in critics of VaR due to the most recent financial turmoil. (For more details see Huang (2010) and references within).

Sadeghi and Shavvalpour (2006) argue that value-at-risk has became an essential tool to quantify risk in oil markets, due to the increase in level of competition and deregulation that lead to relatively free energy markets characterised by high price shifts.

[1] Press releases of 1998 by the Bank for International Settlements. www.bis.org.

Cabedo and Moya (2003) suggest that the value-at-risk approach, regardless of the calculated method, is suited to quantify maximum changes in oil prices in association with a likelihood level and that this quantification is fundamental for risk management strategies. Similar value-at-risk measure can be used to quantify maximum changes in tanker freight prices that provide shipping practitioners with a vital tool to improve their risk management strategies.

Studies of volatility dynamics and subsequently estimated risk measures within the shipping freight markets are scars and can be classified to belong to two schools of thoughts. One that support the use of semi-parametric and parametric and another that support the use of non-parametric based approaches to measure short-term freight risk. On the one hand, Kavussanos and Dimitrakopoulos (2007) investigate the crucial issue of tanker market risk measurement, by employing an Extreme Value and Filtered Historical Simulation approach. They conclude that EVT and FHS yield accurate daily risk forecasts and they are the best models for short-term (daily) risk measures. Furthermore, Nomikos *et al* (2009) investigate the volatility of shipping freight rates suing a fractional integrated conditional variance model structure. They calculate VaR measures based on a FIGARCH specification and compare against other conditional variance models such as SGARCH and IGARCH. They conclude that different models are suitable for different size of vessels regardless of trade, suggesting that the most important risk factor is size effect, where smaller vessels illustrate more persistence in volatility in comparison to larger vessels. Most importantly they find evidence of fractional integration of freight rate volatility. Finally, Abouarghoub and Biefang-Frisancho Mariscal (2011) investigate short-term risk exposure in tanker freight markets by adopting conditional and unconditional value-at-risk measures, based on different conditional variance models. They find that FHS-conditional variance based methods produce the most accurate risk predictions.

On the other hand, Kavussanos and Dimitrakopoulos (2011) address the issue of model selection in their investigation of medium-term risk for tanker freight rates. They consider both daily and medium-term risk measures that correspond to the required market risk estimation horizons for large and small shipping companies, respectively. They suggest that shipping companies that own a large number of vessels (large portfolio of ships) and are engaged in daily negotiations for voyage fixtures on a single route or on indices are more interested in daily horizon risk assessments. On the other hand, they suggest that medium horizon risk assessments are more suitable for shipping companies that operate a single vessel or a small number of vessels. In their opinion the latter is due to absence of vessels to be hired until the end of the fixture of the existing vessel. For example a company that operate only one vessel and have their vessel fixed on a voyage for the next two-weeks will be negotiating terms for new employment in two weeks time and vice versa for large shipping companies. Therefore, a medium risk measure is more of interest to them than a short-term risk measure. As this study is focused on short-term freight risk measurement and management it's of interest to us to consider their analysis. Kavussanos and Dimitrakopoulos (2011) in their analysis of VaR and ETL for short investment horizons find that random walk and historical simulation outperform systematically more complex VaR and ETL models in predicting freight rate risk, arguing that this is conditional to the complicated structure of freight rate returns which is captured better by non-parametric VaR models. Their findings are aligned with the findings of Angelidis and Skiadopolous (2008), where they conclude that the simplest non-parametric models should be used to measure market risk for shipping freight rates. They arrive to this after investigating four indices published by the Baltic Exchange; three of these indices, imitate a portfolio of freight rate position for the dry bulk sector and only one series representing freight rate for a specific single tanker route. Both of these findings in maritime literature is in contradiction to evidence from other financial studies that suggest that sophisticated VaR models outperform simple specifications, for example Kuester *et al* (2006).

The choice of the appropriate model to measure risk within different markets is subject to underlying empirical work, thus, the literature recognises the lack of consensus regarding the most suitable method to estimate market risk, Kuester *et al* (2006). The few papers that explore different ways to measure shipping freight risk have differed in their interpretation of the most suitable measure for conditional freight volatility and consequently for the most appropriate freight risk measure. Furthermore, it has been suggested in the literature that incorporating regime changes in volatility models might improve VaR estimates within freight markets, Alizadeh and Nomikos (2007). Abouarghoub and Biefang-Frisancho Mariscal (2011) suggest the possibility of conditional freight volatility switching between different regime states that are dynamically distinct. A similar investigation of the volatility of freight returns in the dry bulk shipping markets carried out by Jing *et al* (2008) find that asymmetric characteristics are distinct for different vessel sizes and market conditions.

In summary, there are dissimilarities in findings within maritime literature regarding the most suitable measure of risk that is applicable for freight markets, which can be attributed to the possibility of freight rate returns switching between different volatility structures that are dynamically distinctive.

2.8. Conclusion

The few papers that investigate freight dynamics have disagreed on the most appropriate measure for conditional freight volatility and consequently on freight risk measures. Furthermore, recent empirical work provide ground for us to assume that dissimilarities in maritime literature can be attributed to the possibility of freight returns switching between distinct conditional volatility state regimes, with each state being defined by distinctive characteristics. Moreover, classic maritime literature characterises the supply curve in tramp shipping by two distinct regimes depending on whether or not the fleet is fully employed. Thus, freight supply is highly elastic at low freight levels and highly inelastic at high freight levels. Therefore, there is a gap in the literature for a framework that provides and empirical insight into the dynamics of shipping tanker freight rates for the elastic and inelastic part of the freight supply curve that should improve freight risk measures for single routes and portfolios of freight rates.

Furthermore, the literature suggests that recent strengths in oil prices are better explained through the structural school of thought with no recent studies investigating the impact of this on tanker market. Thus, there is scope for investigating any existing exogenous and endogenous structural breaks within freight earnings. Especially that maritime information provider calculates and report data sets that represents daily earning for different tanker segments.

Chapter Three

3. Methodology: An overview of the framework within this thesis

3.1. Introduction

This chapter presents an overview of the framework employed in this thesis. Each one of the working chapters includes a detailed description of the methodology relevant to the empirical work carried out within. It is important to note that the empirical work within this chapter in general is applied to two distinctive tanker freight rate measures. First, the cost of transporting one tonne of cargo on a round voyage for a specific vessel size in dollars per tone is referred to as the flat-rate and is calculated and reported annually by the WorldScale committee. The tanker industry uses a freight rate index as a more convenient way of negotiating the freight rate per barrel of oil transported on many different routes regardless of the voyage length and geographical location. Relevant empirical work for this freight measure is applied to the time-series returns. Second, a time charter equivalents (TCE) that is quoted in dollars per day, which is the cost of hiring a particular vessel for one day. Relevant empirical work for this is applied to the time series price-levels and returns.

The motivation for model selection within this thesis is twofold. First, the choice of value-at-risk as a risk measure is simply because value-at-risk is undoubtedly the most common measure of financial risk for most financial institutions, due to its simplicity and ease to communicate. Second, the great popularity of value-at-risk and the emergence of the most recent financial crisis, have created the need to adjust VaR methods to incorporate extreme and clustering downside risks, for example see Huang (2010). Therefore, the motivation for the choice of conditional freight volatility model and the underlying assumption of the distribution of the risk factors of freight returns is based on the ability of models to capture the most important characteristics of shipping freight markets; these are extreme high volatility, clusters in returns and leverage effects.

3.2. Value-at-risk for single assets and a portfolio of returns

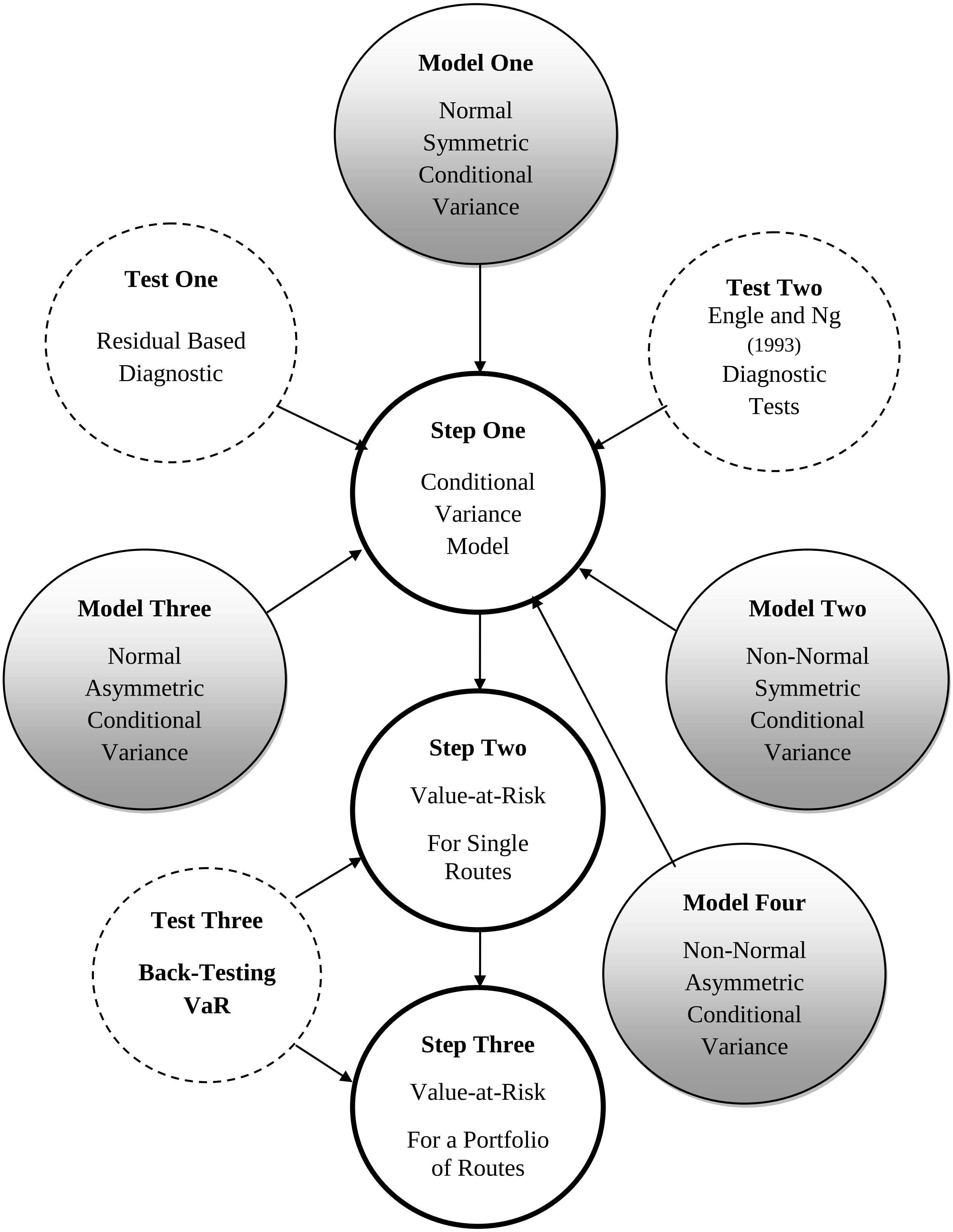
In this thesis value-at-risk (VaR) is measured conditional on the underlying distribution of risk factors of returns by computing three variations of the risk measure, a normal VaR, a non-normal VaR and a filtered historical simulation value-at-risk (FHS-VaR). The computation of a one-day ahead VaR for single tanker routes (single time series) is carried out in two steps. First, the one-day ahead conditional volatility is estimated through variety of conditional variance models to evaluate the best suited for each tanker route.

Second, the underlying distribution of risk factors of freight returns is assumed for both parametric and non-parametric approaches. A detailed methodology is provided in section 4.3. Furthermore, these univariate value-at-risk measures for single tanker freight routes are converted to multivariate value-at-risk measures for a portfolio of tanker freight returns. The detail of the applied methodology is presented in section 5.3.

In the flowchart 3.1 we illustrate the general steps undertaken in this thesis to compute one-day ahead VaR for single tanker routes and a portfolio of tanker freight returns. The four different specifications of the applied conditional variance models are denoted by models one, two, three and four and are illustrated in shaded gray circles. While the dashed circles represent the main tests carried out at different estimated steps, these are residual based diagnostic and Engle and Ng diagnostic tests for each applied conditional variance model, and back-testing for computed VaR values. Finally, the bold circles denoted by steps one, two and three represent the three main estimating steps.

Therefore, for comparison purposes, four specifications of conditional variance models are evaluated and tested for misspecifications and are then used to compute three VaR measures that differ in their definition of the underlying distribution of risk factors. These specifications are represented in section 4.3 by equations 4.5, 4.7 and 4.8, subsequently. Once value-at-risk is estimated for single tanker routes, they are converted to a multivariate measure, for a portfolio of tanker returns. This is represented in section 5.3 by equation 5.4. Thus, univariate VaRs estimated are computed for five major dirty tanker segments, these are described and represented in Table 4.1 along with relevant voyage particulars for each route. Furthermore, a multivariate VaR measure is estimated for each implemented univariate VaR model for a portfolio of tanker freight returns that consists of these five distinctive routes.

Diagram 3. 1: A flowchart illustrating the framework for estimating Value-at-Risk based on single conditional variance models



Note Figure 3.1: illustrates the different steps within this thesis to estimate short-term freight risk using a value-at-risk. Source author.

3.3. Single-state conditional variance models

A variety of conditional variance models is estimated to capture volatility dynamics within tanker freight returns. These models combine the ability to capture conditional volatility in the data through a GARCH framework, while at the same time modelling the extreme tail behaviour through standardized returns and an extreme-value-theory (EVT) based method. As described in section 3.2 estimating a one-day ahead conditional volatility is an important component of measuring value-at-risk. Thus, we investigate the suitability of parametric, non-parametric and semi-parametric approaches to measure value-at-risk and determine the most appropriate method for measuring short-term risk exposure within tanker freight markets. The estimation of these models along the relevant diagnostic and misspecification tests where computed using OxMetrics 6 programme available in Laurent (2009) G@RCH6 included in Doornik and Hendry (2009b) PcGive13 package. The estimations of these models are explained in detail in section 4.3.6.

As suggested in the maritime literature the distributions of freight returns exhibit clear departure from normality, positive skewness, high peaks, fat-tails and extreme high volatility. Thus, the ability of a conditional variance model to capture volatility dynamics within freight rates is largely subject to the assumption of the underlying distribution of returns. Furthermore, financial literature is rich with different models that are developed to account for different features that attribute to the non-normality of asset returns. For example stationary fat-tailed distributions such as Student's *t* see Rogalski and Vinso (1978).

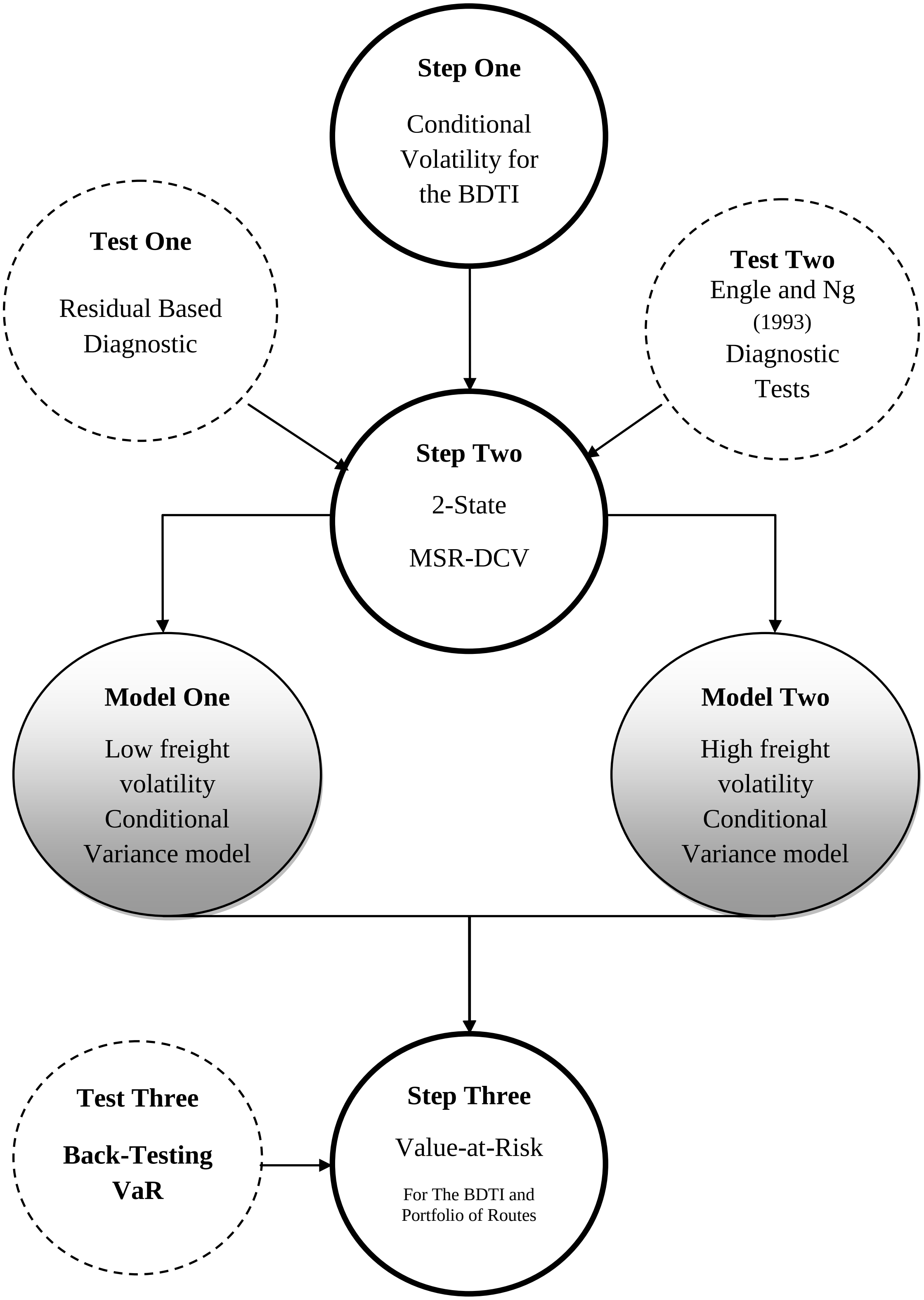
Bollerslev and Wooldridge (1992) show that under the normality assumption, the quasi-maximum likelihood (QML) estimator is consistent if conditional mean and conditional variance are correctly specified. However, Engle and Gonzalez-Rivera (1991) argue that this estimator is inefficient and that the degree of inefficiency increases with the degree of departure from normality. Therefore, the use of fat-tailed distributions as an assumption for describing returns is widespread in the literature (Palm, 1996). Among many, Bollerslev (1987), Hsieh (1989), Baillie and Bollerslev (1989) and Palm and Vlaar (1997) show that fat-tailed distributions perform better than normal distributions.

Furthermore, to account for the fat-tailed feature of asset returns a number of different time series models have been developed and employed in the literature, such as historical simulation techniques, Student's-*t*, generalized error distribution (GED), mixture of two normal distributions and Markov-switching conditional variance models. In this thesis we benefit from the ability to use the G@RCH6 software of PcGive13 package to model a variety of GARCH models such as GARCH, EGARCH, GJR, APARCH, IGARCH, FIGARCH-BBM, FIGARCH-CHUNG, FIEGARCH, FIAPARCH-BBM, FIAPARCH-CHUNG and HYGARCH. Furthermore, the distribution of returns can be estimated using the symmetric and asymmetric fat-tailed distributions. For example in the G@RCH programme of the PcGive13 package there are four choices, which are the Gaussian (normal) distribution, Student-*t* distribution, the generalized error distribution (GED) and the Skewed-Student *t* distribution. This thesis employs the Student-*t* distribution as the choice for non-normal distribution and only report models that provide positive and highly significant parameters.

3.4. Two-state Markov regime-switching distinctive conditional variance models

In reviewing the maritime literature one finds a gap that is worth exploring. This is to investigate the possibility of the second moment for freight returns switching between two sets of constant parameter values, one set representing a lower freight volatility regime state and the other a higher freight volatility regime state. The challenge is to capture the volatility dynamics within these distinct regime states through the best match from the GARCH-family. Therefore, a two-state Markov regime-switching conditional variance (2-S MRS-CV) model provides a useful insight into freight tanker information by distinguishing between distinctive freight volatility states. The volatility dynamics of these distinctive states are matched against the best fit from GARCH-family models, which is referred to in this thesis as a two-state Markov regime-switching distinctive conditional variance (2-S MRS-DCV) model. The estimation of these models is done using the OxMetrics 6 programme within the regime-switching models included in Doornik and Hendry (2009c) PcGive 13 package. The 2-S MRS-CV is applied to five major tanker segments, while the 2-S MRS-DCV is applied to the Baltic Dirty Tanker Index (BDTI) that is a proxy for freight rates within for whole tanker sector and computed using the RATS6 programme package. The formation and estimations of these models are explained in detail in section 4.3.6.5.

Diagram 3.2: A flowchart illustrating the framework for estimating Value-at-Risk based on a two-state conditional variance model

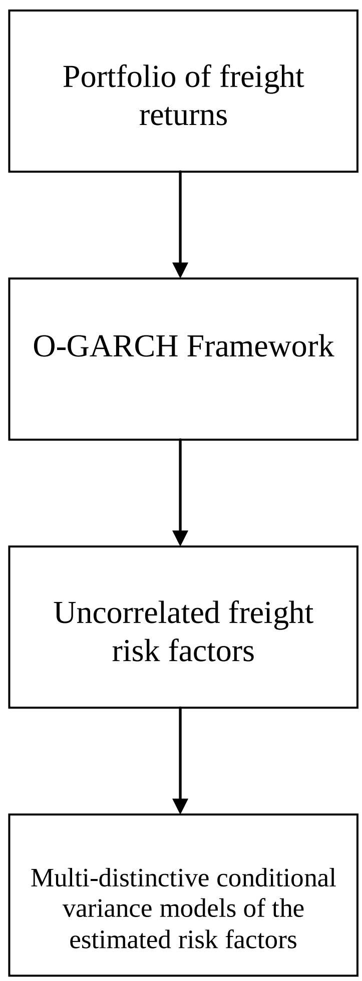


Note Figure 3.2: illustrates the different steps within this thesis to estimate short-term freight risk using a value-at-risk. Source author.

3.5. Uncorrelated freight risk factors

A principal component analysis process is implemented to extract uncorrelated risk factors from a portfolio of tanker freight returns that are then modelled by distinctive conditional variance models. The investigated portfolio of freight returns consists of nine shipping routes and the employed framework is illustrated in Figure 3.3 and explained in details in section 5.3.2. The estimation of this Orthogonal GARCH model is computed using OxMetrics 6 programme within the multivariate GARCH models of Laurent (2009) G@RCH 6 software that is included in Doornik and Hendry (2009a) PcGive 13 package.

Diagram 3.3: A flowchart of estimated conditional variances of the uncorrelated freight risk factors

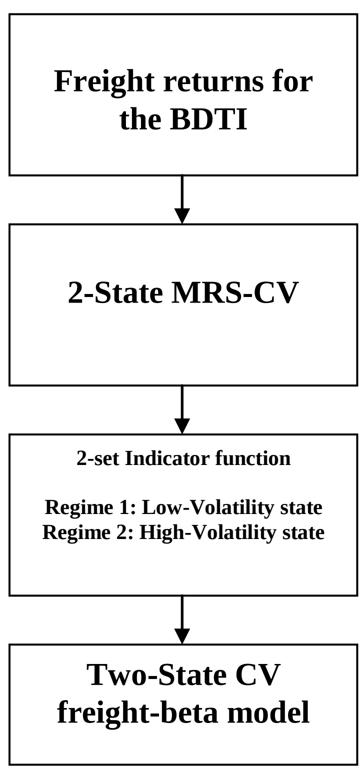


Note Figure 3.3: a flowchart of the steps of modelling the volatility dynamics of extracted uncorrelated risk factors from a portfolio of freight returns. Source author.

3.6. Two-state conditional volatility freight-beta

To test the hypothesis of a constant freight beta against the alternative of a distinct freight-beta that is conditional on changing freight volatility, we propose a two-state conditional variance freight-beta system that is flexible to capture freight dynamics within a lower and higher freight volatility regime states. In other words, to investigate the sensitivities of freight returns to market volatility movements, we implement a framework that account for the distinctive nature of volatility dynamics within freight returns. This is estimated in two steps. First, a Markov regime-switching model is used to define a two-set indicator function; these are two dummy variables to distinguish between a lower and a higher volatility regime states. This is applied to the Baltic Dirty Tanker Index, which is a proxy of overall tanker freight rates. Second, using two sets of dummy variable that define the two distinctive estimated freight volatility regime states, we structural a two-state conditional variance freight-beta framework. These steps are explained in details in sections 5.3.3 and 5.3.4, respectively.

Diagram 3.4: A flowchart of estimating the two-state conditional volatility freight-beta



Note Figure 3.4: illustrates the different steps to estimate short-term freight risk using a value-at-risk based on a two-state freight volatility regime states. Source author.

3.7. The dynamics of tanker freight earnings

A Markov regime-switching framework is employed to investigate the dynamics within tanker freight earnings through a twofold postulate. First, the hypothesis of a significant and homogenous structural shift within freight tanker earnings that is assumed to be caused by a structural change in oil price levels that has triggered a prolonged period of shipping expansion. This expansion period is referred to in this thesis as the supper-boom-cycle. Second, volatility dynamics within freight returns are better explained through a conditional freight limitation framework that is based on a state dependence structure. This conditional freight limitation framework distinguishes between two distinctive periods that are largely controlled by either ship-owners or cargo-owners in a perfect competitive environment, in particular pre and during the most recent financial crisis. This framework is explained in details in section 8.3 and the empirical work is reported in section 8.4. Furthermore, the flowchart 3.5 illustrates these different steps.

3.7.1. Multi-state Markov regime-switching models

The first stage is to test the unconditional stationarity of freight earnings level-price this is computed using the Augmented Dickey-Fuller (ADF) test for linear unit-root against linear stationarity for all tanker routes under investigation. The applied test and empirical results are explained in details in sections 7.3.1 and 7.4.5 in Table 7.3, respectively.

The second stage is to estimate a multi-state Markov regime-switching model to investigate the homogeneity of a significant structural break and the asymmetry of freight earnings dynamics pre- and post-2000. First, through trial and error along with information selection criteria a three-state Markov regime-switching model is applied to a data sample of twenty years of weekly observations that represent daily freight earnings for distinctive tanker segments. This identifies a significant and homogenous structural shift within freight earning levels that is confirmed by a visual inspection of tanker freight price-level across all tanker segments post-2000. Second, the post-2000 period is identified as a supper-boom-cycle and is investigated by a three-state Markov regime switching model. The framework for this is explained in detailed steps in section 7.3.2 and the empirical results are reported in sections 7.4.6, 7.4.7 and 7.4.8. Furthermore, the exogenous and endogenous structural-break tests are presented in section 7.3.3 and empirical results are discussed and reported in section 7.4.5 and Table 7.3, respectively. Moreover, the employed three-state Markov regime-switching framework to the super-boom-cycle is used to identify expansions and contraction periods within the ten-year periods. This is explained in section 7.3.4 and results are reported and illustrated in section 7.4.8.

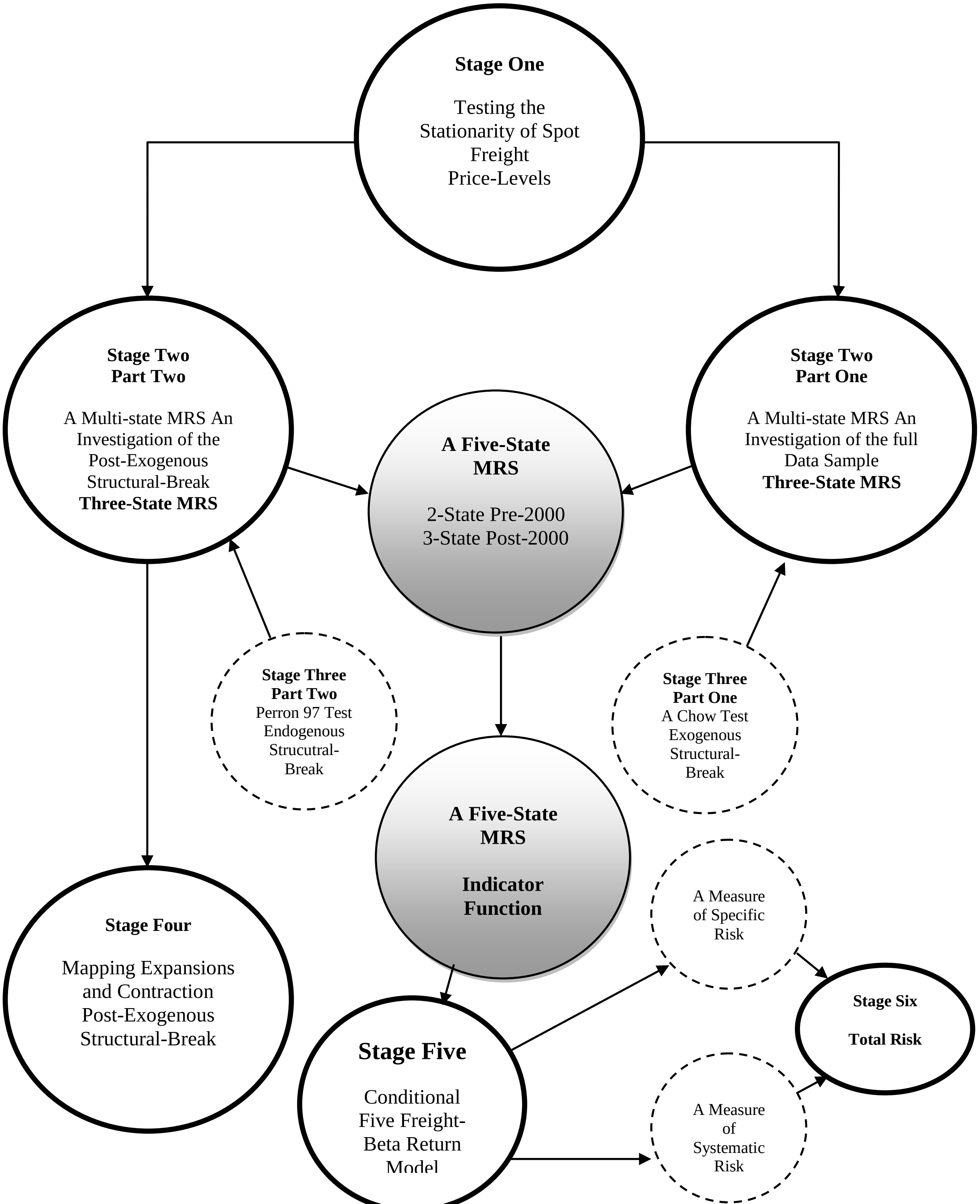
3.8. Conditional five-beta freight-return model

This thesis investigates the variation of freight risk-return relations on the basis that up and down market movements are defined as shipping-agent-controlled. Therefore, each freight earning return is classified as belonging to a distinct earning state using indicator functions and constructing a conditional five-beta freight return model. In other words, the consistency of a freight-beta sensitivity measure across different market conditions is tested. Furthermore, this framework is suitable to measure and compare total freight risk across tanker segments by computing their relevant specific and systematic risks.

This thesis postulates that the sensitivity of freight earning returns is inconsistent across various market conditions that accounts for asymmetries pre- and post- the empirically identified structural shift and are shipping agents controlled. To test this postulate we define five market conditions with different earning regime states based on a Markov regime-switching framework and develop a conditional five-beta freight earning-return model. Each estimated beta corresponds to different market movements. These are lower and higher freight earning levels, pre- and post-2000, in addition to a transitional earning state for the period post-2000. Thus, this multifactor model investigates the dynamic structural of freight returns in different market conditions and is constructed in three steps. First, an appropriate shipping earning index that represents earnings within the shipping industry is used as a proxy for market movements. Thus, a Markov regime-switching framework is applied to the *ClarkSea Index* (CSI), a time series that reflects daily earnings within the whole shipping industry instead of just the tanker sector. This time series is described and illustrated in sections 8.4.1 and Figure 8.1. The MRS model identifies five different earning regime states, in which each daily earning is classified to belong to a distinct earning stat. These are pre-low, pre-high, post-low, post-transitional and post-high freight earning state structures. This framework is explained in details in section 8.3.1 and empirical results are reported in section 8.4.2

Second, the sensitivity of unconditional freight earnings in each tanker segment to the overall shipping sector is investigated through an unconditional single-beta freight earning return model. The methodology for this framework is presented in section 8.3.2 and results are reported in section 8.4.4.1. Finally, the unconditional single-beta model is extended to a conditional five-beta freight earning return multivariate model, to accommodate to changing market conditions pre- and post- the identified structural-break. This framework is presented in section 8.3.3 and empirical results are reported in section 8.4.4.2. Furthermore, total freight risk is decomposed to specific and systematic risks for unconditional/conditional single-/five-beta freight earning return models. This is presented in the relevant methodology sections and results are reported in section 8.4.6.

Diagram 3.5: A flowchart illustrating the framework for testing for structural breaks and measuring conditional freight-beta



Note Figure 3.5: illustrates the framework for testing for structural-breaks within freight earnings price-levels, measuring conditional freight-beta for freight returns and total freight risk. Source author.

3.9. Summary

The suitability of parametric, non-parametric and semi-parametric models in measuring freight risk for single tanker routes and a portfolio of freight returns is reinvestigated in this thesis. Most importantly, the distinctive nature of freight conditional volatility is examined through a two-state Markov regime-switching conditional variance model. Furthermore, a market information insight into the elastic and inelastic part of the freight supply curve is studied by matching these two distinctive volatility states to the best match from the GARCH-family. Moreover, the ability of such a framework to improve freight risk measures are compared against other proposed models in the literature.

Finally, freight earnings levels are examined for the first time to investigate the existence of exogenous and endogenous structural breaks within the tanker market, in particular pre and during the most recent financial crisis.

Chapter Four

4. Value-at-Risk: Measuring freight risk for single tanker routes

4.1. Introduction

The main focus of this chapter is to establish an appropriate framework to measure freight risk in the tanker shipping spot market. These markets operate under conditions of perfect competition, and are extremely volatile, with clear evidence of high volatility, seasonality and clusters in returns, they also exhibit leverage effects, and feature non-zero and high levels of skewness and kurtosis respectively. Studies in the area of freight risk still remain scarce and the understanding of the relationship between freight risk and its return remains a gap in shipping literature worth exploring. Thus, empirical work carried out in chapters four, five and eight aim to fill this gap in knowledge. The benefit of such a study can be summarized as; to aid ship-owners in improving profit margins, through optimized operations; to improve vessel investment decisions; to reduce financial risk exposure for shipping portfolio managers and to improve the use of freight derivatives for risk management.

The few papers that explore different ways to measure shipping freight dynamics have differed in their interpretation of the most suitable measure for conditional freight volatility and consequently for the most appropriate freight risk measure, which has been borrowed from the financial literature. Furthermore, recent empirical work in maritime studies suggests the possibility of conditional freight volatility switching between different regime states that are dynamically distinct Alizadeh and Nomikos (2007) and Abouarghoub and Biefang-Frisancho Mariscal (2011). Therefore, these dissimilarities in findings within maritime literature are attributed in this study to the possibility of freight rate returns switching between different volatility structures. Most important, an appropriate risk measure should adapt to these dynamics. Consequently, it seems critical that a value-at-risk measure for freight returns accommodates these distinct dynamics that are associated with different conditional freight volatility levels.

Therefore, the empirical work of this chapter is threefold. First, we explore the usefulness of forecasting one day value-at-risk measures for shipping tanker freight returns through implementing the use of models that combine the ability to capture conditional heteroscedasticity in the data through a GARCH framework, while at the same time modelling the extreme tail behaviour through standardized returns and an EVT-based method. Furthermore, this study investigates the suitability of parametric, non-parametric and semi-parametric approaches to measure value-at-risk and determine the most appropriate methods for measuring level of risk exposure for shipping tanker freight markets. Second, as this is a study of the volatility structure of the tanker freight market and its exposure to market shocks, a two-state regime conditional variance framework is introduced, to test the hypothesis that shipping tanker freight returns shift between two regimes, a higher freight volatility regime and a lower freight volatility regime and to examine the effect of market shocks on the volatility of freight returns. Finally, an appropriate conditional variance model is matched to each distinct regime state to better explain the dynamics within freight returns.

There are several contributions. Firstly, to build up on the limited existing literature of measuring value-at-risk for shipping freight markets by improving measures of conditional freight volatility and the underlying assumption of the distribution of risk factors of freight returns. This thesis clearly distinguishes between the underlying distribution of the risk factors for VaR and the conditional distribution of returns for the conditional variance model. Secondly, motivated by recent findings in the literature, we investigate the hypothesis that freight dynamics are distinct and conditional on the freight volatility regime state that prevails at the time for five tanker segments. Finally, this chapter proposes a two-state Markov regime-switching and distinctive conditional variance model by matching the two-state conditional freight variance to the most suitable GARCH specification. This provides for the first time an empirical insight into the dynamics of shipping tanker freight rates for the elastic and inelastic part of the freight supply curve. Thus, this is applied to the BDTI that represents freight movements in the whole tanker industry instead of just five tanker routes.

The remainder of the chapter is structured as follows. Section 4.2 examines relevant literature. Section 4.3 documents the methodology used in this study, which includes:

value-at-risk methodology, non-parametric approach, parametric approach, semi-parametric approach, extreme value theory, Markov regime-switching, back-testing and misspecification tests. Section 4.4 discusses empirical work and findings. This includes conditional volatility estimations, value-at-risk empirical results and Markov regime-switching estimations. Section 4.5 concludes the chapter.

4.2. Literature review

Analysing volatilities for tanker freight returns is a major issue for participants in freight markets. The understanding of freight volatility measures is vital in improving ship-owners' profitability, and reducing financial risk exposure for investors and shipping portfolio managers. Furthermore, the vast and growing shipping derivative markets provide the necessary hedging tools for ship-owners and charterers to manage their freight risk exposures, but only provided those exposures are fully-understood.

This chapter initially attempts to measure the level of risk exposure in the tanker spot freight markets by examining the volatility structure of five major tanker routes. This is performed using non-parametric, parametric and semi-parametric approaches that are based on different GARCH structures to measure conditional freight volatility. We also attempt to capture tanker freight sensitivity to market shocks, by decomposing market shocks coefficients parameters, in the conditional volatility measure, into positive and negative components. In our analysis we come across clear evidence of clusters in daily freight returns, as others have done. Therefore, first, we introduce a two-state Markov regime-switching conditional variance framework to investigate the possibility of two different volatility structures in shipping tanker freight markets. Second, we investigate the two-state Markov-switching conditional variance model for the best match from the GARCH-family to capture the dynamics within these distinct freight volatility states. The results are profound.

Shipping freight price movements are considered to be mean-reverting in the long run, and subject to spikes caused by shocks in supply and demand balance, see Adland and Cullinane (2006) and Koekebakker *et al* (2006). With a nonstorable feature, huge capital requirements, challenging volatility levels, seasonality and sensitivity to energy prices and market sentiment, the involvement in shipping freight markets provide huge challenges for all participants. Therefore, exploring and developing a risk measurement framework that fits such extreme market conditions is paramount important. Such attempts are scarce in shipping literature.

On that note, one widely-used tool for the measurement of risk exposure is value-at-risk (VaR). VaR methods for traditional financial markets are well documented in Dowd (1998), Jorion (2006), Holton (2003), Manganelli and Engle (2004) and Engle (1993), whilst energy VaR is detailed in Clewlow and Strickland (2000) and Duffie *et al* (1998). A general introduction of VaR for shipping markets can be found in Alizadeh and Nomikos (2009). Angelidis and Skiadopolous (2008), attempt to investigate risks in shipping freights returns using a VaR approach, where they conclude that the simplest non-parametric models should be used to measure market risk. A similar investigation of the volatility of freight returns in the dry bulk shipping markets was conducted by Jing *et al* (2008). They find that asymmetric characteristics are distinct for different vessel sizes and market conditions. A paper by Kavussanos and Dimitrakopoulos (2007), investigates the issue of tanker market risk measurement, by employing an Extreme Value concept and a Filtered Historical Simulation approach. They conclude that Extreme Value and Filtered Historical Simulation yield accurate daily risk forecasts and are the best models for short term daily risk forecasts.

Another paper presented at the annual IAME in Copenhagen by Nomikos *et al* (2009) investigates the volatility of shipping freight rates using a FIGARCH model structure, for measuring volatility for tanker and bulk freight rates. They compared their model for calculating VaR against other conditional volatility structures such as SGARCH and IGARCH. They conclude that different models are suitable for different size of vessels regardless of trade. This, according to the authors, is an indication of some form of size effect where smaller vessels illustrate more persistence in volatility. They also find strong evidence of fractional integration in freight rate volatility. In general, empirical maritime researchers have disagreed on the most suitable measure for freight risk using the VaR methodology. This study attributes these dissimilarities to the postulate that freight rate returns switch between distinctive volatility structures.

VaR measurement is based on the volatility of the portfolio in question and freight volatility had always been ambiguous for shipping market participants. Therefore, this study adopts models that are capable of dealing with conditional volatility (standard deviation) of the time series, such models are the GARCH-family, which are presented and analysed in a later section. The conventional approaches to estimate VaR in practice can be broadly classified as parametric and non-parametric. Under the parametric approach, a specific distribution for returns must be presumed, with a Normal distribution being a common choice. In contrast, non-parametric approaches make no assumptions regarding the return distribution. These measures are based on historical information and can be classified into three methods, historical simulation approach, Monte Carlo Simulation method and Variance-Covariance methods, Sadeghi and Shavvalpour (2006). For details of advantages and disadvantages of each method see Crouhy *et al* (2006).

In addition, an important method for improving VaR estimates in shipping freight market lies in extreme value theory (EVT) measurement, which specifically targets extreme returns. Focusing on the left side of return distribution rather than the entire distribution, by definition, VaR-EVT measures the economic impact of rare events. Numerous applications of VaR-EVT have been implemented in the financial literature. Embechts *et al* (1997) and Reiss and Thomas (2001) provide a comprehensive overview of EVT as a risk management tool. Longin *et al* (1995) examines extreme movements in U.S. stock prices and shows that the extreme returns obey a Fréchet fat-tailed distribution. Ho *et al* (2000) and Gençay and Selçuk (2004) apply EVT to emerging stock markets which have been affected by a recent financial crisis. They report that EVT dominates other parametric models in forecasting VaR, especially for more extreme returns tail quantiles. Gençay *et al* (2003) reach similar conclusions for the Istanbul Stock Exchange Index (ISE-100). Müller *et al* (1998) compare the EVT method with a time-varying GARCH model for foreign exchange rates. Bali (2003) adopted the EVT approach to derive VaR for U.S Treasury yield changes. Andrews and Thomas (2002) combine historical simulation with thresh-old- based EVT model to fit the tails of the empirical profit and loss distribution of electricity. They report that the model fits the empirical tails better than the Normal distribution. Rozario (2002) derives VaR for Victorian half-hourly electricity returns using a thresh-old-based EVT model. While the model performs well for moderate tails covering to one per cent, it struggles when α (1-p) is below one per cent, a fact Rozario attributes to the model's failure to account for clustering in the data. It is important to note that EVT relies on an assumption of i.i.d.[2], Chan and Gray (2006). Clearly this is not the case for shipping freight return series, and arguably financial returns in general. One approach to this problem is the GARCH-EVT model provided by McNeil and Frey (2000). The advantage of this combination lies in its ability to capture conditional heteroskedasticity in the data through a GARCH framework, while at the same time modelling the extreme tail behaviour through an EVT method. As such, the GARCH-EVT approach might be regarded as semi-parametric, Manganelli and Engle (2004). Bali and Neftci (2003) apply the GARCH-EVT approach to U.S. short-term interest rates and show that the model yields more accurate estimates of VaR than that obtained from a Student t-distribution GARCH model. Fernandez (2005) and Byström (2004) also find that the GARCH-EVT model performs better than the parametric models in forecasting VaR for various international stock markets. In an energy application, Byström (2004) employs a GARCH-EVT framework to NordPool hourly electricity returns and finds that extreme GARCH-filtered residuals obey a Fréchet distribution. Furthermore, the GARCH-EVT model produces more accurate estimates of extreme tails than a pure GARCH model. At present, applications of EVT to estimate VaR in shipping market are sparse.

An important contribution of this study is the proposal of a two-state Markov regime- switching distinctive conditional variance procedure. Markov-switching models were originally introduced by Hamilton (1988, 1989) and since then there has been a wide range of contributions, including Engle and Hamilton (1990), Hamilton and Susmel (1994), Hamilton and Lin (1996), and Gray (1996).

As far as we are aware this is the first attempt to model freight returns through a two-state Markov-switching distinctive conditional variance model, that is based on the assumption that volatilities within tanker freight returns switch between, higher and lower freight volatility state regimes. Similar, to financial returns, the evidence of volatility clustering is apparent in freight returns. Thus, assuming that conditional freight variance switches between two-state regimes, one of higher freights volatility and another of lower freights volatility is an appropriate assumption. In other words, if freight returns are subject to shifts between two state regimes, the conditional variance would change between two distinct conditional variance structures. Abouarghoub and Biefang-Frisancho Mariscal

[2] i.i.d. stands for independently and identically normally distributed with mean equal to zero and variance equal to 1.

(2011) study the volatility structure of the tanker freight market and its exposure to market shocks and find evidence of different volatility structures within tanker freight returns. They conclude that shipping tanker freight returns shift between higher and lower volatility regimes, and that market shocks in general increase the volatility of freight returns and has a lasting effect.

Furthermore, it is well documented in the shipping economics literature that shipping spot freight prices are determined through the interaction of demand and supply of freight services, for example see Alizadeh and Nomikos (2011), in other words, conditions of perfect competition prevail in shipping freight market, and demand for shipping services (freight) is an inelastic derived demand, due to the fact that freight costs represents a small fraction of the final price of transported goods, this demand is influenced by numerous factors, such as world economic conditions, international seaborne trade, seasonality, distance to transport goods and the size of cargo consignment. On the other hand, supply of shipping services measured in tonne-miles is highly elastic at low freight rate levels and highly inelastic at high freight rate levels. Supply also depends on factors such as; stock of fleet ready to be employed, productivity of the shipping building market, level of activity in the scraping market and current prevailing freight rate prices. For a more detailed documentation see Stopford (2009)[3].

Therefore, the concept of incorporating the change in freight market conditions in volatility models to enhance the performance of such models in capturing the dynamics of freight volatility has been recognised in maritime literature. For example Alizadeh and Nomikos (2009) state that the freight market is characterised as a bimodal market, due to the shape of the supply and the demand functions for shipping services. On the one hand, during an excess of tonnage supply, freight rates are low, which means that shocks to the market can be observed by spare capacity, thus, the market has distinctly low volatility. On the other hand, during scarcity of tonnage supply, freight rates are high, which means that markets are sensitive to shocks and the trading fleet is fully employed, thus, the market is distinctly volatile. Thus, in maritime literature lower freight volatility and higher freight volatility conditions are associated with the elastic and inelastic parts of the freight supply curve. Therefore, the proposed two-state Markov-switching distinctive conditional variance model aims to capture the dynamics within the lower freight volatility

[3] For more details see stopford (2009), chapter 4, pages 135-172.

and higher freight volatility states that correspond to the elastic and inelastic parts of the freight supply curve, respectively.

Furthermore, this chapter focuses on measuring tanker freight volatility, with the aim of establishing a framework for measuring freight risk exposure in tanker spot freight markets. One controversial tool used widely in the banking sector as a threshold for risk measurement is Value-at-Risk (VaR), which, undoubtedly is the industry benchmark for risk measurement. This is simply because VaR summarises risk in a single number that can be easily communicated and easily understood. Jorion's (2006, p. 106) definition of this risk measure is "*VaR is the worst loss over a target horizon, such that there is a low, prespecified probability that the actual loss will be larger*". Thus, the VaR of a particular portfolio is defined as the maximum loss on a portfolio and this definition consists of two quantitative factors, the holding period and the confidence level. In other words, VaR is a technique which uses statistical analysis of historical market trends and volatilities to estimate the likelihood that a given portfolio losses will exceed a certain amount. VaR methods for traditional financial markets are well documented in Dowd (1998), Duffie and Pan (1997) and Jorion (2006), whilst energy VaR is detailed in Clewlow and Strickland (2000) and Eydeland in Wolyniec (2003), for electricity markets Kam and Philip (2006) undertake a VaR approach, using a number of parametric and non-parametric models where they conclude that an EVT-based model is a useful technique for forecasting VaR. A general introduction to VaR for shipping markets can be found in Alizadeh and Nomikos (2009). Another attempt to investigate shipping freight risk using a VaR approach was conducted by Angelidis and Skiadopolous (2008), where they conclude that the simplest non-parametric models should be used to measure market risk for shipping freight rates. In their work they attempt to measure market risk for freight rates through a number of parametric and non-parametric approaches, as well as adapting an Extreme Value Theory method, for four Baltic exchange indices; the Baltic dry index (BDI), the 4 time charter average Baltic Panamax index (4 TC Avg BPI), the 4 time charter average Baltic Capesize index (4 TC Avg BCI) and the dirty tanker index (TD3). They conclude that the simplest non-parametric models are superior methods for calculating freight risk. The only exception occurs in the case of tanker freight rates, which matches the findings of this study. Thus, they state that freight rate risk is higher in the tanker markets than in the dry sector.

In summary, the few papers that investigate freight dynamics have disagreed on the most appropriate measure for conditional freight volatility and consequently freight risk measures. This study attributes this dissimilarities in maritime literature to the possibility of freight returns switching between distinct conditional volatility state regimes[4] and each state has it's define characteristics. Furthermore, approved conditional variance models in the literature that provide the best results and forecasts are models that capture the general behaviour within freight returns. This can be evidence of embedded models within the main approved conditional volatility framework. Therefore, this study aims to investigate the validity of the previous hypothesis.

[4] There is a possibility of more than two states, this study investigates the possibility of two states not excluding the possibility of more than two; for example a neutral state.

4.3. Methodology

In this chapter value-at-risk (VaR) is measured conditional on the underlying distribution of the risk factors of returns by computing three variations of the risk measure, a normal VaR, a non-normal VaR and a FHS-VaR. Thus, in this thesis a one-day ahead VaR is estimated in two steps. Firstly, using a variety of volatility models to model the one-day ahead conditional variance for tanker freight returns and capturing extreme shocks by accounting for fatter tales in the distribution of returns. A popular method of representing the distribution of returns that is used in empirical work is a normal distribution. However, it is well-documented in the literature that financial returns are not normally distributed, thus, volatility models are adjusted to account for fatter tails through a Student-t(d) distribution. Secondly, the underlying distribution of risk factors of freight returns is assumed for both parametric and non-parametric approaches. The former accounts for normal and non-normal distribution of returns and the latter assume a free method of distribution through a filtered historical estimation (FHS) approach. In the latter, volatility models are combined with historical past standardized returns to compute one day one per cent and five per cent VaRs measures, these VaR measures are performed using GARCH-based, FHS, and EVT specifications, which are compared to benchmarks such as Historical Simulation method and the JP Morgan RiskMetrics model.

Value-at-risk (VaR) refers to the maximum amount in money terms that an investor is likely to lose over some period of time, with a specific confidence level (1-α). Value-at-risk (VaR) is always reported in positive values, although it is a loss. There are two basic parameters for VaR. First, the significance level α or the confidence level $1-\alpha$. The significance/confidence level of VaR depends on the attitude of the risk manager, the more conservative the manager the lower the value of α and the higher the value of the confidence level $1-\alpha$. Second, the risk horizon (holding period) denoted by h, this is the period of time over which the potential loss is measured. Under the Basel II Accord, banks are required to assess their market risk capital requirement by measuring VaR at one per cent significance (99 per cent confidence) level with a risk horizon of ten days. For more details see Alexander (2008b). Generally, the choice of the length of the horizon for VaR depends on the objective of the study and how frequently the portfolio is rebalanced. For instance, mutual funds tend to re-balance portfolios on a monthly basis, while banks adjust them on a daily basis. We estimate daily VaRs because we take the position of a financial investor with investments in the shipping market who adjusts their portfolios on daily basis. Sort-term value-at-risk measure can be used to quantify maximum changes in daily tanker freight prices that provide shipping practitioners with a vital tool to improve their risk management strategies, in particular, operators of large number of vessels that require daily adjustments of a portfolio of freight positions.

In simple terms a VaR measure for freight returns *r* with a specific significance level α at time *t* for a period *h* ahead and conditional on the information set at time *t*, can be defined as the amount of loss and can be expressed as:

$$\Pr\left(r_{t+h} \leq VaR^{\alpha}_{t+h} | \Omega_t\right) = \alpha \tag{4.1}$$

In this chapter value-at-risk is measured by adopting parametric, non parametric and semi-parametric approaches. Thus, a calculation of value-at-risk is conducted in three different ways and the only difference between the three VaR models is the underlying distribution of risk factor returns. We distinguish between three distributions, namely the normal, the Student-t distribution and the generalized Pareto distribution. Section 4.3.1, presents the VaR based on the normal distribution, section 4.3.2 presents VaR based on a non-normal distribution[5], sections 4.3.3 presents VaR based on historical information, sections 4.3.4 presents VaR based on filtered historical simulation, section 4.3.5 discusses the different conditional volatility models, section 4.3.6 discusses back-testing tests for VaR models and section 4.3.7 presents misspecification tests used to evaluated the different models.

4.3.1. A normal value-at-risk measure

Assuming that estimated freight rates returns *h* days ahead are independently normally distributed (i.i.d.):

$$r_{t+h} \sim N\left(\mu_{t+h}, \sigma^2_{t+h}\right) \tag{4.2}$$

where the parameters μ_{t+h} and σ^2_{t+h} are the mean and variance of the returns at time *t*+*h* forecasts made at time *t* of the mean and volatility of expected freight returns over the next

[5] In this thesis non-normal distribution refers to the Student-t distribution.

h days. Let's assume that $\bar{r}_{t+h}^{\alpha}$ represents a percentage of the portfolio value r_t and that it is the lower α quantile of the distribution r_{t+h}. This can be expressed as $\Pr(r_{t+h} < \bar{r}_{t+h}^{\alpha}) = \alpha$. Thus, in reference to the standard normal distribution, equation 4.2 is transformed to:

$$\Pr(r_{t+h} < \bar{r}_{t+h}^{\alpha}) = Pr\left(\frac{r_{t+h}-\mu_{t+h}}{\sigma_{t+h}} < \frac{\bar{r}_{t+h}^{\alpha}-\mu_{t+h}}{\sigma_{t+h}}\right) = Pr\left(Z < \frac{\bar{r}_{t+h}^{\alpha}-\mu_{t+h}}{\sigma_{t+h}}\right) = \alpha \qquad (4.3)$$

where Z is a standard normal variable. Thus, $\frac{\bar{r}_{t+h}^{\alpha}-\mu_{t+h}}{\sigma_{t+h}} = \Phi^{-1}(\alpha)$, where $\Phi^{-1}(\alpha)$ is the standard normal quantile α value. As the normal distribution is symmetrical the following holds, $\Phi^{-1}(\alpha) = -\Phi^{-1}(1-\alpha)$. Therefore, based on the argument above the 100 α per cent h-day parametric normal VaR at time t can be expressed as:

$$VaR_{t+h}^{\alpha} = \Phi^{-1}(1-\alpha)\sigma_{t+h} \qquad (4.4)$$

Thus, the distribution of risk factor returns for this VaR measure is assumed to be normal. Therefore, a one-day ahead normal value-at-risk (N-VaR) is measured for freight returns across different tanker segments and is based on variety of conditional variance structures. In other words, five variations of the one-day N-VaR is estimated for each tanker segment under investigation by estimating freight conditional variance σ_{t+1} using different GARCH models. These GARCH variations are RiskMetrics, Symmetric-GARCH, Asymmetric-GARCH, Symmetric-GARCH-t(d) and Asymmetric-GARCH-t(d).

4.3.2. A non-normal value-at-risk measure

As we discussed in the literature review chapter (chapter 2) the distribution of returns does not follow the normal distribution, on the contrary the actual returns distribution has fatter tails. In order to account for the fatter rails, the Student-t distribution is used in non-parametric VaR estimations. Assuming the freight returns has a Student distribution with ν degrees of freedom than we write $freight\ returns \sim t_{\nu}$ and its density function as:

$$f_{\nu}(t) = (\nu\pi)^{-1/2}\Gamma\left(\frac{\nu}{2}\right)^{-1}\Gamma\left(\frac{\nu+1}{2}\right)(1+\nu^{-1}t^2)^{-\left(\frac{\nu+1}{2}\right)} \qquad (4.5)$$

The gamma function Γ is an extension of the factorial function to non-integer values (for details see Alexander, 2008b). This distribution has zero expectations and zero skewness and the variance is not one for $v > 2$, but $Variance\ (r_t) = v(v-2)^{-1}$. Let the α quantile of the standard Student-t distribution be denoted by $t_v^{-1}(\alpha)$. Thus, the quantile α of the standardised Student t distribution with a zero mean, variance of one and v degrees of freedom is expressed as $\sqrt{v^{-1}(v-2)}t_v^{-1}(\alpha)$. As the ordinary Student-t quantiles satisfy $-t_v^{-1}(\alpha) = t_v^{-1}(1-\alpha)$ and because the distribution is symmetric about a mean of zero the VaR is than written as:

$$Student - t(d)\ VaR_{t+h}^{\alpha} = \sqrt{v^{-1}(v-2)}t_v^{-1}(1-\alpha)(\sigma_t) \tag{4.6}$$

Note the similarities of the N-VaR in equation 4.4 and the t-VaR in equation 4.6 both VaRs are principally determined by the (time-varying) variance and the critical value of the particular assumed distribution (here: normal or Student-t) that corresponds to the chosen confidence level.[6] The confidence level is determined (exogenously) by the risk manager/investor of the regulator and the variance has to be estimated. The value with which the (estimated) standard deviation is multiplied is the (critical) z-value of the (standard) normal distribution that corresponds to the chosen confidence level. The t-VaR is determined in the same way, only that the (critical) value is taken from the Student-t distribution and that there is an additional correction factor which is the expression under the root in equation 4.6. Normally, the t-VaR is (ceteris paribus) higher than the N-VaR. in other words, estimating the N-VaR when the returns are Student-t distributed leads to a systematic underestimation of the VaR. While we are here only comparing the N-VaR and t-VaR, assuming the 'wrong' distribution is a major potential problem applying the non-parametric approach, because it may lead toe systematic under- or over-estimation of VaRs. On the other hand, if returns can be well approximated by, let us say, the Student-t distribution, than t-VaR is fairly good description of reality[7]

Therefore, a one-day ahead non-normal value-at-risk (Non-N-VaR) is measured for freight returns across different tanker segments and is based on a variety of conditional

[6] Note that we assume that the mean is equal to zero. This is a conventional assumption for daily returns and is also supported by the data here (see Table 4.3 in page 79).

[7] For a more detailed discussions of the advantages and disadvantages of parametric approaches to VaR, see Crouhy *et al* (2006) and Alexander (2008b).

variance structures. In other words, five variations of the one-day Non-N-VaR is estimated for each tanker segment under investigation by estimating freight conditional variance σ_{t+1} using different GARCH models. These GARCH variations are RiskMetrics, Symmetric-GARCH, Asymmetric-GARCH, Symmetric-GARCH-t(d) and Asymmetric-GARCH-t(d).

4.3.3. Historical simulation (HS) method

The historical simulation (HS) is a completely model-free approach which does not impose any structure on the return distribution. The simple non-parametric HS technique assumes that tomorrow's freight returns, r_{t+h}, is well explained by the empirical distribution of the past *m* observed freight returns, that is, $\{r_{t-\tau}\}_{\tau=0}^{m}$. Therefore, one day ahead value-at-risk with a confidence level (1-α), is simply calculated as 100pth percentile of a sequence of past portfolio returns in the form;

$$\boldsymbol{VaR_t^{\alpha} = -percentile\,\{\{r_{t-\tau}\}_{\tau=1}^{m}, \alpha\}} \tag{4.7}$$

typically *m* is chosen in practice to be between 250 and 1000 days corresponding to approximately 1 to 4 years. For the purposes of this study we use a 250 days period to capture patterns of seasonality in tanker spot freight rates as suggested in maritime literature, see Kavussanos and Alizadeh (2002b).

4.3.4. A filtered historical simulation value-at-risk (FHS-VaR) measure

A historical sample of data is used to estimate value-at-risk with no reference to the risk factor return distribution. Thus, the filtered historical simulation combines the best of the model-based methods of variance with model-free methods of distribution. Once the one-day ahead volatility is estimated then the one-day ahead value-at-risk is simply computed using the percentile of the database of standardized returns in the form of;

$$VaR_{t+h}^{\alpha} = \sigma_t\, percentile\ \{\{\hat{z}_{t-\tau}\}_{\tau=1}^{m}, \alpha\} \tag{4.8}$$

where $\hat{z}_{t-\tau}$ represents standardized returns drawn form past observed returns and calculated as $\hat{z}_{t-\tau} = R_{t-\tau} / \sigma_{t-\tau}$, for $\tau = 1, 2, \ldots, m$.

Thus, the distribution factors of return for this VaR measure is filtered historical simulated (FHS) and follow a free method of standardised returns. Therefore, a one-day ahead FHS-value-at-risk (FHS-VaR) is measured for freight returns across different tanker segments and is based on variety of conditional variance structures. In other words, seven variations of the one-day FHS-VaR are estimated for each tanker segment under investigation by estimating freight conditional variance σ_{t+1} using different GARCH models. These variations are Historical Simulation, RiskMetrics, Symmetric-GARCH, Asymmetric-GARCH, Symmetric-GARCH-t(d), Asymmetric-GARCH-t(d) and AGARCH-t(d)-EVT.

4.3.5. Modelling conditional volatility

As we pointed out in the previous sections, all VaR (expect for HS) are determined by an estimate of the variance. In this section we turn to the modelling of the time-varying variance.

Furthermore, one important objective of this chapter is to establish a framework to model non-normal conditional distribution of shipping freight returns for spot freight markets. To this end, we are particularly interested in normal and non-normal approaches to variance modelling. The assumption of *i.i.d.* normality implies that the likelihood of, l_t, of freight returns, r_t, is expressed as:

$$l_t = \frac{1}{\sqrt{2\pi\,\sigma^2_{t+h}}} exp\left(-\frac{r^2_{t+h}}{2\sigma^2_{t+h}}\right) \tag{4.9}$$

and thus the joint likelihood of the entire series of returns is

$$L = \prod_{t=1}^{T} l_{t+h} = \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma^2_{t+h}}} exp\left(-\frac{r^2_{t+h}}{2\sigma^2_{t+h}}\right) \tag{4.10}$$

Under a normal assumption framework we maximize the likelihood function 4.10 to estimate the parameters coefficients, Aldrich (1997). However, maximising the logarithm of the function 4.10 is equivalent to maximising the function it self. This is convenient as it replaces products with sums see Christoffersen (2003). In other words, for variance models impeded with assumed normally distributed row returns we maximize the following joint likelihood function of the observed sample.

$$Max\ In\ L = Max \sum_{t=1}^{T} In(l_{t+h}) = Max \sum_{t=1}^{T} \left[-\frac{1}{2} In(2\pi) - \frac{1}{2} In(\sigma_{t+h}^{2}) - \frac{r_{t+h}^{2}}{2\sigma_{t+h}^{2}} \right] \quad (4.11)$$

For variance models impeded with standardized returns $z_{t+h} = r_{t+h}/\sigma_{t+h}$ with $z_{t+h} \sim t(d)$. Where standardized returns are assumed to follow a student *t* distribution we maximize the following joint likelihood function, where *d* parameter is degrees of freedom;

$$In\ L = \sum_{t=1}^{T} In\big(f(r_{t+h}; d)\big) = InL_1 - \sum_{t=1}^{T} \frac{In(\sigma_{t+h}^{2})}{2} \quad (4.12)$$

Where L_1 is computed in the following form:

$$In\ L_1 = \sum_{t=1}^{T} In\big(f(z_{t+h}; d)\big) = T\left\{ In\left(\Gamma\left(\frac{d+1}{2}\right)\right) - In\left(\Gamma\left(\frac{d}{2}\right)\right) - \frac{In(\pi)}{2} - \frac{In(d-2)}{2} \right\}$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(1+d)In(1+\frac{(r_{t+h}/\sigma_{t+h})^{2}}{d-2} \quad (4.13)$$

For more details see Bollerslev *et al* (1988) and Bollerslev and Wooldridge (1992).

4.3.5.1. The symmetric GARCH (SGARCH) model

Bollerslev (1986, 1987) developed the symmetric normal general autoregression conditional heteroscedasticity (SGARCH) model, which is a generalization of the ARCH model that was developed by Engle (1982) and is based on an infinite ARCH specification and allows a reduced number of estimated parameters by imposing nonlinear restrictions.

The first model that we consider is the SGARCH or GARCH(p,q) model. This study, like most empirical studies, applies the GARCH(1,1) model assuming that the dynamic behaviour of the conditional variance depends on absolute values of market shocks and the persistence of conditional variance. This is represented as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad \varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2) \quad (4.14)$$

where σ_t^2 represents the dynamic conditional variance, ω refers to the constant, α is the market shock coefficient, β is the lagged conditional variance coefficient and ε_t denotes the market shock and is assumed to be normally distributed with zero mean and time varying conditional variance. Using the lag operator *L*, the above equation can be converted to:

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \tag{4.15}$$

where $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_q L^q$ and $\beta(L) = \beta_1 L + \beta_2 L^2 + \cdots + \beta_p L^p$. If all roots of the polynomial $|1 - \beta(L)| = 0$ lie outside the unit circle, thus, equation 4.15 is expressed as:

$$\sigma_t^2 = \omega[1 - \beta(L)]^{-1} + \alpha(L)[1 - \beta(L)]^{-1}\varepsilon_t^2 \tag{4.16}$$

In the above process the conditional variance linearity depends on all previous squared residuals. Palm (1996) argues that in the case that past realizations of squared residuals is larger than the unconditional variance, $\varepsilon_t^2 > \sigma^2$, than the conditional variance of r_t is larger than the unconditional variance computed by:

$$\sigma^2 \equiv E(\varepsilon_t^2) = \frac{\omega}{1 - \sum_{i=1}^{q}\alpha_i - \sum_{j=1}^{p}\beta_j} \tag{4.17}$$

The above equation is rearranged so that ω in the conditional variance equation is replaced by $\sigma^2\left(1 - \sum_{i=1}^{q}\alpha_i - \sum_{j=1}^{p}\beta_j\right)$, where σ^2 is calculated by measuring the variance of the full sample observed returns. This procedure is referred to as variance targeting for GARCH models.

The work of Bollerslev (1986) showed that for a symmetric normal GARCH (SNGARCH) model the kurtosis of a time series is larger than three and can be calculated by computing the following $3[1 - (\alpha + \beta)^2]/[1 - (\alpha + \beta)^2 - 2\alpha^2]$. Furthermore, Bollerslev (1986) derived the autocorrelations of residuals ε_t^2 and found that they decline exponentially with a decay factor of $\alpha + \beta$ indicating that $\rho_1 = \alpha + [\alpha^2\beta/(1 - 2\alpha\beta - \beta^2)]$ and $\rho_k = (\alpha + \beta)^{k-1}\rho_1, \forall k = 2, 3, ..K$. Moreover, Bollerslev (1986) finds that restricting $\omega > 0,\ \alpha_i \geq 0\ for\ i = 1, \ldots, q\ and\ \beta_i \geq 0\ for\ j = 1, \ldots, p$, is required for the conditional variance to be positive. Nelson and Cao (1992) argue that restricting all coefficients to be nonnegative is too restrictive and that some of these coefficients are found to be negative in practice while the conditional variance remains positive without imposing any restrictions. For more details see Laurent (2009). In general a conditional variance model consists of two equations, a conditional mean equation and a conditional variance equation that specifies the behaviour of returns. The conditional variance error ε_t is the error process in the conditional mean equation that is expressed in this thesis as:

$$r_t = c + \varepsilon_t \tag{4.18}$$

where c is a constant and is assumed to equal average returns $\bar{r}$, thus, it is reasonable to assume that $\varepsilon_t = r_t - \bar{r}$. Therefore, in this study the mean for daily freight returns is assumed to be zero, which is an appropriate assumption for daily returns, Alexander (2008a), thus, equation (4.14) is rewritten as:

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad r_t | I_{t-1} \sim N(0, \sigma_t^2) \tag{4.19}$$

where $\alpha + \beta < 1$. The variance is updated by the weighted squared return and the weighted variance of the previous period. The coefficient α is the weight assigned to squared return at time *t*, r_t^2 and β is the weight assigned to variance at time *t*, σ_t^2. The implication of the GARCH model is that there is a relatively stable long-run variance to which the estimated variance returns over time.[8] The long-run, or the unconditional variance can be derived as: $\sigma^2 = \omega/(1 - \alpha - \beta)$. By substituting the long-run variance into equation 4.19, it can be shown that the updated variance is the weighted average of the long-run variance, the squared return and yesterday's variance. Put simply, the predicted variance is the long-run plus or minus something dependent of the squared return and the squared previous day's variance. The sum coefficient of alpha and beta measures the persistence of the model. If the sum (alpha + beta) is close to one, the model is said to have a high persistence. This means that it will take a long time for the variance to return to its long-run level, once shocks push it away from its long-run level.

[8] This is consistent with the RiskMetrics model that is discussed below.

4.3.5.2. The asymmetric GARCH (AGARCH) model

Simple GARCH models by definition do not capture conditional non-normality in returns. However, it has been argued in the literature that bad news represented by negative returns increases price volatility by more than good news represented by positive returns, of the same magnitude. This is referred to as the leverage effect and is vital in modelling conditional variances for financial time series. In simple terms, a leverage effect is an increase in the volatility subsequent to a drop in the stock price, for example see Black (1976) among others. Most importantly, for commodities, Aboura and Chevallier (2013) argue that tail risk is much higher in the oil market than in stock markets, and that this greater risk motivates the analysis of oil volatilities as a possible driver of oil prices. Geman and Shih (2009) propose a model that captures the behaviour of commodity prices and their random volatilities motivated by the fact that mean-reversion, inverse leverage effect and changing volatility are properties that characterises commodity spot prices. The presence of an inverse leverage effect is evident in commodity markets such as the crude oil market, for example see Geman (2005). This is a positive correlation between oil prices and their volatilities, meaning that commodities price volatilities tend to increase along with their prices, in contrast to equity markets, due to market participants concerns of supply shortages or distribution to the production chain, for more details see Aboura and Chevallier (2013).

Therefore, the simple GARCH model is modified so that the weight given to the return depends on whether the return is positive or negative and is expressed in variety of ways. Nelson (1991) introduced the exponential GARCH (EGARCH) model, a function of both the magnitude and the sign, to accommodate the asymmetric relation between stock returns and volatility changes. In this study we use another popular model to capture freight asymmetry proposed by Glosten, Jagnnathan and Runkle, (Glosten, 1993).

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \theta I_{t-1} r_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4.20}$$

where θ represent the leverage effect coefficient and I_t is a dummy variable that takes the value of one if freight return at time *t-1* is negative and zero if return is positive. If the estimated coefficient theta is significant and positive, negative returns increase (on average) the variance more than positive returns. If theta is insignificant, there is no difference between the effects of positive and negative returns on the variance.

4.3.5.3. The RiskMetrics model

The RiskMetrics (RM) model weighs the past squared returns so that they decline exponentially as we move backwards in time. More recent (squared) returns are considered to be more important in determining the variance than (squared) returns that are far back in the past. The model can be written as:

$$\sigma_t^2 = \omega + (1\text{-}\lambda)\, r_{t\text{-}1}^2 + \lambda\, \sigma_{t\text{-}1}^2 \tag{4.21}$$

RM is a special version of the GARCH (1,1) with $\omega=0$ and an undefined long-run variance. The coefficient lambda needs to be estimated, but when estimating lambda over a wide variety of assets, RM found that the estimates were quite similar and they set λ =0.94 which has been adopted widely in empirical work and is also adopted here. In the RM model forecasts of tomorrow's volatility are simply a weighted average of today's volatility and today's squared return.

4.3.5.4. A fractionally integrated GARCH (FIGARCH) model

Ding *et al* (1993) study the daily S&P500 index and find that square returns are positively autocorrelated over more than ten years. Thus, volatility tends to slowly change over time and a shock effect can take a considerable time to decay. Laurent (2009) argues that the distinction between stationary and unit root processes is restrictive. On the one hand, the generation of shocks in a stationary process occurs at an exponential rate of decay, thus, capturing only the short-memory. On the other hand, for a unit root process the persistence of shocks is infinite. The short- run behaviour of the time-series can be captured by the parameters of an ARMA model, while the long-run dependence is better captured by a fractional differencing parameter. Therefore, Baillie, Bollerslev and Mikkelsen (BBM) introduced the Fractionally Integrated GARCH (FIGARCH) model to capture the correlogram of the observed volatility, (Baillie *et al*, 1996). The FIGARCH (p,d,q) model is expressed using lag operators as:

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d\}\varepsilon_t^2 \tag{4.22}$$

with $0 \leq d \leq 1, \omega > 0,\ \beta - d \leq \phi \leq \frac{2-d}{3}$ and $d\left(\phi - \frac{1-d}{2}\right) \leq \beta(\phi - \beta + d)$. These conditions ensure that the conditional variance of the FIGARCH (p,d,q) is positive for all *t*. The high significance of the estimated parameter and log-likelihood along with tests results justifies the use of a long-memory process in the conditional variance. The main characteristics of this model is that it is not stationary when $d > 0$.

$$(1 - L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(d+1)}{\Gamma(k+1)\Gamma(d-k+1)} L^k \tag{4.23}$$

$$= 1 - dL - \frac{1}{2}d(1-d)L^2 - \frac{1}{6}d(1-d)(2-d)L^3 - \cdots$$

$$= 1 - \sum_{k=1}^{\infty} c_k(d)L^k \tag{4.24}$$

where $c_1(d) = d, c_2(d) = \frac{1}{2}d(1-d)$, etc, and $\sum_{k=1}^{\infty} c_k(d) = 1$ for any value of *d*. Therefore, the FIGARCH model is nonstationary similar to the IGARCH model. For more details see Laurent (2009).

4.3.5.5. A conditional variance extreme value theory model (CV-EVT)

A shortcoming of the VaR measure is that it ignores the magnitude of extreme negative returns, which is important for financial risk managers. Extreme Value Theory (EVT) fills this gap. Thus, modelling conditional normality is performed by combining a variance model with an EVT application based on standardized returns $\hat{z}_t = R_t/\sigma_t \sim idd\ D(0,1)$. We adopt EVT approach of McNeil and Frey (2000) to account for extreme tail loss in our VaR measure of freight returns as many studies have done this for financial returns. For example Chan and Gray (2006) use EVT to measure VaR for electricity returns. McNeil and Frey (2000) propose a solution to model the much recognised fat-tails in financial distributions of returns by using a GARCH approach to filter the return series and than apply EVT to the GARCH residuals. Their GARCH-EVT combination accommodates both time-varying volatility and fat-tailed return distributions. In this study this approach is denoted by AGARCH-t-EVT. This approach is twofold. First, an appropriate conditional variance model is chosen to model freight volatility based on parameters significance levels, regression maximum likelihood value and model selection criteria[9]. Second, EVT is applied to standardised returns $\hat{z}_t$ that is based on the chosen conditional variance model to model the tail quantile of $F_{1-\alpha}^{-1}$ to drive VaR. McNeil and Frey (2000) describe their EVT method as a Peak Over Threshold (POT) method that identifies extreme standardised residuals (returns in this study) that exceed a high threshold *u*.

Consider that the standardised residuals z_t are random variables that are i.i.d. and are drown from an unknown distribution function F_z. Let *u* denote a high threshold beyond which observations of *z* are considered exceedences. The magnitude of these exceedences is given by $y_t = z_t - u$, for $\mathrm{i} = 1, \ldots N_y$, where N_y is the total number of exceedences in the sample. The distribution of y for a given threshold u is expressed as:

$$F_u(y) = Pr\{z - u \leq y | z > u\} = \frac{F_z(y+u) - F_z(u)}{1 - F_z(u)} \tag{4.25}$$

where $F_u(y)$ is the probability that *z* exceeds the threshold *u* and being below *y*. Assuming that *z* exceeds *u* and that $z = y + u$ equation 4.25 can be expressed as:

$$F_z(z) = [1 - F_z(u)]F_u(y) + F_z(u) \tag{4.26}$$

Pickands (1975) prove that $F_u(y)$ can be approximated by the Generalized Pareto Distribution (GPD) that is defined as:

$$G_{\xi,v}(y) = \begin{cases} 1 - \left(1 + \frac{\xi y}{v}\right)^{-1/\xi} & if\ \xi \neq 0 \\ 1 - \exp(-y/v) & if\ \xi = 0 \end{cases} \tag{4.27}$$

where ξ and *v>0* are shape and scale parameters, respectively, with the shape parameter capable to correspond to changes in the shape of the estimated distribution. Because $F_u(y)$ is approximated by equation 4.27 and that $F_z(u)$ is determined by $(T - N_y)/T$, thus, equation 4.26 can be expressed in an inverted tail estimator to estimate VaR.

$$F_z^{-1}(1 - \alpha) = u + \frac{v}{\xi}\left[\left(\frac{T}{N_y}\alpha\right)^{-\xi} - 1\right] \tag{4.28}$$

[9] In this study the AGARCH-t model is found to be superior in measuring short-term conditional volatility, for more details see empirical results section 4.4.2.

Let T denote the total sample size and N_y denote the number of observations beyond the threshold u. Therefore, the conditional variance extreme value theory (CV-EVT) VaR measure is defined as:

$$VaR^{\alpha}_{t+h} = \sigma_{t+h} F_z^{-1}(1-\alpha) \tag{4.29}$$

Thus, the Extreme Value Theory is built on the concept that as the threshold, u, gets larger, it converts to the generalized Pareto (GP) distribution. Chan and Gray (2006) in their choice of threshold u follow the approach of Gencay and Selcuk (2004) that determine a reasonable value for u by using a combination of two popular techniques, the mean excess function (MEF) and the Hill plots (Hill, 1975). In this study we use a rule of thumb suggested by Christoffersen (2003) to set the threshold so as to keep the largest 5 per cent for a sample of 1000 (approximately five years) observations for estimating ξ that is, we set N_y=50. The threshold u will then simply be the 95th percentile of the estimated sample. EVT main focus is on extreme negative returns; therefore, our EVT analysis is centred on negative returns instead of returns themselves. For a more detailed discussion of EVT see Christoffersen (1998, 2003), Christoffersen *et al* (2001) and Chan and Gray (2006).

4.3.5.6. Markov-switching GARCH models

This study investigates for the first time the possibility of the second moment for freight returns switching between two sets of constant parameter values, one set representing a higher freight volatility regime state and the other a lower freight volatility regime state. Furthermore, each regime state is modelled by capturing the dynamics within these distinct regime states through the best match from the GARCH-family. In other words, a two-state Markov-switching conditional variance (2-S MSCV) framework provides a useful insight into freight tanker information by distinguishing between two freight volatility regimes. These distinct states are matched against the best fit from GARCH-family models to capture the dynamics within these regime states. This framework in this thesis is referred to as a two-state Markov-switching distinctive conditional (2-S MSDCV) variance framework.

The log-likelihood of both Markov regime-switching models are maximised subject to the constraint that the probabilities lie between zero and one and sum to unity. In this thesis the estimation method used is the feasible non-linear programming approach of Lawrence and Tits (2001). These estimations are evaluated using the filtering procedure of Hamilton (1990) followed by the smoothing algorithm of Kim (1994), for more details and preceding references regarding the filtering algorithm see Hamilton (1994) and Krolzig (1997).

Therefore, the dependent variable in a regression that represents the second moment of freight returns is presented in two different ways. First, tanker freight volatilities are assumed to switch between two higher and lower constant regime states, these states are estimated along their transitional probabilities and time duration periods for five tanker segments to provide an insight into freight market information in regards to vessel size and type of trade. Second, a time series that represents freight returns for the whole tanker industry (returns on a portfolio of different tanker vessels) is assumed to switch between two distinctive conditional variance regime sates, the parameters of these distinctive volatility frameworks are assumed to be constant and are estimated simultaneously. This provides an insight into the dynamics of freight rates for the elastic and inelastic part of the freight supply curve.

This switching process is captured by time variance estimates of the conditional probability of each state and an estimate of a constant matrix of state transition probabilities. In the Markov-switching model the regression coefficients and the variance of the error terms are all assumed to be state dependent and returns are assumed normally distributed in each state. The Markov regime-switching conditional variance model is expressed as:

$$\sigma_t^2 = \begin{Bmatrix} \sigma_{1,t}^2 \rightarrow state\ 1 \\ \sigma_{2,t}^2 \rightarrow state\ 2 \end{Bmatrix} \qquad \sigma_t^2 \sim N(0, \sigma_{s_t}^2) \tag{4.30}$$

The framework expressed in equation 4.30 is employed across five tanker segments to investigate the hypothesis of tanker freight returns shifting between two-state, lower and higher volatility regime states. Furthermore, to model the dynamics of thesis distinctive two-state volatility regimes we employ a Markov-switching distinctive conditional variance model that is expressed as:

$$\sigma_t^2 = \left\{ \begin{array}{c} \sigma_{HV,t}^2 = \omega_{HV}[1-\beta_{HV}(L)]^{-1} + \alpha(L)[1-\beta_{HV}(L)]^{-1}\varepsilon_{HV,t}^2 \\ \sigma_{LV,t}^2 = \omega_{LV}[1-\beta_{LV}(L)]^{-1} + \{1-[1-\beta_{LV}(L)]^{-1}\phi(L)(1-L)^d\}\varepsilon_{LV,t}^2 \end{array} \right\}$$

$$\sigma_t^2 = \left\{ \begin{array}{c} \sigma_{HV,t}^2 \rightarrow SNGARCH \\ \sigma_{LV,t}^2 \rightarrow FIGARCH \end{array} \right\} \qquad \sigma_t^2 \sim N(0, \sigma_{s_t}^2) \tag{4.31}$$

where *LV* and *HV* refer to lower freight volatility state and higher freight volatility state, respectively. In equation 4.31 the conditional variance for freight returns is better expressed through a two-state Markov-switching distinctive conditional variance model, where the dynamics within the lower volatility state and the higher volatility state are captured by a fractional integrated conditional variance model (FIGARCH) and a normal symmetric conditional variance mode (NSGARCH), respectively. The choice of these two specifications to model the two distinct regime states is based on trial and error.

The state variance is assumed to follow a first-order Markov chain where the transition probabilities for the two states are assumed to be constant in the form of:

$$\Pi = \begin{bmatrix} \pi_{HH} & \pi_{LH} \\ \pi_{HL} & \pi_{LL} \end{bmatrix} = [\pi_{ij}] \tag{4.32}$$

Where π denotes the probability of being in state one (the higher volatility state) , π_{HH} denotes the probability of staying in the higher volatility state, π_{LL} denotes the probability of staying in the lower volatility state, π_{HL} denotes the probability of switching from the higher volatility state to the lower volatility state, π_{LH} denotes the probability of switching from the lower volatility state two to the higher volatility state, at any given point in time. The relations between these transition probabilities are explained as; $\pi_{LH} = (1-\pi_{LL})$; $\pi_{HL} = (1-\pi_{HH})$ and the transitional probability of lower volatility state = $(1-\pi)$. The unconditional probability of being in the higher volatility state regime is expressed as $\pi_{LH}/(\pi_{HL}+\pi_{LH})$. The set of parameters to be estimated for the conditional variance model in equation 4.30 is represented by the following vector.

$$\theta = (\mu, \sigma_{HV}, \sigma_{LV}, \pi_{HH}, \pi_{LL}) \tag{4.33}$$

Assuming that the Markov chain is represented by a random state indicator vector ξ_t whose *i*th element equals one if $s_t = i$ and zero otherwise. Thus, in a two-state Markov chain the state indicator vector is:

$$\xi_t = \begin{pmatrix} \xi_t^{HV} \\ \xi_t^{LV} \end{pmatrix} = \begin{cases} \begin{pmatrix} 1 \\ 0 \end{pmatrix} & if\ state\ HV\ rules\ at\ time\ t \\ \begin{pmatrix} 0 \\ 1 \end{pmatrix} & if\ state\ LV\ rules\ at\ time\ t \end{cases} \tag{4.34}$$

Therefore, the conditional probabilities of the state indicator ξ_t at time *t*, given all information up to time *t*-1, is denoted by $\xi_{t|t-1}$, this conditional expectation is the product of the transitional matrix Π and the state indicator at time *t*-1:

$$\xi_{t|t-1} = E_{t-1}(\xi_t) = \Pi\xi_{t-1} \tag{4.35}$$

Starting values are set as:

$$\hat{\xi}_t = \begin{pmatrix} \hat{\xi}_t^{HV} \\ \hat{\xi}_t^{LV} \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}\ or\ \begin{pmatrix} 0 \\ 1 \end{pmatrix} \tag{4.36}$$

The model is estimated using maximum likelihood method that is constructed based on the investigated sample. The inclusion of conditional regime probabilities in the maximum likelihood estimation requires a sub-iteration at every step of the numerical algorithm used to maximize the log likelihood function. For more details see Alexander (2008b) and references within. As the errors terms are assumed to be normally distributed in each state, the normal density function with expectation μ and standard deviation σ is expressed as:

$$\varphi(r_t | s_t = i, \Phi_{t-1}) = \frac{1}{\sqrt{2\pi\,\sigma_{it}^2}} exp\left[-\frac{1}{2}\left(\frac{r}{\sigma_{it}}\right)^2\right] \tag{4.37}$$

The regression coefficients and error standard deviation starting values are set equal to their values from standard linear regression, where $\hat{\sigma}_{LV} = \hat{\sigma}_{HV}$ and $\hat{\pi}_{HH} = \hat{\pi}_{LL}$. The set of parameters to be estimated for the distinctive conditional variance model in equation 4.31 is represented by the following vector.

$$\theta = (\mu, \omega_{HV}, \omega_{LV}, \beta_{HV}, \beta_{LV}, d, \sigma_{HV}, \sigma_{LV}, \pi_{HH}, \pi_{LL})' \tag{4.38}$$

where the log-likelihood function that is estimated is expressed as follows:

$$l = \sum_{t=1}^{T} \log \left[\frac{\pi}{\sqrt{2\pi\sigma_{HV,t}^2\left(\theta_{\sigma_{HV}^2}, \Phi_{t-1}\right)}} exp\left(-\frac{1}{2}\left(\frac{r}{\sigma_{HV,t}\left(\theta_{\sigma_{HV}^2}, \Phi_{t-1}\right)}\right)^2 \right) \right.$$

$$\left. + \frac{(1-\pi)}{\sqrt{2\pi\sigma_{LV,t}^2\left(\theta_{\sigma_{LV}^2}, \Phi_{t-1}\right)}} exp\left(-\frac{1}{2}\left(\frac{r}{\sigma_{LV,t}\left(\theta_{\sigma_{LV}^2}, \Phi_{t-1}\right)}\right)^2 \right) \right] \tag{4.39}$$

where π and $(1-\pi)$ are the conditional probabilities of being in state one (in this thesis is referred to as the higher freight volatility state (HV)) and being in state two (or in some other notations referred to as sate zero, in this thesis is referred to as the lower freight volatility state (LV)), respectively. The expression $\left(\theta_{\sigma_{HV}^2}, \Phi_{t-1}\right)$ refers to the unknown parameters of the relevant conditional variance model that need estimation and conditional on available information at the time. For extensive details of the construction of the log-likelihood function for Markov regime-switching GARCH models see the appendix of Gray (1996).

4.3.6. Backtesting VaRs

Backtesting of VaR is a test of the accuracy with which the chosen VaR model predicts losses. For purposes of examining the accuracy of forecasts, we split the total sample in two periods. The first period is for model estimation; this is used for calculating VaRs for the second period, which is then back tested against actual returns for the same period. The VaR_{t+h}^{α} measure promises that only α ×100% of the time the actual return will be worse than the forecast VaR_{t+h}^{α} measure. For the purposes of evaluating the accuracy of forecasts, this study conducts the unconditional coverage test, the independent test and the conditional test. For more details see Christofferson, (1998). The hit sequence of VaR violations are defined as:

$$I_{t+h} = \begin{cases} 1, if\ r_{t+h} < -VaR_{t+h}^{\alpha} \\ 0, if\ r_{t+h} > -VaR_{t+h}^{\alpha} \end{cases} \tag{4.40}$$

Thus, a sequence $\{I_{t+h}\}_{t=1}^{T}$is constructed across T days indicating when the past violations occurred. For the purposes of evaluating the accuracy of forecasts the following three tests are carried out.

4.3.6.1. The unconditional coverage test

The unconditional coverage hypothesis tests the fraction of violations obtained for a particular risk model, denoted as π, if it is, significantly different from the promised fraction, α. (for details see Christofferson, 1998; McNeil and Frey, 2000). The unconditional coverage hypothesis is computed using the following likelihood ratio test.

$$LR_{uc} = -2In[(1-\alpha)^{T_0}\alpha^{T_1}/((1-T_1/T)^{T_0}(T_1/T)^{T_1})] \sim x^2 \tag{4.41}$$

where T_0 is the number of times the VaR is not exceeded and T_1 is the number of times the losses are grater than VaR. As the number of observation, T, goes to infinity, the test will be distributed as a x^2 with one degree of freedom. Thus, the null hypothesis of unconditional coverage is rejected if the estimated value of LR_{uc} is greater than the tabulated Chisq(1) value. For a typical 5 per cent significance level, the tabulated Chisq(1) equals 3.84 and an estimated LR_{uc} value that is greater that 3.84 indicates that the chosen VaR model under-predicts losses. In other words, the VaR model is rejected.

4.3.6.2. The independence test

The unconditional coverage test examines the number of violations exceeding the α threshold value, but it fails to test the spread of these violations. In other words, the problem that the independence test addresses is that the VaR model may on average correctly predict losses at given significance level, but that the model under-predicts losses around the same time. Thus, the independence test examines clusters of violations. To this end, assume the hit sequence is dependent over time and that it can be described as a so-called first-order Markov sequence. For a sample of T observations, the likelihood function of the first-order Markov process is expressed as

$$L(\Pi_1) = (1-\pi_{01})^{T_{00}}\pi_{01}^{T_{01}}(1-\pi_{11})^{T_{10}}\pi_{11}^{T_{11}} \quad (4.42)$$

The likelihood ratios test to test the independence hypothesis that $\pi_{01} = \pi_{11}$ can be written as:

$$LR_{ind} = -2In\left[L(\hat{\pi})/L(\hat{\Pi}_1)\right] \sim x_1^2 \quad (4.43)$$

where $L(\hat{\pi})$ is the likelihood under the alternative hypothesis from the LR_{uc} test, Christofferson, (1998). Thus, the null hypothesis of independence is rejected if the estimated value of LR_{ind} is greater than the inverse of the one-tailed probability of the chi-squared distribution with one degrees of freedom, x_1^2, and vice versa.

4.3.6.3. Conditional coverage testing

Therefore, the importance of both previous tests in evaluating VaR forecast becomes paramount. Testing jointly for independence and correct coverage is conducted using the conditional coverage test

$$LR_{cc} = LR_{uc} + LR_{ind} \sim x_2^2 \quad (4.44)$$

Thus, the null hypothesis of jointly independence and correct coverage is rejected if the estimated value of LR_{cc} is greater than the inverse of the one-tailed probability of the chi-squared distribution with two degrees of freedom, x_2^2, and vice versa.

In summary, if the null hypothesis for either one of these tests is rejected at a certain required level then the VaR model used to generate these results are misspecified. Thus, accepting the null hypothesis of the unconditional coverage test, independent test and the conditional coverage test, indicate that the VaR model is correct on average, the violations are not clustered and the joint significance of both previous tests, respectively.

4.3.7. Misspecification tests

In this chapter we conduct several misspecification tests to investigate the robustness of the proposed models. First, an information criterion method is used to evaluate the goodness of fit of the conditional variance models that constitute our freight risk measure. In general, econometric models are estimated using the maximum likelihood estimation method, in doing so there is the possibility of improving the log-likelihood by adding parameters, which may result in over fitting. This problem is overcome in the literature by model selection criteria. They resolve this problem by introducing a penalty term for the number of parameters in the model. The following criteria are used to rank and compare the proposed models in this study. Akaike (1974), Schwarz (1978), Shibata (1981), and the following mathematical formulae are used:

$$Akaike = -2\frac{Log\ L}{n} + 2\frac{k}{n} \tag{4.45}$$

$$Schwarz = -2\frac{Log\ L}{n} + 2\frac{\log(k)}{n} \tag{4.46}$$

$$Shibata = -2\frac{Log\ L}{n} + log\left(\frac{n+2k}{n}\right) \tag{4.47}$$

Log L is the log-likelihood value; *n* is the number of observations and *k* is the number of estimated parameters. The optimal model is selected by minimizing the values obtained by computing the above equations.

Second, employed conditional heteroscedasticity models in this chapter are diagnosed using Tse (2002) proposed Residual-Based Diagnostic (RBD) for conditional heteroscedasticity, this is applied with various lag values to test for the presence of heteroscedasticity in the standardized residuals by running the following regression:

$$E(\hat{z}_t^2) - 1 = d_1 \hat{z}_{t-1}^2 + \cdots + d_M \hat{z}_{t-M}^2 + u_t \tag{4.48}$$

where $\hat{z}_t^2 = \hat{\varepsilon}_t / \hat{\sigma}_t$. As $\hat{z}_t^2$ depends on a set of parameters and assuming that $E(\hat{z}_t^2) = 1$, we run the above regression on the information available at the time and examine the statistical significance of the regression parameters. Tse (2002) derives the asymptotic distribution of the estimated parameters and shows that a joint test of significance of the $d_1, \ldots, d_M$ follows a $x^2(M)$ distribution. Tse (2002) proposed framework overcomes the shortcomings of the BoxPierce portmanteau statistic that is the most widely used diagnostic for conditional heteroscedasticity models.

Third, misspecification of the conditional variance equation and the presence of leverage effects are investigated through the diagnostic test of Engle and Ng (1993). It is suggested in the literature that a negative return shock could cause higher volatility than a positive return shock of the same size. This leads a SGARCH model to underpredict the effect of volatility following bad news and overpredicts the effect of volatility following good news. Furthermore, if large return shocks have a larger volatility effect than smaller once, and is not captured well by the quadratic function in the standard conditional variance (SGARCH) model, then this model underpredicts the effect of volatility after a large return shock and overpredicts the effect of volatility after a smaller return shock. These observations led Engle and Ng (1993) to suggest three diagnostic tests for volatility models; these are the Sign Bias Test (SBT), the Negative Sign Bias Test (NSBT) and the Positive Sign Bias Test (PSBT).

Therefore, let $SBT_{,t-1}$ and $NSBT_{t-1}$ denote dummy variables which take the value of one when $\hat{\varepsilon}_t^2$ is a negative value and zero otherwise, and $PSBT_{t-1}$ denote a dummy variable that takes the value of one when $\hat{\varepsilon}_t^2$ is a positive value and zero otherwise. This test examines if squared normalized residuals can be predicted by observed information in the past through the following variables $SBT_{,t-1}, NSBT_{t-1}\hat{\varepsilon}_{t-1} and/or PSBT_{t-1}\hat{\varepsilon}_{t-1}$, and can not be captured by the implemented volatility model. Therefore, in this study using Engle and Ng (1993) framework we test the presence and the size magnitude of the leverage effect remaining in the residuals of our conditional variance models. Thus, running the following regressions using a T-test to test for the significance of the coefficients $\alpha_1, b_1 and\ c_1$.

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1 SBT_{t-1} + u_t \tag{4.49}$$

$$\hat{\varepsilon}_t^2 = b_0 + b_1 NSBT_{t-1}\hat{\varepsilon}_{t-1} + u_t \tag{4.50}$$

$$\hat{\varepsilon}_t^2 = c_0 + c_1 PSBT_{t-1}\hat{\varepsilon}_{t-1} + u_t \tag{4.51}$$

A rejection of the null hypothesis in any of the above regressions indicates the significance of $\alpha_1, b_1 and\ c_1$, which refers in subsequent order to the presence of leverage effect, the sensitivity to negative shock size impact and the sensitivity to positive shock size impact. The significance of all of these coefficients indicates the misspecification of the conditional variance model.

4.4. Empirical work

In this section we present the empiricals and findings, starting with simple analysis of the data sample in section 4.4.1, followed by discussions of estimations and structures of the different conditional volatility models for single tanker routes and their relevant misspecification and diagnostic tests in section 4.4.2. Section 4.4.3 discusses back testing results for VaR models. Furthermore, Markov-switching empirical work is reported for different tanker segments and for a time series that represents freight returns on a shipping portfolio that consists of all tankers that are employed in transporting crude oil and oil products in section 4.4.4.

4.4.1. Simple analysis and the data sample

In a quest to measure the level of risk exposure in shipping tanker freights, a value-at-risk methodology is applied to five major dirty tanker shipping routes that are described and represented in Table 4.1 along with voyage assumptions for each route, these are used to convert a measure of freight that is quoted in dollars per tonne to a measure of freight that is quoted in dollars per day, which is the cost of a daily hire of a particular vessel. The data sample consists of five Baltic Dirty Tanker Indexes (BTDIs), these are indications of freight movements for dirty oil products. The five chosen indexes are the oldest and most active tanker freight markets, they also represent three important segments of the tanker industry, VLCC, Suezmax and Aframax.[10] These voyage charter routes are quoted in World scale points. A voyage charter provides transport for a specific cargo between two ports for a fixed price per ton of cargo. For purposes of this study returns are computed in the following form:

$$r_{t+1} = In(S_{t+1}) - In(S_t) \tag{4.52}$$

where S_t denotes spot price at time t and S_{t+1} spot prices at time $t+1$. The Baltic Dirty Tanker Index (BDTI) tracks freight rate movements for the tanker market and consist of 18 voyage charter routes quoted in WorldScale points. The World Scale point is a fraction of the flat rate instead of a plus or minus percentage and is derived assuming that a tanker

[10] VLCC refers to a very large crude carrier with a capacity of more than 200k dwt, Capesize refers to vessels with capacity between 120-200k dwt and Aframax refers to vessels with capacity between 80-120k dwt.

operates on a round voyage between designated ports. This calculated schedule is the flat rate expressed in US$ per tonne. The tanker industry uses this freight rate index as a more convenient way of negotiating and comparing freight prices per ton of oil transported on different routes.

For the purposes of this study, we examine daily shipping freight returns for five major dirty tanker shipping routes; the full data sample period is from 27-JAN-98 to 30-OCT-09. The data period used for estimation is from 27-JAN-98 to 24-DEC-07, and the data period used for evaluation is from 02-JAN-2008 to 30-OCT-09. Over the second period, we use a sample of 462 days (approximately five quarters) which is rolled on over time to estimate one-day VaRs. We obtain thus 462 VaR estimates per model, which are used to test and evaluate the VaR model. The period over which the VaR models forecast and are evaluated against, cover the height of the financial crisis and its gradual recovery. Looking for instance at the distribution of the variance over the forecast period for the different tanker routes under investigation (Appendix I) shows the stark difference in volatility of shipping freight returns at the beginning, middle and the end of the evaluation period. The data sample was downloaded from Clarkson Intelligence Network website, where all spot prices are expressed in World Scale points.

The primary goal of the chapter is to examine market shock effects and the level of risk exposure in shipping tanker freight prices, through assessing the capability of a number of approaches to accurately measure VaR for shipping freight returns. Therefore, the full data sample is divided into an in-sample period; on which the model estimation section are based, and an out-of-sample period over which VaR performance is measured. Descriptive statistics along with preliminary tests for daily spot and return freight prices for five shipping tanker routes are represented in Tables 4.2 and 4.3, respectively. Statistics are shown for full-sample, as well as in-sample and out-off sample periods. These are minimum, mean, maximum, standard deviation, skewness, excess kurtosis and normality tests for freight price-levels and returns that are reported for the whole sample in Table 4.2. While the same tests along with ADF and ARCH effect tests are reported for In-sample and Out-sample in Table 4.3. Higher standard deviations and significant changes in skewness values for the period from January 2008 to October 2009, in comparison to positive values of skewness for the whole- and In-sample, is an indication of a possible change in volatility dynamics. This coincides with a period of depression in global markets due to the recent financial crisis. This is clear in a significant change from highly positive skewness to a much lower value for route TD3, and a change from highly positive to negative values for routes TD4, TD5 and TD7. Furthermore, the positive skewness, high kurtosis and the Jarque-Bera normality test clearly illustrate the non-normality of the distribution. The mean daily returns are quite close to zero, which support the zero mean assumption. There is clear evidence of volatility clustering in daily freight returns. There are high freight volatility periods mixed with low freight volatility periods, which suggests the presence of heteroscedasticity, see Figure 4.1 that compares three illustrations of freight rates across five different tanker segments. These are plots of freight price-levels, freight returns and a normal symmetric conditional variance of freight returns. As a high ARCH order is vital to catch the dynamic of conditional variance, we apply Engle's LM ARCH test on daily freight returns for different lags. This confirms the presence of ARCH effects which is what the literature suggests (Engle, 1982). The high positive value of skewness and the high kurtosis for daily tanker freight returns are tested; their *t*-tests and *p*-values are reported in Table 4.3. The stationarity of daily freight returns was tested using the Augmented Dickey-Fuller unit root test see Dickey and Fuller (1981) and are reported in Table 4.3.

Table 4.1: Dirty tanker routes and cargo description

Route	Route Description	Capacity Metric tons	Port Costs $	Bunker Cons Per Day	Days of Voy	Total Bunker Consumption
TD3	MEG (Ras Tanura) to Japan (Chiba)	260,000	160,837	70 tons	45.5	3,185 tons
TD4	West Africa (boony) to US Gulf (LOOP)	260,000	161,334	65 tons	39	2,535 tons
TD5	West Africa (boony) to USAC Gulf (Philadelphia)	130,000	133,167	60 tons	35	2100 tons
TD7	North Sea (Sullom Voe) to continent (Wilhelmshaven)	80,000	204,600	36.5 tons	8.3	303 tons
TD9	Caribben (Puerto la Cruz) to US Gulf (Corpus Christi)	70,000	87,000	47 tons	15	705 tons

Note Table 4.1: Describes the five Dirty Tanker shipping routes under investigation. First, second and third columns, represents shipping voyage route number, voyage route description and vessel capacity, respectively. The third column is also an indication of vessel type and size. VLCC, VLCC, Suezmax, Aframax and Panamax vessels operate on routes, TD3, TD4, TD5, TD7 and TD9, respectively. Forth, fifth and last columns represent daily bunker consumption in metric tons, number of steaming days and total bunker consumption for the voyage, respectively.

Source: Route descriptions are defined by the Baltic Exchange and the assumption for each round voyage is published by Imarex.

Table 4.2: Spot & returns freight rate statistics

Variable	Minimun	Mean	Maximum	Variance	Std Dev	Skewness	Excess Kurtosis	Jarque Bera
S TD3	**25.36**	**88.67**	**342.97**	**2612.7**	**51.1**	**1.678**	**3.673**	**3041.2[0.00]**
S TD4	**29.81**	**91.91**	**304.17**	**2135.2**	**46.2**	**1.345**	**2.37**	**1579.5[0.00]**
S TD5	**38.19**	**126.75**	**399.79**	**3289.0**	**57.3**	**1.176**	**1.703**	**1036.5[0.00]**
S TD7	**61.59**	**141.81**	**359.09**	**2949.3**	**54.3**	**1.06**	**0.938**	**660.19[0.00]**
S TD9	**52.5**	**179.73**	**450.45**	**6081.3**	**77.9**	**1.007**	**0.672**	**553.83[0.00]**
R TD3	**-0.502**	**-0.0000846**	**0.39961**	**0.00256**	**0.0506**	**0.255**	**14.152**	**24633[0.00]**
R TD4	**-0.343**	**-0.0000569**	**0.28743**	**0.00133**	**0.0364**	**0.11**	**12.986**	**20719[0.00]**
R TD5	**-0.357**	**-0.0001049**	**0.28881**	**0.00189**	**0.0436**	**0.46**	**7.904**	**7777.1[0.00]**
R TD7	**-0.499**	**-0.0001037**	**0.42700**	**0.00245**	**0.0495**	**0.877**	**17.136**	**36446[0.00]**
R TD9	**-0.517**	**-0.0001305**	**0.46239**	**0.00372**	**0.0609**	**0.643**	**13.952**	**24114[0.00]**

Note Table 4.2: Represents summary of basic statistics of spot prices and return values for shipping freight rates, for five tanker routes and for the full-sample period, this starts from 27-Jan-98 to 30-Oct-09 and includes the estimation and testing periods. Total observations are 2949 and 2948 for freights spot prices and freight returns, respectively. It is clear from minimum, maximum and standard deviation of freight prices and returns the large spread and high volatility in freight price. All routes show signs of positive skewness, high kurtosis and departure from normality represented by the Jarque-Bera test. Values in [ ] are p values, which are significance for all routes. S stands for spot and R for returns.

Source: Data downloaded from Clarkson intelligence network and analysed by author.

Table 4.3: Daily returns statistics

Route	Minimun	Mean	Maximum	Std Dev	Skewness	Excess Kurtosis
In-Sample period From 27-01-1998 to 24-12-2007 (2486 observations)						
R TD3	-0.502	0.000613	0.399	0.049	0.3149	15.55
					(6.42) [0.00]	(158.4) [0.00]
R TD4	-0.284	0.000439	0.257	0.033	0.4943	11.73
					(10.07) [0.00]	(119.6) [0.00]
R TD5	-0.208	0.0003408	0.261	0.039	0.7723	7.04
					(15.73) [0.00]	(71.7) [0.00]
R TD7	-0.499	0.000283	0.427	0.046	1.3503	20.91
					(27.50) [0.00]	(213.0) [0.00]
R TD9	-0.419	0.000521	0.462	0.055	0.6867	14.27
					(13.98) [0.00]	(145.3) [0.00]
Out-Sample period From 02-01-2008 to 30-10-2009 (462 observations)						
R TD3	-0.373	-0.003834	0.303	0.055	0.048001	8.641
					(0.423) [0.67]	(38.1) [0.00]
R TD4	-0.343	-0.002726	0.287	0.051	-0.408971	9.901
					(3.60) [0.00]	(43.7) [0.00]
R TD5	-0.357	-0.002506	0.288	0.061	-0.015508	5.866
					(0.14) [0.89]	(25.8) [0.00]
R TD7	-0.355	-0.002187	0.338	0.064	-0.010758	7.673
					(0.95) [0.34]	(33.8) [0.00]
R TD9	-0.517	-0.003633	0.425	0.087	0.563757	8.459
					(4.96) [0.00]	(37.3) [0.00]

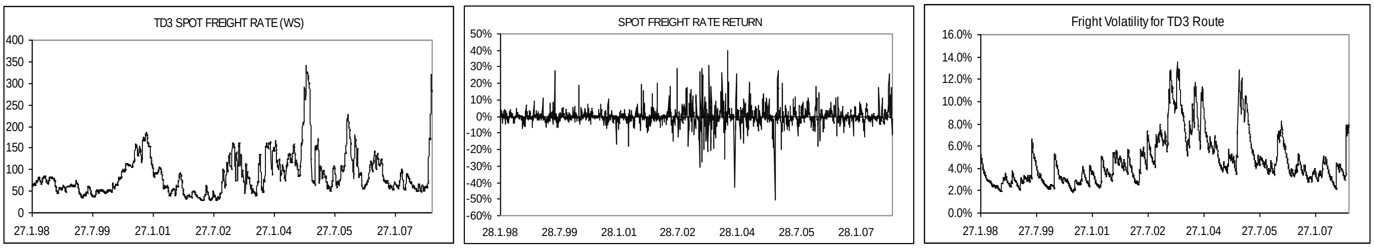
Route	ADF(Lag)	ARCH Test				Normality Test
		1-2	1-5	1-10	1-20	
In-Sample period From 27-01-1998 to 24-12-2007 (2486 observations)						
R TD3	-28.91	50.414	23.471	14.504	8.7271	25088
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD4	-30.81	53.204	21.575	13.565	7.5352	14386
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD5	-31.34	32.155	13.733	9.4817	5.3898	5381.1
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD7	-28.12	25.711	10.41	10.875	5.6966	46039
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD9	-33.53	53.07	22.137	11.905	6.53.97	21276
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Out-Sample period From 02-01-2008 to 30-10-2009 (462 observations)						
R TD3	-11.17	4.1156	9.7671	5.4019	4.3997	1437.72
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD4	-13.82	1.9608	0.89421	0.43301	2.4363	1899.71
	(0) [0.00]	[0.14]	[0.48]	[0.93]	[0.00]	[0.00]
R TD5	-13.31	5.6914	2.5976	1.1466	2.0348	662.541
	(0) [0.00]	[0.00]	[0.02]	[0.33]	[0.01]	[0.00]
R TD7	-13.00	1.4509	0.84634	0.4335	2.4565	1134.17
	(0) [0.00]	[0.23]	[0.52]	[0.93]	[0.00]	[0.00]
R TD9	-16.81	7.7191	3.7598	1.9065	1.3484	1402.02
	(0) [0.00]	[0.00]	[0.00]	[0.04]	[0.14]	[0.00]

Note Table 4.3: Represents basic statistics summary of spot freight returns, for five tanker routes. The table is of two parts that report returns statistics and tests results, respectively. Furthermore, each part is subsequently divided to two sections. First section represents statistics for in-sample period from 27-01-1998 to 24-12-07. Second section represents statistics for out-off-sample period from 02-01-2008 to 30-10-2009. Reported statistics are minimum, mean, maximum, standard deviation, skewness and Ex kurtosis. While reported tests are ADF test of stationary, presence of ARCH effect and normality test. It is clear from minimum, maximum and standard deviation values of freight returns for both periods, the large spread and high volatility in freight returns. All routes show signs of positive and negative skewness, high kurtosis and departure from normality represented by the Jarque-Bera test, which is significance for all routes. J-B is the Jarque-Bera normality test. The 5% critical value for this statistic is 5.99. Values in [ ] are p values.

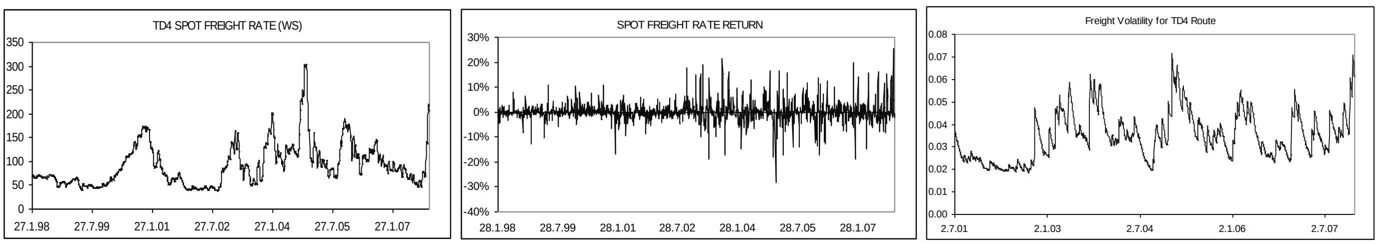
Source: Author's estimations.

Figure 4.1: An illustration of spot price, returns and symmetric conditional volatility measure

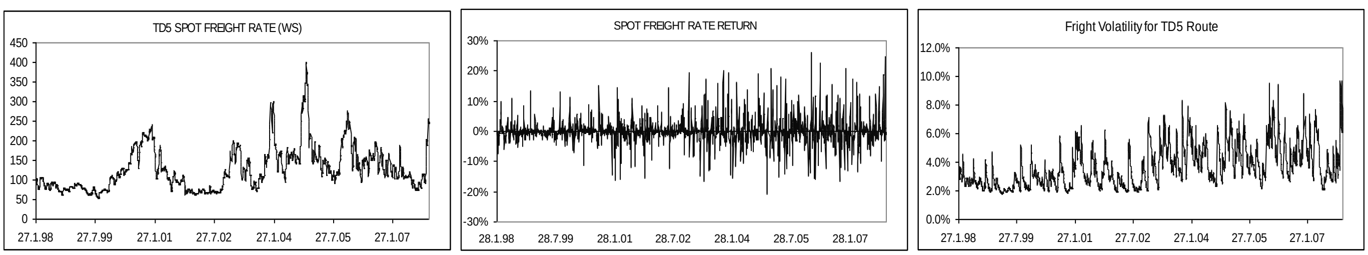
BDTI TD3: 250,000mt, Middle East Gulf to Japan



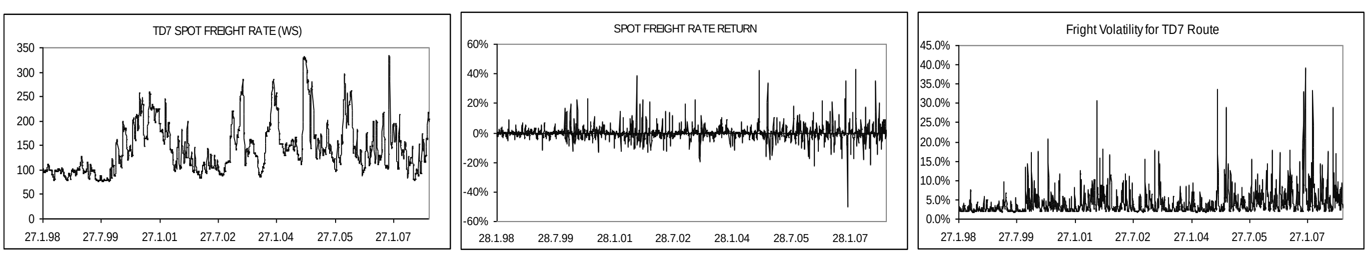
BDTI TD4: 260,000mt, West Africa to US Gulf



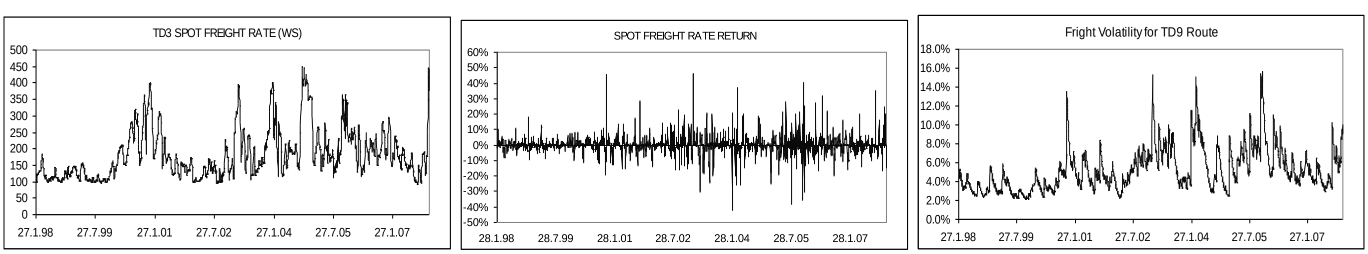
BDTI TD5: 130,000mt, West Africa to USA



BDTI TD7: 80,000mt, North Sea to Continent



BDTI TD9: 70,000mt, Caribbean to US Gulf



Note Figure 4.1: shows summary plots for daily shipping spot freight rates data for five major dirty tanker routes: TD3, TD4, TD5, TD7 and TD9.The left, middle and right columns display spot freight rate prices in world scale, returns and the volatility of daily returns respectively. The volatility is measured using a Symmetric GARCH model. **Source:** Author’s estimations.

4.4.2. Conditional volatility model estimations

This study aims to measure level of risk exposure in tanker shipping freights through computing a one-day VaR measure, based on a conditional volatility framework. Therefore, we implement the use of symmetric and asymmetric GARCH models in different variations, to capture the dynamics of the conditional variance, these models are, the SGARCH, SGARCH-*t*-(*d*), AGARCH and AGARCH-*t*-(*d*) models. The in-sample parameters estimations are performed using the Maximum Likelihood Estimation (MLE) method, with variance targeting and a constrained positive conditional variance; these are represented in Table 4.4 subsequently for all models. The first section represents parameter estimations for Symmetric GARCH model. The second section represents parameter estimations for *t*-Student Symmetric GARCH model, which is capable to better adjust to high markets shocks in absolute values. The third section represents parameter estimations for the Asymmetric GARCH model that captures leverage effects in the series. The final part of the table represents parameter estimations for *t*-Student Asymmetric GARCH model that accounts for leverage effects and extreme non-normality, this means that it is better in dealing with high negative shocks in freight returns. The values of estimated parameters along their *t*-statistics and volatility persistence for each model are also reported. Furthermore, reported results include values of skewness and excess kurtosis of the standardised residuals of the estimated model, along with their *t*-tests and *p*-values. Moreover, the normality test of Jarque and Bera (1987) is also reported. In most models (except for the asymmetric GARCH for routes TD3 and TD4, where squared returns do not affect the variance, the parameters are significant and their sum is below one, indicating stationarity in the variance) persistence (PER) is generally high, ranging from 0.99 to 0.58. Shocks to the variance push it off its constant long-run level for prolonged periods. The unconditional variances for the different routes are reported in Table 4.2 (under the variance column). Turning to the results of the AGARCH models in Table 4.4, theta is positive and significant in all AGARCH-t models, but insignificant in all normal AGARCH models. For half the models, we find that negative returns increase the variance in comparison to positive returns. The main drawback of the Student-t distribution is that even they account for fat-tails, they are symmetric and do not account for skewness and kurtosis, which are important for applications such as value-at-risk. This limitation is represented by the 'degrees of freedom' the only parameter in the *t* distribution and the lower the degrees of freedom the lower the peak of the distribution and longer the tails. Therefore, in Table

4.4 we report for AGARCH-t models the DF for all routes. These low values estimates indicate that conditional variance for tanker routes are fat-tailed and that tankers operating on TD3, TD7 and TD4 routes exhibit sorter tails than tankers operating on TD5 and TD9. The goodness of fit is determined by the information criteria, where the best model shows the lowest value. The AGARCH-t models tend to show a better fit than the other models. Results indicate that in general estimated coefficients and skewness for the conditional variance models and their standardised residuals, respectively, are positive and significant. All models exhibit high kurtosis levels, high volatility persistence and deviate from normality.

Thus, in Table 4.4 estimated coefficients are significant and positive except for the leverage effect parameter for route TD7, which is an indication of the unsuitability of the AGARCH framework for modelling Aframax vessel operations in the North Sea area. Empirical results indicate that over all the *t*-Student AGARCH framework has the better fit with the characteristics of tanker shipping freight markets, accounting for asymmetric market shocks, large losses and conditional volatility. This is in agreement with the findings of Alizadeh and Nomikos (2009), where they suggest that a leverage effect is present in freight spot rates, in contrast to supply and demand fundamentals that suggest an inverse leverage effect, which is higher volatility in the market when freight rates are high and supply and demand conditions are very tight. However, the model does not sufficiently account for fat tail losses as compared with the data. This shortcoming has been overcome by adopting an Extreme Value Theory approach.

Table 4.4: Estimated GARCH models

	TD3	TD4	TD5	TD7	TD9
Symmetric GARCH					
α	0.052266 (2.2)**	0.423769 (6.)***	0.144240 (2.6)***	0.570416 (8.6)***	0.253777 (4.1)***
β	0.937909 (31.3)***	0.155865 (1.73)*	0.804416 (10.1)***	0.175099 (1.8)*	0.591865 (4.9)***
ω	0.000024	0.000463	0.000081	0.000546	0.000461
PER	0.990170	0.579630	0.948660	0.745510	0.845640
MLE	4353.36	5205.99	4718.29	4538.49	3965.50
Skewness	0.62846(12.8)***	-0.15908(3.24)***	0.75115(15.29)***	0.69826(14.22)***	0.00762(0.15)
Ex Kurtosis	13.59 (138.5)***	16.98 (172.9)***	7.38 (75.22)***	16.71 (170.2)***	14.6 (148.4)***
J-B	19318 [0.00]	29870 [0.00]	5880.5 [0.00]	29114 [0.00]	21990 [0.00]
Akaike	-3.500688	-4.186640	-3.794282	-3.649627	-3.188656
Schwarz	-3.501739	-4.187692	-3.795334	-3.650678	-3.189707
Shibata	-3.500689	-4.186642	-3.794284	-3.649628	-3.188657
Symmetric GARCH-t(d)					
α	0.608579 (8.4)***	0.603571 (10.5)***	0.216544 (3.3)***	0.737084 (21.0)***	0.637302 (17.3)***
β	0.259230 (2.51)**	0.163018 (1.78)*	0.739758 (8.8)***	0.130825 (2.8)***	0.139701 (3.3)***
ω	0.000327	0.000257	0.000069	0.000283	0.000666
DF	3.236782(30.6)***	2.943359(33.8)***	2.785575 (35.1)***	3.074745(34.8)***	2.780335(40.5)***
PER	0.867810	0.766590	0.956300	0.867910	0.777000
MLE	5001.433	5863.614	5277.778	5286.859	4701.828
Skewness	0.95631(19.5)***	-0.54964(11.2)***	0.76306 (15.5)***	0.72785 (14.8)***	-0.06271 (1.27)
Ex Kurtosis	21.8 (222.3)***	24.0 (244.6)***	8.0 (81.5)***	15.9 (162.8)***	18.5 (189.0)***
J-B	49702 [0.00]	59822 [0.00]	6874.5 [0.00]	26670 [0.00]	35658 [0.00]
Akaike	-4.021265	-4.714895	-4.243586	-4.250892	-3.780232
Schwarz	-4.022795	-4.716424	-4.245116	-4.252422	-3.781761
Shibata	-4.021268	-4.714898	-4.243589	-4.250895	-3.780235
Asymmetric GARCH					
α	0.09351 (0.821)	0.07458 (0.831)	0.120514 (2.1)**	0.671043 (5.1)***	0.163872 (2.38)**
β	0.802301 (3.3)***	0.849388 (4.9)***	0.807239 (9.9)***	0.192970 (1.82)*	0.624246 (5.2)***
ω	0.000138	0.000048	0.000082	0.000526	0.000408
θ	0.09658(0.916)	0.06538 (1.210)	0.04097 (1.232)	-0.2191 (-1.280)	0.150081 (2.56)**
PER	0.944095	0.956669	0.948239	0.754475	0.863159
MLE	4341.25	5207.74	4720.98	4546.97	3978.48
Skewness	0.44780(9.1)***	0.54845(11.2)***	0.80969(16.5)***	0.37043(7.5)***	0.17474(3.7)***
Ex Kurtosis	22.6 (230.5)***	11.6 (118.5)***	7.4 (75.5)***	16.9 (172.3)***	14.1 (143.8)***
J-B	53107 [0.00]	14130 [0.00]	5955.6 [0.00]	29693 [0.00]	20649 [0.00]
Akaike	-3.490144	-4.187238	-3.795640	-3.655644	-3.198291
Schwarz	-3.491674	-4.188768	-3.797169	-3.657173	-3.199821
Shibata	-3.490147	-4.187241	-3.795642	-3.655647	-3.198294
Asymmetric GARCH-t(d)					
α	0.509476 (5.2)***	0.474906 (5.5)***	0.155855 (2.8)***	0.750230 (12.9)***	0.496058 (6.5)***
β	0.288558 (2.7)***	0.193566 (1.89)*	0.746735 (9.1)***	0.130917 (2.8)***	0.161557 (3.2)***
ω	0.000304	0.000242	0.000063	0.000283	0.000641
θ	0.158352 (1.99)**	0.223629 (2.31)**	0.114674 (2.6)***	-0.02656 (-0.282)	0.255004 (2.47)**
DF	3.244153 (30.7)***	2.941253(34.4)***	2.812469 (35.9)***	3.076287 (34.6)***	2.779176 (40.5)***
PER	0.877209	0.780287	0.959927	0.867865	0.785118
MLE	5003.39	5866.36	5283.83	5286.90	4705.08
Skewness	1.212 (24.7)***	-0.402 (8.2)***	0.92450(18.8)***	0.69406 (14.1)***	0.09367 (1.9)*
Ex Kurtosis	25.68 (231.1)***	24.5 (249.9)***	8.2508 (84.1)***	15.984 (162.9)***	18.167 (185.1)***
J-B	53900 [0.00]	62430 [0.00]	7405.6 [0.00]	26665 [0.00]	34189 [0.00]
Akaike	-4.022034	-4.716299	-4.247652	-4.250120	-3.782039
Schwarz	-4.024137	-4.718402	-4.249754	-4.252223	-3.784142
Shibata	-4.022039	-4.716304	-4.247657	-4.250125	-3.782045

Note Table 4.4: Represents parameters estimation results for Symmetric GARCH, Student-t Symmetric GARCH, Asymmetric GARCH, Student-t Asymmetric GARCH models, respectively. Variables estimated are α, β, ω, θ and DF these are freight shocks coefficient, one lagged volatility coefficient, the constant, negative freight shocks coefficient and degrees of freedom, respectively. PER represents persistence of the model and MLE denotes Maximum likelihood estimation. Values in ( ) are t statistics and *,** and *** represents 1%, 5% and 10% significance levels. Values in ( ) are t statistics and ***,** and * represents 1%, 5% and 10% significance levels. Normality tests are conducted on standardized returns for each model, this includes Skewness, Kurtosis and J-B tests. Akaike, Schwarz and Shibata criteria are used for ranking models, * indicate minimum values.

Source: Author's estimations.

The different proposed conditional variance models from Table 4.4 are scrutinised by a variety of misspecification tests. The results are presented in Table 4.5 for all conditional variance models used to compute VaR in this chapter. Results reported in Table 4.5 are for four conditional variance models, these are normal symmetric, non-normal symmetric, normal asymmetric and non-normal asymmetric conditional variance models. For each model two sets of tests are reported for five different tanker segments. First set of tests are Engle and Ng (1993) diagnostic tests that test the adequacy of the implemented conditional variance framework. Second set of tests are the Residual Based Diagnostic (RBD) for conditional heteroscedasticity. For both tests a reported zero P-value (values in brackets) is an indication of a rejected null of corrects specification of the conditional variance model and the presence of heteroscedasticity in the residuals of the regression, respectively.

These reported results are best analysed vertically in respect to parcel size and horizontally in respect to tests valuations. First, test results that refer to volatility models that are correct specified and heteroscedasticity absence, support the case of a non-normal symmetric and asymmetric conditional variance framework to capture freight volatility within larger tanker segments, and support the case of a normal symmetric and asymmetric conditional variance framework to capture freight volatility within smaller tanker segments. These results are reported in bold values in Table 4.5, where larger size tankers are represented by TD3 and TD4 routes and smaller tanker sizes are represented by TD7 and TD9 routes. In other words, higher freight volatility occurring in larger tanker segments are better captured by volatility models that are non-normal specified, while lower freight volatility occurring in smaller tanker segments are better captured by volatility models that are normal specified. Second, first section of reported tests in Table 4.5 examine the impact of the sign and the size of negative and positive return shocks on freight volatilities that were not captured by the conditional variance model under investigation. Employed models differ in their ability to capture leverage effect and negative and positive size effect in conditional freight volatility, with non-normal specification bettering other models. Furthermore, the capability of these models in capturing larger negative and positive shocks in comparison to normal specified models is clearly pronounced in Table 4.5. For example the non-rejection of the null hypothesis for the NSBT and PSBT tests indicating the non-significance of the coefficients under investigated postulated the correct specification of the conditional variance model in capturing larger negative and positive shocks in freight returns. Highlighted values in gray in Table 4.5 indicate results that are significant up to 10 per cent. This refers to the rejection of the null hypothesis of correct specification. Third, second section of reported tests in Table 4.5 examine remaining heteroscedasticity in residuals that were not captured by the conditional variance model under investigation. In general all conditional variance models under study capture heteroscedasticity in freight returns well with normal asymmetric conditional variance models performing exceptionally well in capturing short- and long-term heteroscedasticity.

Table 4.5: Misspecification and diagnostic tests

	TD3	TD4	TD5	TD7	TD9
Symmetric GARCH					
Misspecification of the conditional variance framework					
SBT	0.6332 [0.526]	2.4765 [0.013]	2.2038 [0.027]	**1.3689 [0.171]**	**1.2954 [0.195]**
NSBT	2.9125 [0.004]	0.9083 [0.364]	1.9640 [0.049]	**0.1737 [0.862]**	**1.0245 [0.306]**
PSBT	4.0900 [0.000]	0.3178 [0.751]	2.0163 [0.044]	**0.5007 [0.616]**	**0.6401 [0.522]**
The Residual-Based Diagnostic (RBD) for Conditional Heteroscedasticity					
RBD (2)	41.9053 [0.000]	0.0610 [0.969]	-32.28 [1.000]	**0.3642 [0.834]**	**0.6233 [0.732]**
RBD (5)	275.579 [0.000]	0.0760 [0.999]	-23.95 [1.000]	**1.3096 [0.934]**	**0.9492 [0.966]**
RBD (10)	-50.847 [1.000]	9.3969 [0.495]	3.43 [0.969]	**8.5731 [0.573]**	**1.9246 [0.997]**
Symmetric GARCH-t(d)					
Misspecification of the conditional variance framework					
SBT	**0.4088 [0.683]**	2.5333 [0.011]	2.3168 [0.020]	1.4014 [0.161]	1.3114 [0.189]
NSBT	**0.1359 [0.892]**	**0.0821 [0.935]**	0.8682 [0.385]	0.8579 [0.391]	0.7646 [0.445]
PSBT	**0.6645 [0.506]**	**1.5827 [0.114]**	0.3329 [0.739]	0.8971 [0.369]	1.3028 [0.193]
The Residual-Based Diagnostic (RBD) for Conditional Heteroscedasticity					
RBD (2)	**0.061 [0.970]**	**0.0255 [0.987]**	7.9583 [0.019]	0.6701 [0.715]	0.0436 [0.978]
RBD (5)	**1.999 [0.849]**	**0.1919 [0.999]**	10.3833 [0.065]	4.0965 [0.536]	10.4882 [0.063]
RBD (10)	**12.21 [0.272]**	**5.6719 [0.842]**	5.6033 [0.847]	19.1854 [0.038]	22.6069 [0.012]
Asymmetric GARCH					
Misspecification of the conditional variance framework					
SBT	0.5985 [0.549]	1.9947 [0.046]	2.2315 [0.026]	**0.9115 [0.362]**	**1.4964 [0.135]**
NSBT	1.5086 [0.131]	2.0149 [0.044]	1.7544 [0.079]	**0.4454 [0.656]**	**0.6569 [0.511]**
PSBT	2.3986 [0.016]	3.6442 [0.000]	2.4951 [0.013]	**0.2320 [0.816]**	**1.5024 [0.133]**
The Residual-Based Diagnostic (RBD) for Conditional Heteroscedasticity					
RBD (2)	-1.168 [1.000]	-0.031 [1.000]	-7.80429 [1.000]	**0.326 [0.849]**	**1.810 [0.404]**
RBD (5)	0.289 [0.998]	3.185 [0.672]	-4.11908 [1.000]	**1.368 [0.928]**	**2.410 [0.789]**
RBD (10)	2.456 [0.992]	5.738 [0.836]	3.40566 [0.970]	**9.540 [0.482]**	**3.041 [0.980]**
Asymmetric GARCH-t(d)					
Misspecification of the conditional variance framework					
SBT	**0.7859 [0.432]**	2.7952 [0.005]	2.6314 [0.009]	1.3402 [0.180]	1.7137 [0.087]
NSBT	**0.2286 [0.819]**	**0.2049 [0.837]**	0.4517 [0.651]	0.8440 [0.398]	0.8777 [0.380]
PSBT	**0.5217 [0.602]**	**1.3380 [0.181]**	0.9704 [0.332]	0.9147 [0.360]	1.0778 [0.281]
The Residual-Based Diagnostic (RBD) for Conditional Heteroscedasticity					
RBD (2)	**0.076 [0.963]**	**0.008 [0.996]**	299.34 [0.00]	0.666 [0.717]	0.023 [0.988]
RBD (5)	**1.267 [0.938]**	**0.116 [0.999]**	2363.9 [0.00]	4.113 [0.533]	10.555 [0.061]
RBD (10)	**8.852 [0.546]**	**4.419 [0.926]**	4.19 [0.94]	19.25 [0.037]	25.451 [0.005]

Note Table 4.5: Represents misspecification tests for conditional variance models. The table is subsequently divided to four sections, Tests for SGARCH, Tests for Student-t SGARCH, Tests for AGARCH and Tests for Student-t AGARCH models. SBT is the sign bias test, PSBT is the positive sign bias test, and NSBT is the negative sign bias test. RBD is the residual based diagnostic for presence of conditional heteroscedasticity. Values in ( ) are number of lagged standardized residuals. Values in [] are p values. Values in bold highlight the best specified models based on test results and shaded values highlight the significance results indicating the rejection of the null hypothesis and the failure of the model to capture the relevant effect.

Source: Author's estimations.

4.4.3. Back-testing results for VaR models

The estimated variances from the GARCH models in Table 4.4 are used to calculate one-day VaR models over the out-of sample period from 02-01-2008 to 30-10-2009. We calculated N-VAR, t-VAR (Non-N-VAR) and FHS-VAR models whose back testing results are shown in Tables 4.6 (top panel), Table 4.6 (bottom panel) and Table 4.7 (both top and bottom panel), respectively. The performances of calculated one-day VaR measures are back-tested against actual returns for out of sample. The back-testing results clearly highlight the superiority of filtered historical simulation parametric models over other industry benchmark models. In other words, semi-parametric VaR measures are better capable to adapt to the conditional volatility of freight returns. The one-day one per cent and five per cent VaR forecasts are explained in subsequent sections of Tables 4.6 and 4.7. For example in Table 4.6, the first section represents calculated risk measures based on normal specifications and second section represents calculated risk measures based on non-normal specifications. Table 4.7 represents calculated risk measures based on filtered historical simulation specification. In both tables we report the unconditional coverage test, the independent test and the conditional coverage test that constituted the backtesting framework proposed by Christofferson (1998). These observed statistics are compared against critical statistics (see Table 4.6 and 4.7 notes) and there 10%, 5% and 1% significance levels are denoted by *, ** and ***, respectively. Out of the three tests, the most failed test is the independent test, which is due to clustered violations in time. This is a clear evidence of clusters within freight returns, a feature that is documented in maritime literature. This is quite clear in TD3 where all models pass the unconditional coverage test and (apart from models reported in the bottom panel of Table 4.7) fail the other two tests. This is an indication of strong clustered violations of calculated sort-term VaR measures relevant to actual freight returns. The results clearly indicate that Asymmetric-GARCH-t based models are superior in modelling daily VaRs for tanker freight returns and better capture volatility of returns compared with other models. In addition, estimated coefficients for the superior models are found to be positive, significant and with persistence less than one, which is an indication of the usefulness of these models as a measure of conditional volatilities for shipping freight returns. Furthermore, forecasts obtained through the AGARCH-t-EVT model are better proxies for one-day VaR for tanker freight rates if the risk measure is based on a FHS approach rather than a normal or non-normal VaR measure.

Table 4.8 illustrates VaR hit sequences, which is an indication, in percentage terms, of the level of violations occurring in VaR measures and is computed as follows:

$$\text{VaR Hit Sequence} = \frac{\text{Number of occurring violations}}{\text{Total number of observations}} \times 100 \tag{3.2}$$

where the number of occurring violations is the number of times that negative actual returns have exceeded forecasted VaR measures. Average, minimum and maximum one-day one per cent and five per cent VaR measures are reported in the same table. This is used as a measure of the VaR models' ability to adjust to extreme movements in freight markets. As an approximation, the larger the spread between the reported average, minimum and maximum VaR values for a particular VaR model the higher is its adaptability to extreme market movements.

Table 4.6: Back testing for normal and non-normal value-at-risk modules

		Risk Metrics		SGARCH		AGARCH		SGARCH-t-(d)		AGARCH-t(d)	
		1%	5%	1%	5%	1%	5%	1%	5%	1%	5%
Normal Value-at-Risk Models											
	LRuc	4.74**	0.81	6.41	0.81	14.8***	0.16	2.05	1.47	14.7***	0.16
TD3	LRind	11.9***	29.5***	17.3***	29.5***	17.4***	24.5***	15.1***	23.3***	0.45	0.11
	LRcc	16.7***	30.3***	23.7***	30.3***	32.2***	24.7***	17.1***	24.8***	15.2***	0.27
	LRuc	12.4***	1.86	31.3***	3.96**	19.8***	2.58	2.03	0.37	44.4***	7.5***
TD4	LRind	0.61	2.14	0.00	0.07	0.21	0.00	2.43	0.18	0.11	1.99
	LRcc	13.1***	4.00	31.3***	4.03	20.1***	2.58	4.47	0.55	44.6***	9.4***
	LRuc	10.2***	0.06	22.5***	0.16	25.3***	0.66	3.26*	0.00	31.3***	3.96**
TD5	LRind	0.81	0.77	0.12	0.11	0.06	0.12	2.00	0.02	0.00	1.12
	LRcc	11.1***	0.83	22.6***	0.27	25.4***	0.78	5.26*	0.02	31.3***	5.08*
	LRuc	6.38**	1.28	25.4***	2.58	25.4***	2.58	1.06	0.00	41.2***	6.53**
TD7	LRind	1.31	0.12	0.06	0.00	0.06	0.00	2.95*	0.02	0.06	0.30
	LRcc	7.69**	1.40	25.4***	2.58	25.4***	2.58	4.01	0.02	41.2***	6.82**
	LRuc	1.06	4.36**	14.7***	6.52**	17.2***	10.8***	0.37	0.04	51.7***	17.3***
TD9	LRind	2.94*	3.43*	0.45	0.54	0.32	1.90	3.56*	0.44	0.12	0.04
	LRcc	4.01	7.80**	15.2***	7.06**	17.5***	12.6***	3.94	0.47	51.8***	17.3***
Non-normal Value-at-Risk Models											
	LRuc	0.38	0.81	6.41**	0.21	6.41**	4.75**	8.2***	7.5***	6.38**	6.52**
TD3	LRind	19.6***	29.5***	17.3***	25.7***	10.7***	20.8***	1.04	0.39	1.31	0.54
	LRcc	19.9***	30.3***	23.7***	25.9***	17.1***	25.5***	9.2***	7.89**	7.69**	7.06**
	LRuc	0.66	1.86	31.3***	3.23*	2.03	2.58	8.2***	7.4***	8.2***	7.5***
TD4	LRind	6.6***	2.14	0.00	0.94	2.43	0.00	1.04	1.98	1.04	1.99
	LRcc	7.31**	4.00	31.3***	4.18	4.47	2.58	9.2***	9.4***	9.2***	9.4***
	LRuc	10.3***	0.06	22.5***	0.16	25.4***	0.66	3.26*	0.00	31.4***	3.9**
TD5	LRind	0.81	0.77	0.12	0.11	0.06	0.12	2.00	0.02	0.00	1.12
	LRcc	11.1***	0.83	22.6***	0.27	25.4***	0.78	5.26*	0.02	31.3***	5.08*
	LRuc	2.03	0.37	25.4***	6.52**	19.8***	6.53**	31.4***	13.2***	31.4***	13.2***
TD7	LRind	2.43	3.53*	0.06	0.54	0.21	0.54	0.00	0.41	0.00	0.41
	LRcc	4.47	3.90	25.4***	7.06**	20.0***	7.07**	31.4***	13.7***	31.4***	13.7***
	LRuc	1.92	2.56	14.8***	8.5***	0.66	13.2***	4.72**	18.8***	4.72**	17.3***
TD9	LRind	8.7***	2.52	0.45	0.27	6.6***	2.69	1.63	0.09	1.63	0.04
	LRcc	10.6***	5.08*	15.2***	8.81**	7.31**	15.9***	6.35**	18.8***	6.35**	17.3***

Note Table 4.6: Represents statistical tests of unconditional, independent and conditional coverage of the interval forecasts under each approach for the five routs under investigation, denoted by LRuc, LRind and LRcc, respectively. *, ** and *** denote significance at 10%, 5% and 1% level, respectively. The tests for LRuc and LRind are $x_1^{1\%}$ and $x_1^{5\%}$ for 1% VaR and 5% VaR, respectively. The tests for LRcc are $x_2^{1\%}$ and $x_2^{5\%}$ for 1% VaR and 5% VaR, respectively. Critical values for $x_1^{1\%}$, $x_1^{5\%}$, $x_1^{10\%} x_2^{1\%} x_2^{5\%} x_2^{10\%}$ are 6.63, 3.84, 2.7, 9.21, 5.99 and 4.6, respectively. If value of the likelihood ratio is larger than the critical value the Value-at-risk model is rejected at the significance level.

Source: Author's estimations.

Table 4.7: Back testing for FHS value-at-risk Modules

		Part I							
		HS		**Risk Metrics**		**SGARCH**		**AGARCH**	
		1%	**5%**	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
TD3	LRuc	2.05	1.47	0.03	1.47	1.07	1.47	3.28*	1.47
	LRind	7.9***	39.8***	22.7***	23.3***	17.1***	23.3***	1.99	28.4***
	LRcc	9.9***	41.3***	22.7***	24.8***	18.2***	24.8***	5.27*	29.9***
TD4	LRuc	2.05	1.03	3.28*	0.16	2.03	0.37	2.05	0.37
	LRind	2.43	8.1***	1.99	1.73	2.43	0.18	2.43	0.20
	LRcc	4.48	9.11**	5.27*	1.89	4.47	0.55	4.48	0.57
TD5	LRuc	1.07	0.16	1.06	0.16	3.26*	0.00	3.26*	0.06
	LRind	2.94*	4.01**	2.94*	0.31	2.00	0.02	2.00	0.00
	LRcc	4.01	4.17	4.01	0.47	5.26*	0.02	5.26*	0.06
TD7	LRuc	1.06	0.04	0.03	0.37	1.06	0.00	0.37	0.00
	LRind	2.95*	7.7***	4.34**	3.53*	2.94*	0.02	3.57*	0.02
	LRcc	4.01	7.77	4.36	3.90	4.01	0.02	3.94	0.02
TD9	LRuc	6.41**	1.47	0.03	0.46	0.03	0.04	1.06	0.37
	LRind	1.31	10.6***	4.33**	1.22	4.33**	0.44	2.94*	0.20
	LRcc	7.72**	12.1***	4.36	1.68	4.36	0.47	4.01	0.57
		Part II							
				SGARCH-t-(d)		**AGARCH-t(d)**		**SGARCH-t(d)-EVT**	
				1%	**5%**	**1%**	**5%**	**1%**	**5%**
TD3	LRuc			2.03	0.66	3.26*	0.66	0.37	0.16
	LRind			2.43	0.12	2.00	3.08*	3.56*	0.11
	LRcc			4.47	0.78	5.26*	3.74	3.94	0.27
TD4	LRuc			3.26*	0.36	3.26*	0.36	0.03	1.99
	LRind			2.00	0.18	2.00	0.18	4.33**	0.00
	LRcc			5.26*	0.54	5.26*	0.54	4.36	1.99
TD5	LRuc			0.37	0.03	1.06	0.15	0.03	0.64
	LRind			3.56*	0.06	2.94*	0.11	4.33**	0.27
	LRcc			3.94	0.09	4.01	0.26	4.36	0.91
TD7	LRuc			1.06	0.15	1.06	0.15	0.37	1.03
	LRind			2.95*	0.11	2.95*	0.11	3.57*	0.37
	LRcc			4.01	0.26	4.01	0.26	3.94	1.40
TD9	LRuc			0.37	1.47	1.06	1.47	0.66	3.24*
	LRind			3.56*	0.02	2.94*	0.02	6.6***	0.29
	LRcc			3.94	1.49	4.01	1.49	7.31**	3.53

Note Table 4.7: Represents statistical tests of unconditional, independent and conditional coverage of the interval forecasts under each approach for the five routs under investigation, denoted by LRuc, LRind and LRcc, respectively. *, ** and *** denote significance at 10%, 5% and 1% level, respectively. The tests for LRuc and LRind are $x_1^{1\%}$ and $x_1^{5\%}$ for 1% VaR and 5% VaR, respectively. The tests for LRcc are $x_2^{1\%}$ and $x_2^{5\%}$ for 1% VaR and 5% VaR, respectively. Critical values for $x_1^{1\%}$, $x_1^{5\%}$, $x_1^{10\%}$ $x_2^{1\%}$ $x_2^{5\%}$ $x_2^{10\%}$ are 6.63, 3.84, 2.7, 9.21, 5.99 and 4.6, respectively. If value of the likelihood ratio is larger than the critical value the Value-at-risk model is rejected at the significance level.

Source: Author's estimations.

Table 4.8: Average value-at-risk statistics results

Model	Average VaR		Minimum VaR		Maximum VaR		Hit Sequence	
	1%	5%	1%	5%	1%	5%	1%	5%
				Normal Value-at-Risk				
Risk Metrics	14.05%	9.94%	4.96%	3.50%	28.88%	20.42%	2.26%	3.90%
SGARCH	11.85%	8.38%	6.12%	4.33%	47.37%	33.49%	3.47%	6.25%
AGARCH	11.17%	7.90%	5.96%	4.21%	40.53%	28.66%	3.60%	6.68%
SGARCH-t-(d)	18.38%	9.17%	6.06%	3.62%	93.17%	44.66%	1.48%	5.38%
AGARCH-t-(d)	10.60%	7.49%	4.70%	3.32%	65.54%	46.34%	4.73%	7.64%
				Non-normal Value-at-Risk				
Risk Metrics	20.41%	9.16%	7.39%	3.27%	41.88%	18.84%	0.87%	4.47%
SGARCH	17.09%	7.71%	8.85%	3.99%	68.79%	30.91%	1.61%	6.77%
AGARCH	16.15%	7.27%	8.55%	3.87%	56.89%	26.05%	1.78%	7.55%
SGARCH-t-(d)	15.96%	7.18%	6.92%	3.11%	96.94%	43.89%	2.43%	8.33%
AGARCH-t-(d)	15.31%	6.90%	6.81%	3.07%	94.02%	42.64%	2.43%	8.68%
				Value-at-Risk-FHS				
HS	17.39%	9.22%	11.53%	5.27%	21.62%	11.23%	1.74%	5.86%
Risk Metrics	18.33%	8.80%	5.49%	2.79%	43.26%	20.28%	1.21%	5.42%
SGARCH	16.15%	7.27%	7.76%	3.75%	93.17%	44.66%	1.39%	5.38%
AGARCH	17.66%	9.13%	7.72%	3.81%	77.62%	40.71%	1.56%	5.47%
SGARCH-t-(d)	19.82%	10.01%	6.92%	3.11%	149.16%	69.94%	1.34%	5.55%
AGARCH-t-(d)	19.34%	9.74%	6.81%	3.07%	146.29%	69.13%	1.48%	5.60%
AGARCH-t-(d)-EVT	20.73%	8.51%	9.19%	3.77%	96.44%	40.49%	0.87%	6.12%

Note Table 4.8: Represents Value-at-risk results for all route, the first and other columns represent the different model types used to measure VaR and its corresponding results, respectively. The second column, third and forth column represents average, minimum and maximum $VaR_{1\%}$;$VaR_{5\%}$, for the estimated period, respectively. The last column represents the hit violations sequence as a percentage, calculated as number of actual returns exceedings divided by the total number of observations for the estimated period.

Source: Author's estimations.

The superiority of semi-parametric based models such as the filtered historical simulation and EVT-conditional variance models to measure short-term freight risk is confirmed by results of conditional variance estimations, misspecification tests and diagnostics, back-testing for normal and non-normal VaR models, back-testing for FHS-VaR models and hit sequence results reported in Tables 4.4, 4.5, 4.6, 4.7 and 4.8, respectively. The parameters of these models are positive, highly significant. These models capture heteroscedasticity and large negative and positive shocks in freight returns well. Furthermore, the null hypothesis of correct specification of the VaR model to measure short-term freight risk is not rejected, for these models. They also exhibit lower hit sequence levels in compared to normal and non-normal models.

4.4.4. Markov regime-switching estimations

An appropriate conditional volatility measure is vital for a correct risk measure as it constitutes the building block for value-at-risk (VaR) that is used to estimate freight risk in this thesis. In section 4.4.3 short-term VaR measures are calculated based on single-state conditional variance models that are estimated in section 4.4.2. As argued earlier a better insight into freight information can be provided by a framework that is capable to capture volatilities dynamics within the elastic and inelastic parts of the freight supply curve, which should improve freight risk measures, by calculating short-term VaR based on a two-state distinctive conditional variance model. Therefore, VaR in this section is estimated on the bases that the underlying conditional volatility measure switches between lower and higher volatilities regime states that corresponds to the elastic and inelastic parts of the freight supply curve.

To this end, in this chapter we investigate the hypothesis of the second moment of freight return (conditional variance) being regime state dependence and than we examine the suitability of different conditional variance models to better capture freight dynamics within these distinct regimes. These two steps are carried out by employing a two-state Markov regime-switching conditional variance model on the same data set investigated in earlier sections and a two-state Markov regime-switching distinctive conditional variance model on average Baltic Dirty Tanker Index (BDTI) time series that represents freight rate positions for a fleet of tankers. As suggested in the literature, for example Kavussanos and Dimitrakopoulos (2011) study the BCTI and the BDTI stating that these freight rate indices are averages of individual route indices, and can be thought of as imitating portfolios of freight rate positions, covering a fleet of vessels.

Therefore, empirical work in this section is twofold. First, to investigate the hypothesis that freight volatilities switch between two distinct structures, higher and lower regime states, we employ a two-state Markov regime-switching conditional variance framework to model freight returns within five tanker segments. The likelihood of the Markov regime-switching model is evaluated using the filtering procedure of Hamilton (1990) followed by the smoothing algorithm of Kim (1994) and the empirical method is presented in section 4.3.5.6. Empirical findings support the postulate of conditional freight variance switching between two regime states, lower volatility and higher volatility, with an average daily volatility of 1.32 per cent and 7.38 per cent, respectively. The cluster in volatilities of freight returns is evident in Figure 4.2. In addition, Markov regime-switching empirical findings represented in Table 4.9, suggests an average split of 70 per cent and 30 per cent for periods of lower volatility and higher volatility, respectively. During higher volatility periods, time duration of four days is consistent across all routes, while a range of time durations from 7 days to 13.5 days is found during lower volatility periods. The transition probability of being in higher volatility state and previously being in lower volatility state is in the range from 8 per cent to 16 per cent at any given point of time across all routes, where as the transition probability of being in lower volatility state and previously being in higher volatility state is in the range from 21 per cent to 26 per cent. In summary, freight volatilities tend to have low tendency to shift from lower volatility to higher volatility compared with tendency of shifting from higher to lower volatilities, and once in higher volatility state time duration is shorter compared to lower volatility state. This better understanding of magnitudes, durations and occurrences of volatility clusters within freight returns, should improve risk mitigation and operation efficiency for shipping practitioners.

Estimated results for the two-state Markov regime-switching conditional variance model applied to conditional tanker freight returns are statistically significant and reported in Table 4.9, setting the scene to institute the most suitable conditional variance framework to capture the dynamics within the estimated higher and lower freight volatility states. The columns in Table 4.9 from left to right correspond to conditional tanker segments (tanker sizes), from largest to smaller sector, subsequently. The transitional probability of switching from one freight volatility state to another is expressed in Table 4.9 by the transition probability π_{ij} where i,j={H and L} along there statistical levels. Furthermore, the unconditional transitional probabilities for each tanker segment along with the estimated constant average lower and higher volatility levels. Moreover, for each regime state, the average percentage weight relevant to the whole sample and the average duration in days (resilience) before shifting to another regime state is reported and denoted by average time weight and average duration for the lower and higher volatility state levels, respectively.

Table 4.9: Two-state structures and conditional sensitivity structure

	TD3	TD4	TD5	TD7	TD9
Transition π HL	0.213220 (9.78)	0.264150 (10.7)	0.234581 (10.5)	0.232483 (11.7)	0.266150 (12.2)
Transition π LH	0.088479 (90.8)	0.123940 (76.1)	0.163850 (58.2)	0.124440 (81.4)	0.157330 (64.4)
Transition π LL	0.91152	0.87606	0.83615	0.87556	0.84267
Transition π HH	0.78678	0.73585	0.76542	0.76752	0.73385
Unconditional π	0.293269	0.319359	0.411238	0.348646	0.371517
Low Daily Vol	1.71%	1.11%	1.09%	1.23%	1.47%
High Daily Vol	8.80%	5.64%	6.06%	7.66%	8.76%
Average TLV Weight	73.81%	71.60%	62.79%	68.34%	66.77%
Average LV Duration	13.69 Days	10 Days	7.43 Days	9.39 Days	7.65 Days
Average THV Weight	26.19%	28.40%	37.21%	31.66%	33.23%
Average HV Duration	4.89 Days	3.9 Days	4.43 Days	4.37 Days	3.82 Days

Note Table 4.9: This table presents transition probabilities, unconditional probability, two state volatility measures, average total low/high volatility weighting and daily average duration. The two state volatility regimes are represented by low and high volatility structures.

Source: Author's estimations.

π_{LL}: Transition probability of remaining in the lower volatility state.

π_{LH}: Transition probability of switching from lower volatility state to higher volatility state.

π_{HL}: Transition probability of switching from higher volatility state to lower volatility state.

π_{HH}: Transition probability of remaining in the higher volatility state.

π: Unconditional transition probability

LDV : Low Daily Volatility

HDV : High Daily Volatility

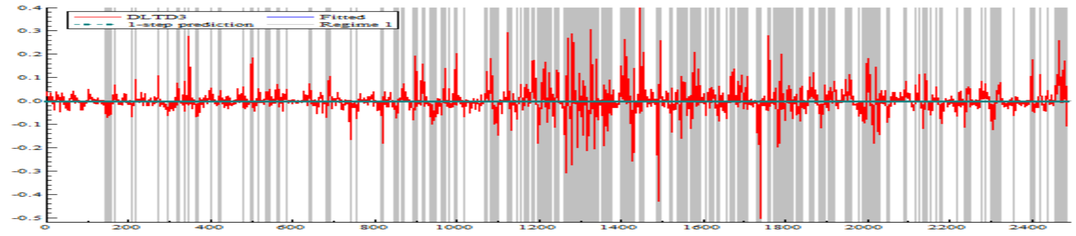
ATLVW : Average Total Low Volatility Weight

ALVD : Average Low Volatility Duration

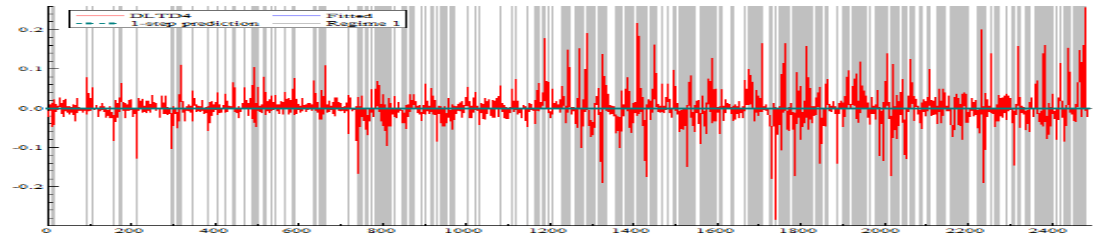
ATHVW : Average Total High Volatility Weight

AHVD : Average High Volatility Duration

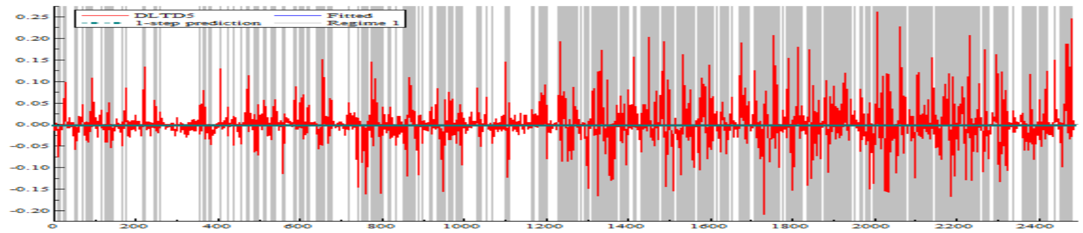
Figure 4.2: Filtered regime probability for different tanker routes



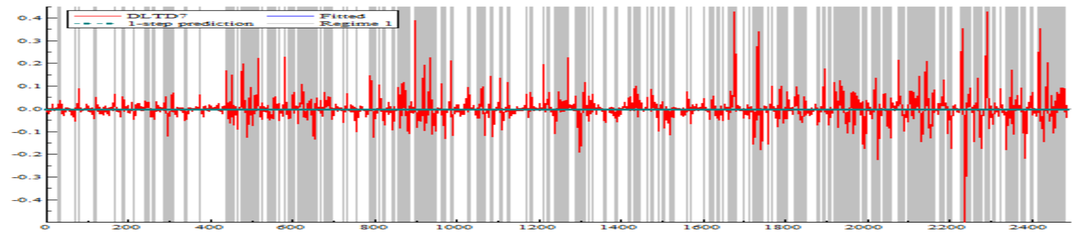
Filtered regime probability for TD3 route



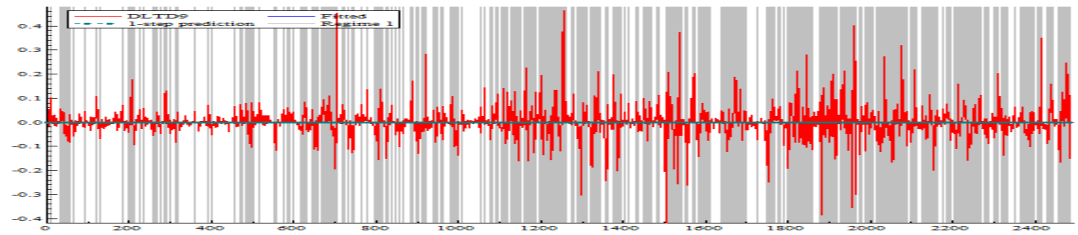
Filtered regime probability for TD4 route



Filtered regime probability for TD5 route



Filtered regime probability for TD7 route



Filtered regime probability for TD9 route

Note Figure 4.2: illustrates filtered regime probabilities for all tanker routes, with the shaded area representing the high volatility regime and the dark area representing daily returns.

Source: Author's estimations using PcGive13 package.

Second, the above results suggest that the dynamics of freight returns are conditional on the level of volatility and that these are better captured by distinctive freight volatility regime states. Furthermore, our volatility modelling analyses suggests that the suitability of conditional volatility models is conditional on vessel size and shipping route, which is reflected in freight returns and captured by either normal or non-normal specifications subject to prevailing volatility levels at the time. Therefore, we investigate the postulate that freight volatilities during these distinct regime states are better captured by distinctive conditional variance models. In doing so, we carryout this on tanker freight returns for the Baltic Dirty Tanker Index (BDTI), which represents freight returns on a portfolio of tankers of different sizes operating on different routes. Thus, a Markov regime-switching distinctive conditional variance framework applied to the BDTI, examines the strength of such a claim and identifies the best fit of a switching conditional freight volatility for the whole tanker market. Our empirical findings postulate that volatilities within tanker freight returns are better modelled by a two-state Markov regime-switching distinctive conditional variance model, for a higher and a lower freight volatility regime states, and most importantly the dynamics of these two distinct regime states are better modelled by a normal symmetric conditional variance framework and a fractional integrated conditional variance framework, respectively.

In Table 4.10 we present the results of the two-state Markov regime-switching conditional variance model. This includes for both lower and higher volatility levels, transition probabilities, unconditional probability, daily volatility level, average volatility state weight and average volatility duration. Furthermore, the two-states and smoothed transitional probability are illustrated in Figure 4.3 to provide a perspective of the reported analyses.

Table 4.10: Two-state Markov-switching conditional variance

Markov-Switching SGARCH Model	
Transition πHH	0.842732 (41.1)†
Transition πLH	0.0790435 (7.50)†
Transition πHL	0.15727
Transition πLL	0.92096
Unconditional π	0.085751357
Daily Low Volatility	0.01114125
Daily High Volatility	0.03612530
Average LV Weight	70.14%
Average LV Duration	16.56 Days
Average HV Weight	29.86%
Average HV Duration	7.12 Days

Note Table 4.10: This table presents transition probabilities, unconditional probability, two state volatility measures, average total low/high volatility weighting and daily average duration. The two state volatility regimes are represented by low and high volatility structures.

Source: Author's estimations.

π_{LL}: Transition probability of remaining in the lower volatility state.

π_{LH}: Transition probability of switching from lower volatility state to higher volatility state.

π_{HL}: Transition probability of switching from higher volatility state to lower volatility state.

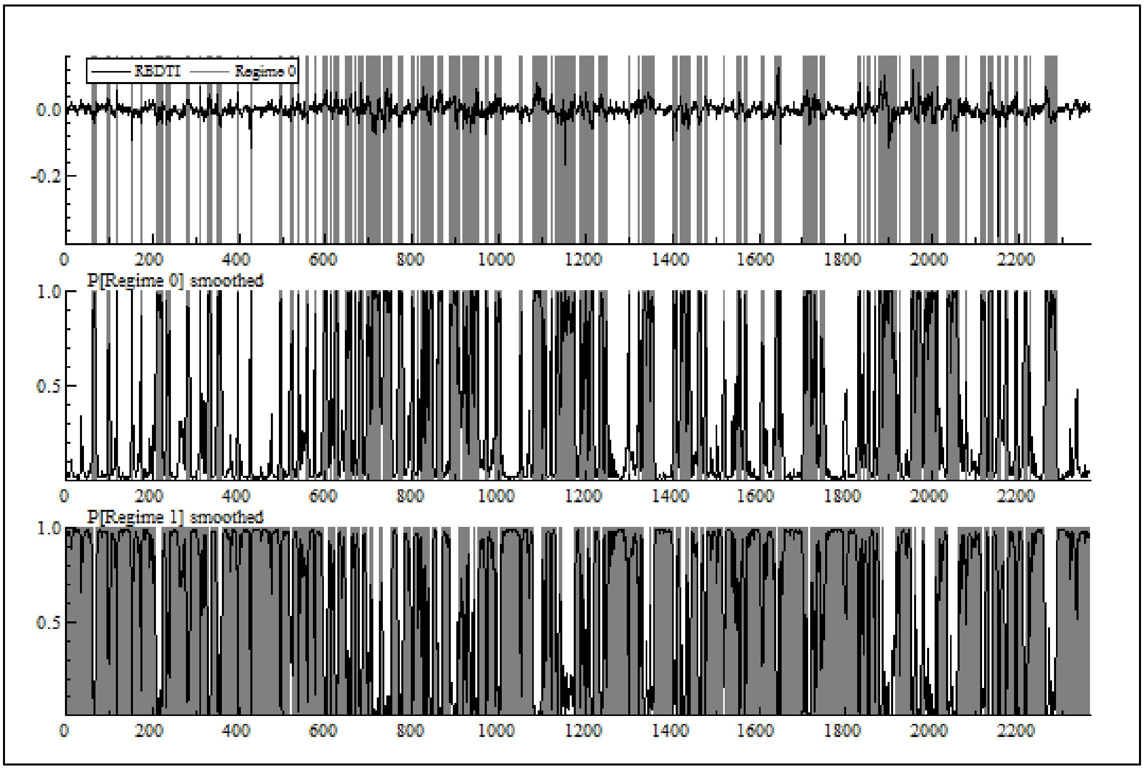
π_{HH}: Transition probability of remaining in the higher volatility state.

π: Unconditional transition probability

LV : Lower Volatility

HV : Higher Volatility

Figure 4.3: Smoothed probabilities for two-state distinctive conditional variance regimes

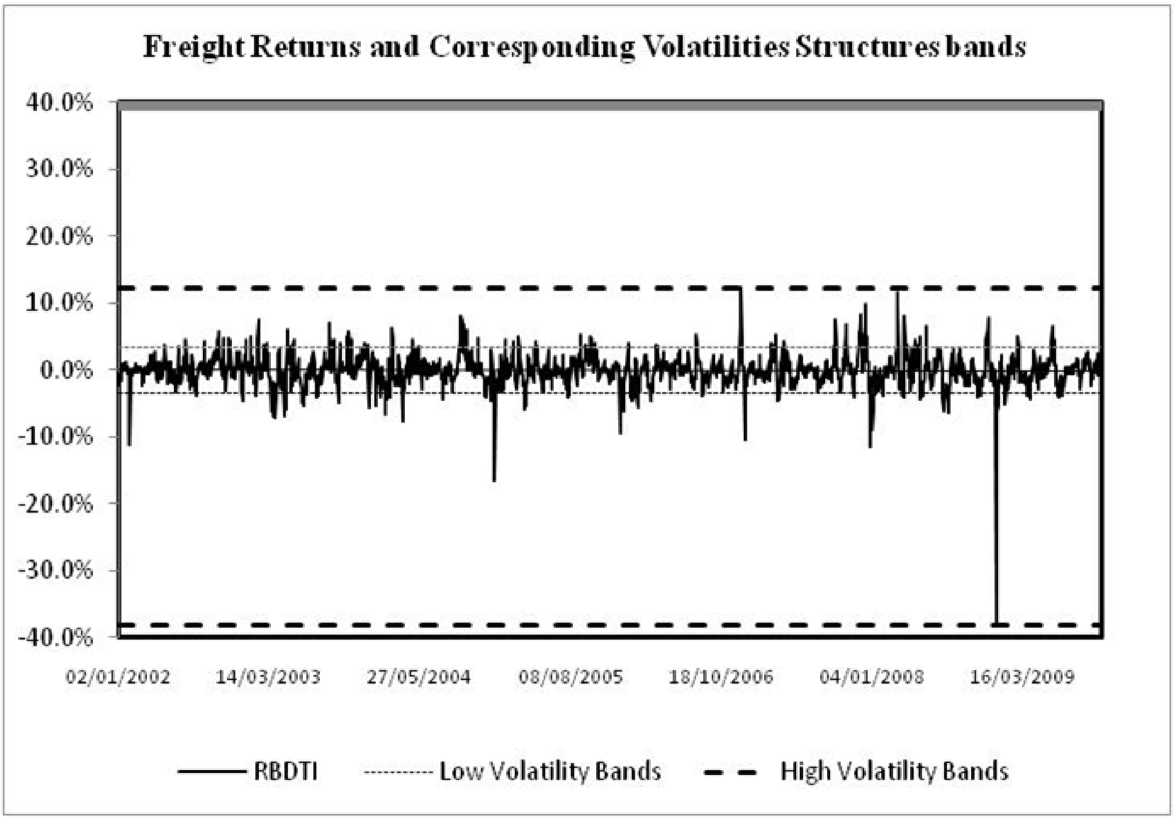


Note Figure 4.3: illustrates fitted regimes to tanker freight returns and smoothed probabilities for the two distinctive conditional freight volatility regime states. The first illustration represents tanker freight returns for the BDTI imposed on the estimated two distinct states, with the gray shaded area represents the higher volatility regime state. The other two illustrations representing smoothed probabilities for the estimated higher freight volatility state and lower freight volatility state, respectively. Regime 0 and Regime 1 refers to higher freight volatility state (HV) and lower freight volatility state (LV), respectively.

Source: Author's estimations using PcGive13 package.

Moreover, a two state analysis point out that volatilities of tanker freight rates tend to switch between two state regimes, a lower volatility state and a higher volatility state with an average duration of 16.5 days and 7 days, within each regime, respectively. Transition probabilities indicate that the tendency of switching from the higher regime to the lower regime once in higher volatility is lower than vice versa, this is represented in an over all 70 per cent of the time in lower volatility and 30 per cent in higher volatility. This average duration within a volatility structure can be vital for long term risk management strategies, for example by identifying which state the market is in, one can forecast volatility ahead number of days and the unconditional volatility corresponding to the relevant state. Figures 4.4 illustrate higher and lower conditional volatilities limitations for tanker freight returns by plotting the latter imposed on upper and lower threshold bands to illustrate the distinct bands of freight volatilities.

Figure 4.4: Tanker freight returns imposed on volatilities higher and lower limitations



Note Figure 4.4: This is an illustration of tanker freight returns represented by the returns of the Baltic Dirty Tanker Index (BDTI) with freight volatility bands illustrated by dashed line for lower and higher volatility levels.

Source: Author's estimations.

Table 4.11 reports empirical estimations and test results for the employed two-state Markov regime-switching distinctive conditional variance model for tanker freight returns. Results are presented for two distinct regime states, lower volatility (LV-BDTI) and higher volatility (HV-BDTI). First, the table starts with basic statistics such as split of number of observations, mean, minimum, maximum, percentage of bad news (negative returns), variance, one-day long-term volatility and annualised long-term volatility. Furthermore, normality tests are carried out on standardised returns for each model that includes skewness, kurtosis and J-B tests. Second, the middle part of the table reports estimations output for two distinct conditional variance models that are used to model tanker freight volatility within the two estimated distinctive regime states. These are a FIGARCH and a SGARCH models for the lower and higher volatility structures, respectively. Reported results include the number of estimated parameters, coefficients values along with their t-statistics and p-values, persistence and the log likelihood values. Third, diagnostic and misspecification tests are reported in the final part of the table. Starting with serial correlation tests using the Box-Pierce statistics with lags from 5 to 50 for squared residuals, Engles's LM ARCH test (Engle, 1982) to test the presence of ARCH effects in freight returns for each distinct regime state, the diagnostic test of Engle and Ng (1993) to investigate possible misspecification conditional variance equation for each distinct regime state, the Residual-Based Diagnostic (RBD) to test for the presence of conditional heteroscedasticity, testing for the consistency of estimated parameters over time Nyblom's Parameter Stability Test statistics are reported along with joint parameter test and Back-Testing for value-at-risk measure using Christofferson (1998) unconditional coverage, independence and conditional coverage tests.

Empiricals reported in Table 4.11 provide significant evidence to support the postulate of a two-state Markov-switching distinctive conditional variance framework to better capture freight volatility for tanker freight returns by representing freight returns in two distinct volatility regime states, lower and higher, and modelled by a fractional integrated conditional variance framework and a normal symmetric conditional variance framework, respectively. Thus, estimated coefficients for both models are positive and highly significance, with no evidence of autocorrelation or heteroscedasticity. The null hypothesis for correct specification, absence of conditional heteroscedasticity and the consistency of parameters over time can not be rejected at any level, providing sufficient evidence of the superiority of the chosen models. Finally, Back-Testing results support the above claims and test the robustness of these models in measuring freight risk. Thus, one-day ahead value-at-risk at one per cent and five per cent significance levels are reported for both distinct regime states using Christofferson (1998) ratios.

In summary, this chapter explores the usefulness of a one day value-at-risk measure for forecasting shipping tanker freight returns, through implementing the use of models that combine the ability to capture conditional heteroscedasticity in the data through a conditional variance framework that simultaneously accounts for freight volatility state dependency. The suitability of conditional volatility models to capture distinctive volatility dynamics within freight returns is conditional on the vessel size and shipping route, and that long-memory is more pronounced in lower volatility levels than higher volatility levels. These results are profound. As they provide a better understanding of the magnitude and the duration of volatility clusters within the lower and higher volatility states for the elastic and inelastic part of the freight supply curve, respectively.

Table 4.11: Freight returns for the BDTI are expressed in two distinct regime states for a sample period from 30-05-2000 to 30-10-2009.

	LV-BDTI	HV-BDTI
No. Observations	1657	704
Mean	-0.00079	0.00053
Minimum	-0.03416633	-0.381223905
Maximum	0.033877622	0.123748819
Negative Returns	51.69%	48.94%
Variance	0.00013024	0.00130504
1-Day LTV	0.01141227	0.03612530
252-Days LTV	18.12%	57.35%
Skemness	0.03353	-1.41859
Kurtosis	2.84937	16.45782
J-B	6734.5† [0.000]	5813.7† [0.000]
Framework	FIGARCH	SGARCH
No. Parameters	3	2
Omega		0.000347
Phi(Alpha)	0.664878 (9.099)† [0.000]	0.145789 (3.11)† [0.002]
Beta	0.874086 (15.86)† [0.000]	0.617518 (4.23)† [0.000]
d-Figarch	0.429895 (10.25)† [0.000]	
Persistence		0.76331
Log Likelihood	5128.56	1309.782
Q2(5)	7.82601 [0.049]	0.49476 [0.920]
Q2(10)	13.3327 [0.100]	0.74946 [0.999]
Q2(20)	34.1957 [0.012]	1.60093 [0.999]
Q2(50)	49.0238 [0.432]	3.78802 [1.000]
ARCH 1-2	0.9419 [0.3901]	0.12051 [0.8865]
ARCH 1-5	1.4836 [0.1920]	0.09539 [0.9929]
ARCH 1-10	1.2752 [0.2390]	0.07406 [1.0000]
SBT	1.27728 [0.20150]	0.24000 [0.81033]
NSBT	0.47198 [0.63694]	0.80933 [0.41833]
PSNT	0.62812 [0.52993]	0.16224 [0.87112]
Joint Test	5.62117 [0.13157]	2.34672 [0.50363]
RBD(2)	5.02241 [0.08117]	0.121761 [0.94094]
RBD(5)	-16.3043 [1.00000]	0.349496 [0.99660]
RBD(10)	11.6791 [0.30711]	0.453088 [0.99999]
NPST ARCH(Phi)	0.1118	0.10651
NPST Beta	0.07661	0.10798
NPST d	0.15242	
NPST Joint Test	0.357359	0.152128
VaR B-T 1% 5%: LRuc	0.71* 0.44*	0.34* 0.21*
VaR B-T 1% 5%: LRind	0.84* 0.23*	0.52* 0.19*
VaR B-T 1% 5%: LRcc	0.33* 0.11*	0.15* 0.10*

Note Table 4.11: presents estimation and test results for a two-state Markov-switching distinct conditional variance models for tanker freight returns. The underlying data is the Baltic Dirty Tanker Index (BDTI) that mimics earnings within the whole tanker market reported in WorldScale points.† and * refer to significance at 1% significance level and correct specifications, respectively. The full sample period is from 30-05-2000 to 30-10-2009 (2361 observed returns). Back-testing is carried out on out-sample period from 02-01-2008 to 30-10-2009 (462 observations). The in-sample period from 30-05-2000 to 24-12-2007 (1899 observations) is used to estimate the two-state Markov regime-switching distinctive conditional variance model.

Source: Author’s estimations.

4.5. Conclusion

This study attempts to investigate the short-term risk exposure in the tanker freight markets by adopting conditional and unconditional value-at-risk measures, which is based on a variety of single conditional variance frameworks and a two-state Markov-switching distinctive conditional volatility framework. In general it has been found that semi-parametric based methods are the most appropriate for measuring level of risk exposure for shipping tanker freight markets. Most importantly, empirical evidence hypothesis the strong possibility of shipping tanker freight returns, shifting between two state regimes, a higher volatility state regime and a lower state volatility regime and that market shocks in general increase the volatility of freight returns and has a lasting effect.

Therefore, in this chapter the hypothesis of freight returns second moment being state dependent is challenged and the suitability of different conditional variance models to better capture freight dynamics within these distinct regimes is investigated. Furthermore, the superiority of a value-at-risk measure based on a two-state Markov-switching distinctive conditional variance framework is compared against value-at-risk measures based on different single conditional variance models. Findings support the postulate that tanker freight dynamics are state dependence and are better captured by distinctive conditional volatility models, and subsequently provide better risk measures, which are conditional on the size of the tanker vessel and the type of trade.

In other words, empirical findings postulate that volatilities within tanker freight returns are better modelled by a framework that is capable of capturing freight dynamics within the higher freight volatility and lower freight volatility states, through a normal symmetric conditional framework and a fractional integrated conditional variance framework, respectively. Most importantly, the fitting of distinct conditional variance models to freight dynamics that are relevant to the prevailing volatility state at the time, identifies the dynamics of each volatility state and provides a market insight into the elastic and inelastic part of the freight supply curve, improving freight returns information. Thus, long-memory in variance is more pronounced in lower freight volatility levels, while higher freight volatility levels are normally distributed and symmetric and have consistent values across all tanker routes. These distinct states are characterised with a lower tendency to shift from the lower volatility structure to the higher volatility structure, compared with the tendency of shifting from higher to lower volatilities, at any time, and once in the higher volatility state, time duration is shorter compared to lower volatility states.

Furthermore, relevant to our empirical work and findings, Alizadeh and Nomikos (2009) estimate the asymmetric effect of shocks on conditional variances for VLCC, TD3 and Capesize, C4 routes[11], concluding that there is clear evidence of leverage effects in the conditional volatility of both routes, and argue that asymmetric GARCH models reveal an asymmetric response of volatilities to shocks with different signs; that is, negative news increases volatility more than positive news with the same magnitude. Moreover, they state that this is in contrast to supply and demand fundamentals of freight markets that suggest an inverse leverage effect, based on the expectation that lower and higher volatilities are associated with lower and higher freight levels, respectively.

In other words, when freight rates are at lower-levels, freight volatility tends to drop coinciding with the elastic part of the supply-curve and a small or a large shock should not have an impact on freight rate so asymmetric-GARCH models should in theory give insignificant coefficients. On the other hand, when freight rates are at high-levels freight volatility tends to increase coinciding with the inelastic part of the supply-curve, asymmetric-GARCH models should in theory give significant coefficients and have a negative sign, Alizadeh and Nomikos (2009). In our opinion, this is a clear indication of a need for a framework that is capable of capturing the distinctive nature of freight dynamics within the elastic and inelastic parts of the supply-curve.

The implications of these finding to vessel operators and shipping portfolio managers are profound. The better understanding of the distinctive volatility dynamics within the lower and higher volatility states that coincide with the elastic and the inelastic part of the freight supply curve, respectively, in addition to the understanding of the magnitudes, durations and occurrences of volatility clusters, is important to improve vessel operations, hedging techniques and trading strategies. Furthermore, it's paramount that the validity of these findings is further investigated for a portfolio of freight returns. Therefore, in chapter five we account for the distinctive nature of freight volatility dynamics in our estimates of value-at-risk, uncorrelated risk factors and conditional freight-beta for a portfolio of freight returns.

[11] The C4 route is part of the definition of the Baltic Capesize Index (BCI) route that refers to a Capesize vessel of 150,000mt capacity transporting normally coal from Richards Bay to Rotterdam.

Furthermore, market conditions such as active operating areas, shorter voyages, lower bunker consumptions and smaller size vessels are the main reason for less volatility persistence. In other words, freight volatilities for larger tanker vessels sizes are more sensitive to the size of markets shocks in comparison to smaller size tankers. These findings need to be explored further by conducting additional research in the structure of freight volatility using markov switching models on different shipping segments. In addition, to further research in the effect of bunker uncertainty and consumption, busy shipping areas and voyage duration effect on high and low freight volatilities should be investigated.

Chapter Five

5. Value-at-risk, risk factors and conditional freight beta procedures for a portfolio of shipping tanker routes

5.1. Introduction

In chapter four a study of freight risk for a number of distinct tanker segments represented by univariate freight return regressions, suggests that volatility dynamics of freight returns are better captured within two distinct volatility states, these are lower and higher freight volatility regime states. Thus, motivated by these findings we account for the distinctive nature of freight volatility dynamics in our estimates of value-at-risk, uncorrelated risk factors and conditional freight-beta for a portfolio of freight returns.

Thus, the empirical work of this chapter is threefold. First, freight risk is measured and compared for a portfolio of tanker freight returns using a variety of single- and multi-state conditional variance methods. Second, uncorrelated risk factors are extracted from a portfolio of tanker freight returns using principal component analysis and modelled by distinct conditional variance models, respectively. Finally, freight-beta is estimated for a system of tanker freight returns using a two-state conditional variance freight-beta framework.

In summary, the empirical work within this chapter complements the previous work of chapter four by converting univariate value-at-risk measures to a multivariate value-at-risk measure to provide a risk measure for a portfolio of shipping tanker freight routes. Furthermore, uncorrelated freight risk factors are extracted from a portfolio of shipping tanker returns using principal component analysis and the distinctive nature of the volatility dynamics of these factors are investigated. Finally, a two-state conditional variance freight-beta system is estimated to examine the validity of a constant freight-beta alternative to a distinct freight-beta that is conditional on a changing volatility structure. The rest of the chapter is organised as follows. Section 5.2 examines the relevant literature on value-at-risk. Section 5.3 presents the employed methodological framework. Section 5.4 discusses empirical work and findings. Section 5.5 concludes the chapter.

5.2. Literature review

Value-at-risk (VaR) is a risk assessment tool that is used by many financial institutions to estimate the potential loss on an investment for a specified time horizon, normally one day or ten days. The popularity of this measurement technique is its simplicity and ease of understanding and use as it summarises risk in a single number. Furthermore, financial institutions are obliged to maintain minimum capital requirements in order to ensure that potential losses cannot cause any major crises, which led them to develop different models to measure and assess their overall risk. Therefore, the adoption of risk methods such as VaR has been widespread among financial institutions, investment houses and trading companies, instituting an integral part of the management structure within any company especially within markets that are volatile and seasonal such as commodities.

However, the use of such tools in the shipping industry to quantify and measure risk exposures remains limited due to the non-storable nature of freight services and also at the time, the non existence of shipping derivative markets. But since the establishment of the FFA market in 2002 and the increase in the number of participants in trading FFAs including shipping companies, methods to quantify freight risk have become an important part of a risk strategy for shipping companies and banks to utilise shipping operations and assess shipping finance, respectively. Therefore, it is vital that different methodologies to quantify freight risk are explored and studied to improve risk management for shipping participants. Studies in this field in the literature remain scarce and very limited. Thus, univariate conditional variance models used in chapter four as bases for univariate value-at-risk measures are projected to measure value-at-risk for a portfolio of freight returns in this chapter.

However, analysing volatility risk factors for a portfolio of returns requires estimating a multivariate GARCH model, which is more difficult to estimate than a univariate one due to the high number of parameters associated with such a framework. Thus, for orthogonalizing and reducing dimensions of the risk factors for a system of returns, principal component analysis (PCA) procedure was developed, where uncorrelated risk factors are extracted from a larger set of correlated risk factors. These PCA are derived from the eigenvectors of either the covariance or the correlation matrix of returns. These eigenvectors are ordered so that the first eigenvector belongs to the largest eigenvalue that explains the most variation in the system. Thus, the first component is the most important and in a highly correlated system it usually represents a common trend capturing almost any parallel shift in the system of returns. The second eigenvector belongs to the second largest eigenvalue that explains the second most important source of variation in the system, and usually captures the linear tilt in the system of returns. The third eigenvector belongs to the third largest eigenvalue that explains the third most important source of variation in the system and is an approximate quadratic function of the system of returns. These three PCA are known as the common trend, tilt and quadratic components, respectively. For more details see Alexander (2008b).

Ding (1994) was the first to suggest combining the powerful principal component analysis tool with GARCH models. The Orthogonal GARCH framework was introduced by Alexander and Chibumba (1996) and subsequently developed by Alexander (2001a, 2001b). The O-GARCH framework uses a reduced set of principal components to represent the system, combining it with GARCH conditional variance equations. Estimating a high order multivariate GARCH model is an impossible task because of the high number of parameters needed to be estimated, this flattens the log-likelihood function, see Alexander (2008a). The reduced set of principal components is represented by a set of variances representing the full system. The O-GARCH is better suitable for highly correlated systems. The main objective of implementing this procedure is to investigate the co-volatilities of tanker freight returns. The strength of the O-GARCH model depends on a highly correlated system; ideally a nine-dimensional multivariate system is represented with one or two principals' components, estimating parameters of a reduced set of conditional variances instead of the full list of parameters of the covariance matrices.

From examining a plot of tanker freight level prices and returns one sees that shipping freight volatilities are highly correlated and move together over time. Thus, capturing these dynamics through a multivariate modelling framework should prove more productive than univariate models, leading to better shipping operations and risk management techniques. The simplest approach to a multivariate MGARCH framework is to study the relations between the volatilities and co-volatilities of several markets, for example Kearney and Patton (2000) and Karolyi (1995) use such an approach across different markets, among other studies, Bollerslev (1990) and Longin and Solnik (1995) who in relation to the above examine whether the correlations between asset returns change over time. This area of study is very popular and widely used. For a recent survey on MGARCH models see Bauwens *et al* (2006).

The ability of MGARCH models to model the means and variances of two or more variables simultaneously make them attractive methods for risk management. A MGARCH model specifies a multivariate model for the mean such as vector auto regression (VAR) and vector error correction model (VECM) and a corresponding multivariate model for the time-varying variance and covariance terms, requiring a significant number of parameters to be estimated, which consequently leads to a significant loss of degrees of freedom. Thus, the main problem associated with MGARCH models is the high difficulty of estimation, simply because of the non-negativity of parameter estimates as well as over parameterisation due to large dimensions of the model. This induced Engle and Kroner (1995) to propose a generalised multivariate GARCH known as BEKK model to solve the non negativity problem associated with the MGARCH model by ensuring that the time-varying variance-covariance matrix is positive definite.

The MGARCH type of models was suggested by Bollerslev *et al* (1988) as superior to univariate models in asset pricing and analysing volatility dynamics and was extended by Koutmos and Tucker (1996) to estimate the interaction between the means and variances of returns on spot and future stock indices using a bivariate exponential GARCH model. In regards to the maritime literature, Kavussanos and Nomikos (2000a, 2000b, 2000c) use multivariate GARCH models to estimate dynamics hedge ratios and examine the performance of such techniques in risk management in BIFFEX freight futures markets. Alizadeh (2001) uses multivariate GARCH models to examine spillover effects amongst volatility of freight rates for three sizes of ships, namely Capesize, Panamax and Handysize in the dry-bulk market. Thus, most multivariate volatility studies agree that MGARCH models outperform univariate volatility models in modelling volatility dynamics.

5.3. Methodology

The framework for this chapter is in three parts. First, univariate value-at-risk measures for single tanker freight routes are converted to multivariate value-at-risk measures for a portfolio of tanker freight returns. Second, an Orthogonal GARCH framework is estimated for a portfolio of tanker freight returns. Finally, a two-state conditional variance freight-beta model is proposed to investigate the sensitivities of freight returns to higher and lower market volatility structures.

5.3.1. Value-at-risk for a multi-shipping portfolio

In general, portfolios are structured on the assumption that the change in the value of the portfolio is linearly related to the change in the market variables. If this assumption holds then the returns and the variance of the portfolio can be estimated as:

$$r_p = \sum_{i=1}^{n} w_i r_i \tag{5.1}$$

and

$$\sigma_p^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2\sum_{i=1}^{n} \sum_{j<i} \rho_{ij} w_i w_j \sigma_i \sigma_j \tag{5.2}$$

where r_p is the return on the portfolio, r_i is the return on the asset i included in the portfolio, w_i is the weight of asset i , and ρ_{ij} is the correlation between returns on asset i and j in the portfolio. Our multivariate value-at-risk measure is used to estimate freight risk for a shipping portfolio that consists of five tanker routes representing different tanker segments. These freight returns are reported for each route in dollars per tonne and calculated in the following steps. First, as discussed in chapter four, daily tanker freight rates are reported as a percentage of a flat-rate known as the WorldScale point system. On the one hand, these quotes for freight rates are acceptable for use as a measure of returns for different shipping routes and subsequently for VaR, as discussed in chapter four and other published papers, see Kavussanos and Dimitrakopoulos (2007), Angelidis and Skiadopolous (2008), Kavussanos and Dimitrakopoulos (2011) and Abouarghoub and Biefang-Frisancho Mariscal (2011). On the other hand, these measures are not appropriate to measure the first and second moments of a portfolio that consists of tanker freight returns in WorldScale points, simply because the flat-rate that is used varies for each tanker segments and without converting these percentage quotes to freight rate nominal value of dollars per tonne, a portfolio of tanker freight returns cannot be valuated properly. Thus, daily freight rates quoted in WorldScale points for each of the five tanker routes that constitute our portfolio are converted to dollars per tonne using the following formula:

$$\$\, per\ metric\ ton\ \left(\frac{dollars}{MT}\right) = \frac{WS \times flat\ rate}{100} = f_{seg,t} \tag{5.3}$$

Where $f_{seg,t}$ denotes the freight rate price in dollars per tonne of cargo on a specific route (tanker segment) in time *t*. In other wards, f_t refers to the cost of transporting one metric tonne of wet cargo on a specific shipping route. This is easier said than done, the main problem here is that historical flat-rate values are difficult to obtain[12], especially before 2001. However, the back-testing in this thesis is for the period from the 2nd of January 2008 to the 30th of October 2009, thus, to valuate our portfolio and back-test our VaR measures we need flat-rate values for each route under investigation for only the years 2008 and 2009.

It is important that we recognise that the work in this chapter is an extension of previous work, where estimated value-at-risk for single freight routes in chapter four are projected in this chapter to compute a value-at-risk measure for a portfolio that combines these freight tanker routes. To distinguish between the two measures for quotation purposes, VaR measures before and after conversion are denoted in this chapter as $\%VaR_{t+h}^{\alpha}$ and VaR_{t+h}^{α}, and refer to value-at-risk measures in WorldScale points (percentage) and dollars per tonne of cargo, respectively.

$\%VaR_{t+h}^{\alpha} \xrightarrow{yields}$ The possible loss in percentage terms in the next *h* period for significance α level.

$VaR_{t+h}^{\alpha} \xrightarrow{yields}$ The possible loss in money terms (dollars) for each tonne of cargo in the next *h* period for significance α level.

One way of measuring VaR of a portfolio that consists of a number of assets is to first estimate individual VaR measures for these assets given a certain confidence level and then pre- and post-multiply the correlation matrix of these assets with the vector ***V*** matrix, which contains the calculated VaR measures for each tanker segment, Alizadeh and Nomikos (2009). Thus, to estimate the VaR of our portfolio we calculate:

[12] In chapter six we use a collected set of historical flat-rates for five tanker routes from 2001 to 2010 to calculate a Time-Charter-equivalents.

$$VaR^{\alpha}_{p,t+h} = (V'CV)^{1/2} \tag{5.4}$$

Where

$$V' = (VaR_{TD3,t}, VaR_{TD4,t}, VaR_{TD5,t}, VaR_{TD7,t}, VaR_{TD9,t})$$

And

$$C = \begin{pmatrix} 1 & \rho_{TD3,TD4} & \rho_{TD3,TD5} & \rho_{TD3,TD7} & \rho_{TD3,TD9} \\ \rho_{TD4,TD3} & 1 & \rho_{TD4,TD5} & \rho_{TD4,TD7} & \rho_{TD4,TD9} \\ \rho_{TD5,TD3} & \rho_{TD5,TD4} & 1 & \rho_{TD5,TD7} & \rho_{TD5,TD9} \\ \rho_{TD7,TD3} & \rho_{TD7,TD4} & \rho_{TD7,TD5} & 1 & \rho_{TD7,TD9} \\ \rho_{TD9,TD3} & \rho_{TD9,TD4} & \rho_{TD9,TD5} & \rho_{TD9,TD7} & 1 \end{pmatrix}$$

The correlation matrix ***C*** is reported in section 5.4.1 in Table 5.4.

As discussed earlier, VaR measures that are based on the WorldScale point system and calculated by equations 4.5, 4.7 and 4.8 for each of the five tanker segments under investigation are converted to dollars per tonne by computing the following:

$$VaR^{\alpha}_{seg,t+h} = \%VaR^{\alpha}_{seg,t+h} \times f_{seg,t} \tag{5.5}$$

Thus, daily value-at-risk measures in the WorldScale (percentage) point system calculated for different tanker segments in chapter four are converted to daily value-at-risk measures in dollars per tonne.

5.3.2. Principal component analysis and conditional variance

In this chapter the value-at-risk framework that is used to assess freight risk for a shipping portfolio that consists of distinct multi-freight routes is an extension of the work carried out in chapter four for single VaR measures. Furthermore, as this thesis is concerned with studying a variety of single and multi-state conditional volatility methods to capture the dynamics of freight returns and better judge the impact on VaR measures for a portfolio of multi-tanker routes. The use of a powerful statistical tool such as principal component analysis (PCA), which is capable of reducing the dimensions of a system of assets returns to estimate risk factors for a multi-freight routes portfolio, is logical.

Models such as PCA are commonly used to assess risk for financial portfolios and hence to provide the risk adjusted performance measures that are used for banker investments, Alexander (2008a). Therefore, a principal component representation of our tanker portfolio is derived from the percentage of return for each tanker freight returns that constitute the portfolio, through an eigenvector analysis of a very large covariance matrix of freight returns within the portfolio. The ability of PCA to express relationship patterns and capture the volatility dynamics of the data set is down to its decomposition technique which is perfect for analysing a correlation structure for a set of assets returns. Furthermore, the attractiveness of this decomposition technique is the fact that it deals with a reduced number of factors that represent a large set of data within a portfolio without a significant loss of information.

In this chapter we make use of a reduced set of principal components with GARCH conditional variance model to extract patterns from a portfolio of tanker freight returns. This is known as the Orthogonal GARCH framework introduced by Alexander and Chibumba (1996) and Alexander (2001b) and extended by van der Weide (2002). Therefore, if we consider a data set of returns with zero mean summarized in a $T \times n$ matrix $\boldsymbol{X}$ and suppose we perform PCA on $\boldsymbol{V}$ the covariance matrix of $\boldsymbol{X}$. Thus, the principal components of $\boldsymbol{V}$ are the columns of the $T \times n$ matrix $\boldsymbol{P}$ defined by:

$$P = XW \tag{5.6}$$

where the $\boldsymbol{W}$ is the $n \times n$ Orthogonal matrix of eigenvectors of $\boldsymbol{V}$ and $\boldsymbol{W}$ that are ordered so that the first column of $\boldsymbol{W}$ is the eigenvector corresponding to the largest eigenvalue of $\boldsymbol{V}$, and so on. Following the work of Alexander we consider using only a reduced set of principal components, where the first k principal components of freight returns are the first k columns of $\boldsymbol{P}$, in which these columns are represented in the $T \times k$ matrix $\boldsymbol{P^*}$. Thus, a principal component approximation can be represented as:

$$X \approx P^* W^{*\prime} \tag{5.7}$$

The variance of 5.7 is:

$$V_t \approx W^* \Omega_t W^{*\prime} \tag{5.8}$$

where $\boldsymbol{W}^*$ is the $n \times k$ matrix in which k columns are given by the first k eigenvectors. The accuracy of the approximation is positively correlated with the value of k. $\boldsymbol{V}_t$ is the $m \times m$ returns conditional covariance matrix at time t and Ω_t is a $k \times k$ diagonal covariance matrix of the conditional variances of the principal components. Hence, according to Alexander the full $m \times m$ matrix $\boldsymbol{V}_t$ with $m(m+1)/2$ different elements is obtained from just k different conditional variance estimates, with $k \leq N$ where N is the number of Orthogonal transformation. Furthermore, the Orthogonal GARCH model requires estimating k separate univariate GARCH models, one for each principal component conditional variance in Ω_t. With Ω_t always positive definite for the O-GARCH matrix and $\boldsymbol{V}_t$ always positive semi-definite and can be expressed as:

$$X'V_tX = X'W^*\Omega_tW^{*\prime}X = Y'\Omega_tY \tag{5.9}$$

where $Y = W^{*\prime}X$. Since $\boldsymbol{Y}$ is zero for some non-zero $\boldsymbol{X}$ and $X'V_tX$ not strictly positive definite, but positive semi-definite.

Therefore, let us consider that freight returns for the different routes under investigation are included in a vector stochastic process $\boldsymbol{R}_t$ of dimension $N \times 1$ and conditional on past information t-1. Thus, a symmetric O-GARCH model applied to a portfolio of freight returns with a number of principal component vectors k is defined as:

$$R_t = \mu_t + \varepsilon_t \tag{5.10}$$

$$\varepsilon_t = V^{1/2}u_t \tag{5.11}$$

$$u_t = Z_m f_t \tag{5.12}$$

where $\boldsymbol{V} = diag(v_1, v_2, \ldots v_N)$, with v_i the population variance of ε_{it} and $\boldsymbol{Z}_m$ is a matrix of dimension $N \times m$ given by:

$$Z_m = P_m L_m^{1/2} = P_m diag(l_1^{1/2} .. l_m^{1/2}) \tag{5.13}$$

where $l_1 \geq \cdots \geq l_m > 0$ being m the largest eigenvalues of the population correlation matrix and covariance matrix of ε_t and u_t, respectively. With P_m the $N \times m$ matrix of associated eigenvectors and the vector $f_t = (f_{1t}, \ldots, f_{mt})'$ is a random process such that $E_{t-1}(f_t) = 0$ and $Var_{t-1}(f_t) = \Sigma_t = diag\ (\sigma^2_{f_{1t}}, \ldots, \sigma^2_{f_{mt}})$, and

$$\sigma_{fi,t}^2 = (1 - \alpha_i - \beta_i) + \alpha_i f_{i,t-1}^2 + \beta_i \sigma_{fi,t-1}^2 \tag{5.14}$$

Consequently,

$$H_t = Var_{t-1}(\varepsilon_t) = V^{1/2} V_t V'^{1/2} \tag{5.15}$$

where $V_t = Var_{t-1}(u_t) = Z_m \sum_t Z'_m$, and V and L_m are the model parameters and α_i's and β_i's are the GARCH factors parameters. In practice V and L_m are replaced by their sample counterparts and *m* is normally chosen by principal component analysis applied to the standardised residuals $\hat{u}_t$.

The O-GARCH model is estimated using a constrained maximum likelihood (ML) approach known as a quasi-likelihood function, where a vector stochastic process R_t for $t = 1,2,\ldots,T$ is a realisation of the data generating process, with a conditional mean, conditional variance matrix and conditional distribution are respectively $\mu_t(\theta_0)$, $H_t(\theta_0)$ and $p(R_t|\zeta_0, \Omega_{t-1})$ where $\zeta_0 = (\theta_0 \eta_0)$ is a *r*-dimensional parameter vector and η_0 is the vector that contains the parameters of the distribution of the innovations z_t. Thus, to estimate $\theta_0$we maximise the likelihood function $L_T(\theta,\eta)$ for the *T* observations with respect to the vector of parameters $\zeta_0 = (\theta, \eta)$ where:

$$L_T(\zeta) = \sum_{t=1}^{T} \log f(R_t|\zeta, \Omega_{t-1}) \tag{5.16}$$

with

$$f(R_t|\zeta, \Omega_{t-1}) = |H_t|^{-1/2} g(H_t^{-1/2}(R_t - \mu_t)|\eta)$$

where the density function $g(H_t^{-1/2}(R_t - \mu_t)|\eta)$ denotes the auxiliary assumption of *i.i.d* for the standardized innovations z_t. η is a vector of nuisance parameters and the likelihood function is expressed as:

$$L_T(\theta) = -\frac{1}{2}\sum_{t=1}^{T}[N \log(2\pi) + log|H_t| + (R_t - \mu_t)' H_t^{-1}(R_t - \mu_t)] \tag{5.16}$$

With respect to the rejection of the normality assumption in the literature, especially for daily and weekly data, Bollerslev and Wooldridge (1992) have shown that a consistent estimator of θ_0 may be obtained by maximizing (5.16) with respect to θ even if the data generating process is not conditionally Gaussian, arguing that the quasi-maximum likelihood (QML) is consistent provided that the conditional mean and the conditional variance are specified correctly. For more details see Alexander (2008a) and the references within.

Finally, in respect to diagnostic tests, in comparison to univariate volatility models, specific tests are limited for multivariate volatility models. Thus, there are two approached to running diagnostic tests. On the one hand, one can choose form the huge body of diagnostic tests devoted to univariate models, where each time series is independently diagnostically tested. On the other hand, one can choose from the few available tests for multivariate models by diagnosing a vector representation of the whole system. In this thesis we feel that the diagnostic tests conducted in chapter four for the different proposed univariate conditional variance models are adequate.

5.3.3. Market volatility state regimes

The findings of chapter four suggest that volatility dynamics within freight returns are state dependent and better defined by a switching conditional volatility framework that is capable of capturing the distinctive nature of volatility dynamics within freight returns. Therefore, this thesis supports the idea that freight volatilities switch between a lower volatility state and a higher volatility state that are better captured by a fractional integrated conditional variance and a normal symmetric conditional variance specification, respectively. To investigate the sensitivities of freight returns to market volatility movements through a freight-beta framework it is paramount that any proposed structure accounts for the distinctive nature of volatility dynamics within freight returns. To do so, we propose a two-state conditional variance freight-beta model. Thus, first we describe our indicator function that is extracted from the MSR estimation and applied to the Baltic Dirty Tanker Index series that is a proxy of overall tanker returns. This time series is described and illustrated in section 5.4.3 and Figure 5.3, respectively. Our Markov regime-switching estimation identifies two different regime states, in which we classify each daily freight return as belonging to a distinct freight volatility state. This is based on the methodology described and on the findings reported in sections 4.3.6.5 and Table 4.11, respectively. Thus, our definition of two regime states using indicator functions is as follows:

$$I_{L,t} = \begin{cases} 1 & if\ returns\ are\ in\ the\ low\ volatility\ state\ (regime\ 1) \\ 0 & otherwise \end{cases}$$

$$I_{H,t} = \begin{cases} 1 & if\ returns\ are\ in\ the\ high\ earning\ state\ (regime\ 2) \\ & 0\ \ otherwise \end{cases}$$

The above abbreviations are dummy variables $I_{L,t}$ and $I_{H,t}$ that indicate lower volatility state and higher volatility state. Based on our indicator framework our data sample follows two market regimes that are classified as; lower freight volatility state and higher freight volatility state. The empirical work for this part is presented in section 4.4.5 and reported in Tables 4.9 and 4.10.

5.3.4. Two-state conditional volatility freight-beta framework

A measure of unconditional freight beta can be modelled through a single-factor framework and expressed simply as:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it} \tag{5.17}$$

where r_{it} and r_{mt} refer to return on asset *i* at time *t* and return on market *m* at time *t*, respectively. while α_i and ε_{it} are a constant and the error term of the regression. Thus, unconditional single-beta freight returns Model can be expressed using a market model in the following form:

$$r_{TDit} = \alpha_{TDi} + \beta_{TDi} r_{BDTIt} + \varepsilon_{TDit} \tag{5.18}$$

where r_{TDit} and r_{BDTIt} refer to tanker freight returns for single routes and returns on the whole market, respectively. α_{TDi} and β_{TDi} represents over/under performance and positive/negative sensitivity of each tanker route relevant to the shipping market benchmark, respectively. ε_{TDit} represents the estimated residuals within the regression and these are assumed to be normally distributed and homoscedastistic.

Following the same argument and assuming that freight returns are conditional on two distinct freight volatility states, a lower and higher volatility states, we express our conditional variance two-state beta freight returns model using dummy variable in the following form:

$$r_{TDit} = \alpha_{TDi} + \beta L_{TDi}(I_{Lt} r_{BDTIt}) + \beta H_{TDi}(I_{Ht} r_{BDTIt}) + \varepsilon_{TDit} \tag{5.19}$$

where $\beta L_{TDi}\ and\ \beta H_{TDi}$ are systematic risks corresponding to market conditional volatilities for two distinct freight volatility regimes, lower freight conditional volatility and higher freight conditional volatility, respectively. Hence, our system of equations is expressed as:

$$\begin{pmatrix} r_{TD1,t} \\ r_{TD2,t} \\ r_{TD3,t} \\ r_{TD4,t} \\ r_{TD5,t} \\ r_{TD6,t} \\ r_{TD7,t} \\ r_{TD8,t} \\ r_{TD9,t} \end{pmatrix} = \begin{pmatrix} \alpha_{TD1} & \beta L_{TD1} & \beta H_{TD1} \\ \alpha_{TD2} & \beta L_{TD2} & \beta H_{TD2} \\ \alpha_{TD3} & \beta L_{TD3} & \beta H_{TD3} \\ \alpha_{TD4} & \beta L_{TD4} & \beta H_{TD4} \\ \alpha_{TD5} & \beta L_{TD5} & \beta H_{TD5} \\ \alpha_{TD6} & \beta L_{TD6} & \beta H_{TD6} \\ \alpha_{TD7} & \beta L_{TD7} & \beta H_{TD7} \\ \alpha_{TD8} & \beta L_{TD8} & \beta H_{TD8} \\ \alpha_{TD9} & \beta L_{TD9} & \beta H_{TD9} \end{pmatrix} \begin{pmatrix} 1 \\ r_{LBTDI,t} \\ r_{HBTDI,t} \end{pmatrix} + \begin{pmatrix} \varepsilon_{TD1,t} \\ \varepsilon_{TD2,t} \\ \varepsilon_{TD3,t} \\ \varepsilon_{TD4,t} \\ \varepsilon_{TD5,t} \\ \varepsilon_{TD6,t} \\ \varepsilon_{TD7,t} \\ \varepsilon_{TD8,t} \\ \varepsilon_{TD9,t} \end{pmatrix} \tag{5.20}$$

This is a conditional variance two-beta freight return system where $r_{LBTDI,t} = I_{Lt} \times r_{BDTIt}$ and $r_{HBTDI,t} = I_{Ht} \times r_{BDTIt}$ and are measures of tanker freight returns sensitivities to distinct conditional volatility, these are; sensitivities to lower freight volatility state and higher freight volatility state, respectively. The system 5.20 is an unrestricted reduced form (URF) and can be expressed in a more compact way as:

$$r_{TDi,t} = Br_{BDTI,t} + v_t \quad t = 1, \dots, T \; and \; v_t \sim [0, \Omega] \tag{5.21}$$

where $\boldsymbol{r}_{TDi,t}$ is a (9×1) vector of endogenous variables, these are freight return observations for distinct tanker routes at time *t* relevant to a defined data set $\boldsymbol{r}_{BDTI,t}$, which represents average freight return for the tanker market, this is a non-modelled variable and classified as restricted, while α's and *Beta's* are (9×1) vectors of unrestricted variables. Hence, each equation in the system has the same variables on the right-hand side. Since α's and *Beta's* are unrestricted variables, the system can be estimated using multivariate least squares method. This requires that $\boldsymbol{V}_t \sim ID_n(0, \Omega)$, where Ω is constant over time and is singular owing to identities linking elements of r_t, these are managed by estimating only the subset of equations corresponding to stochastic endogenous variables. Thus, if $\boldsymbol{V}_t \sim ID_n(0, \Omega)$ is valid OLS coincides with maximum likelihood estimation (MLE).

Therefore, the system expressed in equation 5.20 has $\mathrm{E}[v_t]$=0, $\Omega = \mathrm{E}[v_t v_t']$ and $\boldsymbol{r}_{TDi,t}$ is a (9×1) vector matrix that represents freight earning returns for nine tanker routes, while $\boldsymbol{r}_{BDTI,t}$ is a (3×1) vector matrix that represents freight returns for the overall tanker sector and *B* is a (9×3) matrix representing market parameters. $\boldsymbol{v}_t$ is a

(9×1) vector matrix that represents the corresponding residuals for each equation in the system. Thus, the system can be expressed more compactly by using

$\boldsymbol{R'}_{TDI} = (r_{TDi,1}, r_{TDi,2}, \dots, \dots, r_{TDi,T})$, $\boldsymbol{R'}_{BDTI} = (R_{BDTI,1}, R_{BDTI,2}, \dots, \dots, R_{BDTI,T})$ and $\boldsymbol{V'}_{TDI} = (v_{TDi,1}, v_{TDi,2} \dots \dots, v_{TDi,T})$.

Therefore, equation 5.21 can be expressed as $R_{TDI} = BR_{BDTI} + V$ and as $R'_{TDI} = BR'_{BDTI} + V'$. Where $\boldsymbol{R'}_{TDi}$ is $(n \times T)$, $\boldsymbol{R}_{BDTI}$ is $(k \times T)$ and $\boldsymbol{B}$ is $(n \times k)$, with $k = nm$. Thus, $\widehat{B'} = (R'_{BDTI} R_{BDTI})^{-1} R'_{BDTI} R_{TDI}$ and $\widehat{\Omega} = \widehat{V'}\widehat{V}/(T-k)$. The residuals are defined by $\widehat{V} = R_{DTI} - R_{BDTI}\widehat{B'}$ and the variance of the estimated coefficients is defined as $V[vec\hat{B}'] = E\left[vec(\hat{B}' - B')\left(vec(\hat{B}' - B')\right)'\right]$. In which $vecB'$ is an $(nk \times 1)$ column vector of coefficients.

Furthermore, assuming that $\boldsymbol{V} \sim [0, \Omega]$ holds and that all the coefficient matrices are constant. Thus, the log-likelihood function $\ell(B, \Omega | R_{TDI}, R_{BDTI})$ depends on the following multivariate normal distribution.

$$\ell(B, \Omega | R_{TDI}, R_{BDTI}) = -\frac{Tn}{2}\log 2\pi - \frac{T}{2}\log|\Omega| - \frac{1}{2}\sum_{t=1}^{T} v'_t \Omega^{-1} v_t \tag{5.22}$$

By differentiating the above equation with respect to Ω^{-1} and equating that to zero, we find the following

$$= K_c - \frac{T}{2} log|\Omega| - \frac{1}{2} tr\ (\Omega^{-1} V'V) \tag{5.23}$$

$$= K_c + \frac{T}{2} log|\Omega^{-1}| - \frac{1}{2} tr\ (\Omega^{-1} V'V) \tag{5.24}$$

$$2V'V - dg(V'V) = 2T\Omega - Tdg(\Omega) \tag{5.25}$$

where *tr* and *dg* stands for trace and diagonal of the matrix, respectively. $K_c = \frac{-Tn}{2}(1 + log 2\pi)$ and is a constant. Given that $\Omega = \mathrm{E}(\mathrm{T}^{-1}\mathrm{V}'\mathrm{V})$ we drive the concentrated log-likelihood function (CLF).

$$\ell_c(B, \Omega | R_{TDI}, R_{BDTI}) = K_c - \frac{T}{2}\log|V'V| + \frac{Tn \log T}{2} - \frac{Tn}{2}$$

$$= K_c - \frac{T}{2}\log|(R'_{TDI} - BR'_{BDTI})(R_{TDI} - R_{BDTI}B')| \tag{5.26}$$

Based on least squares theory we minimize $(R'_{TDI} - BR'_{BDTI})(R_{TDI} - R_{BDTI}B')$ to find the maximum likelihood estimates $\hat{B}' = (R'_{BDTI}R_{BDTI})^{-1}R'_{BDTI}R_{TDI}$ and $\tilde{\Omega} = T^{-1}\hat{V}'\hat{V}$. Thus, maximizing $\hat{\ell} = K_c - \frac{T}{2}\log|\tilde{\Omega}|$ with $\tilde{\Omega}$ scaled by *T*. More details of the adopted methods in this chapter can be found in Doornik and Hendry (2009a).

Furthermore, specification test information along with the system regression output is reported in section 5.4.3. The statistics for the unrestricted reduced form (URF) coefficients $\hat{\beta}_i^j$ and their standard errors are calculated to determine whether individual coefficients are significantly different from zero.

$$t - value = \frac{\hat{\beta}_i^j}{SE[\hat{\beta}_i^j]} \tag{5.27}$$

where the null hypothesis H_0 is $\hat{\beta}_i^j = 0$. The null hypothesis is rejected if the probability of getting a value different than zero is less than the chosen significance level. This probability is computed by $t - prob = 1 - Prob(|\tau| \leq |t - value|)$, in which τ has a Student *t*-distribution with *T-k* degrees of freedom. The standard error for each equation in the system is calculated by taking the square root of their residual variance, $\sqrt{\tilde{\Omega}_i}$ for *i*=1,2,..,5. The *residual sum of squares* for each equation is calculated as $RSS = (T - k)\tilde{\Omega}_i$. These are the diagonal elements of $\hat{V}'\hat{V}$. The highest attainable likelihood value for the system is calculated as $\hat{l} = -\frac{1}{2}\log|\hat{\Omega}| - \frac{Tn}{2}(1 + log2\pi)$ and is reported in Table 5.4, along with $-\frac{1}{2}\log|\hat{\Omega}|$, $|\hat{\Omega}|$ and $log|\hat{\Omega}_0|$ values, also the total number of observations *T* and total number of parameters *Tn* in all equations.

In addition, in the empirical section 5.4.3 (the top part of Table 5.4) we report two different measures of *goodness of fit* for our system based on the likelihood-ratio principle R^2_{LR} and the lagrange multiplier principle R^2_{LM} for a single equation system and for the significance of each column of $\hat{B}$, respectively. Furthermore F-tests are conducted and results are reported for both methods, for the employed system of equations, in two parts. First, F-tests against unrestricted regressors, this uses Rao (1952) F-approximation (details provide below) to test the null hypothesis that all coefficients are zero (except the unrestricted variables, in our case is the constant in each equation), this is the reported F-statistic to test the significance of the *r* squared for a single equation system R^2_{LR} based on the likelihood-ratio principle, where

$R_{LR}^2 = 1 - |\widehat{\Omega}||\widehat{\Omega}_0|$ and $R_{LM}^2 = 1 - \frac{1}{n} tr(\widehat{\Omega}\widehat{\Omega}_0)$. Second, F-tests on retained regressors are conducted and reported for the significance of each column of $\hat{B}$ together with their probability values under the null hypothesis that the corresponding column of coefficients is zero, thus, testing whether each variable is significant in the system, with the statistics $F(n, T - k + 1 - n)$.

Furthermore, testing for general restrictions is conducted for each single equation in the system and the overall system. Thus, we test the significance of different estimated betas for each regime state. Thus, writing $\hat{\theta} = vec\ \hat{B}'$ and corresponding variance-covariance matrix $\boldsymbol{V}[\hat{\theta}]$, we test for non-linear restriction of the form $f(\theta) = 0$. Where the null hypothesis $H_0: f(\theta) = 0$ and the alternative hypothesis $H_1: f(\theta) \neq 0$ using a Wald test in the form:

$$w = f(\hat{\theta})' (\hat{J}\ V[\hat{\theta}]\hat{J}')^{-1} f(\hat{\theta}) \tag{5.28}$$

where J is the Jacobian matrix and is the transformation of $\partial f(\theta)/\partial\theta'$. The Wald statistic follows a $x^2(s)$distribution, where s is the number of restriction that corresponds to number of equations in the system. The null is rejected if the test statistic is significant. We report the results for the Wald test for general restrictions along with their corresponding p-values for each equation in the system and a joint test for the whole system in Table 5.4. Finally, correlation of actual and fitted data is reported in Table 5.5. Thus, we estimate the correlation between $r_{TDi,t}$ and $\hat{r}_{TDi,t}$ for all nine distinct tanker routes under investigation.

Furthermore, the previous framework is suitable to extract risk components from freight returns that should improve overall risk management techniques. This is estimated by quantifying both systematic and specific risks within the freight market by relating the distribution of returns to the distribution of risk factors. Systemic risk is undiversifiable, while specific risk is not associated with the risk factor returns and can be reduced in theory by a well diversified portfolio. In respect of our linear regression model specific risk can be measured as the standard deviation of the residuals for each state and systemic risk can be computed by multiplying the obtained freight beta by the square root of the variance of returns. In summary, in this chapter three frameworks are proposed to estimate value-at-risk, uncorrelated risk factors and freight-beta for a portfolio of freight returns.

5.4. Empirical work

In this section we present empirical findings and analysis. First, value-at-risk is calculated out for a portfolio of tanker freight returns to examine the usefulness of univariate conditional variance models in measuring freight risk for a multi-system of freight returns. Second, a multivariate conditional variance framework based on principal component analysis process is estimated to extract tanker freight risk factors. In other words, the powerful principal component analysis tool is combined with different conditional variance models constructing an Orthogonal GARCH framework to model the uncorrelated freight risk factors. Finally, freight-beta is estimated conditional on distinct conditional variance regime states.

Similar to the empirical work carried out in chapter four, value-at-risk is measured for a shipping portfolio that consists of five tanker segments, while O-GARCH and freight-beta frameworks are conducted on a shipping portfolio that consists of nine distinct tanker routes. In Table 5.1 and Figure 5.1 we present a general description and an illustration of the all the tanker routes that are investigated in this chapter, respectively. Additionally, average tanker freight returns are presented by the Baltic Dirty Tanker Index (BDTI) that is illustrated in Figure 5.2.

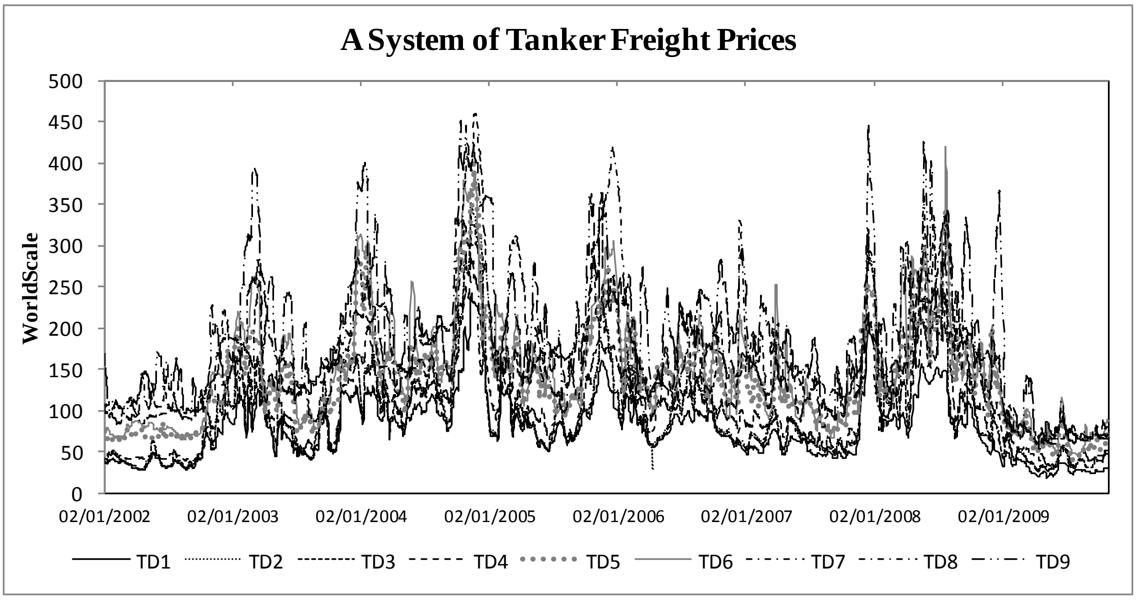
Table 5.1: Description of the main tanker routes that constitute the BDTI

Route	Route Description	Capacity
TD1	MEG (Ras Tanura) to US Gulf (LOOP)	280,000 mt
TD2	MEG (Ras Tanura) to Singapore	260,000 mt
TD3	MEG (Ras Tanura) to Japan (Chiba)	260,000 mt
TD4	West Africa (bonny) to US Gulf (LOOP)	260,000 mt
TD5	West Africa (bonny) to USAC Gulf (Philadelphia)	130,000 mt
TD6	Black sea (Novorossiysk) to Mediterranean (Augusta)	135,000 mt
TD7	North Sea (Sullom Voe) to continent (Wilhelmshaven)	80,000 mt
TD8	Kuwait (Mena el Ahmadi) to Singapore	80,000 mt
TD9	Caribbean (Puerto la Cruz) to US Gulf (Corpus Christi)	70,000 mt

Note Table 5.1: describes the different tanker routes that are investigated and constitute the BDTI that represents average tanker freight cost. The table reports the route number and trading area along with cargo capacity, which is a reference of the type of vessel operating on that particular route.

Source: Baltic Exchange.

Figure 5.1: An illustration of the main tanker routes that constitute the BDTI



Note Figure 5.1: is an illustration of freight price-level for the main tanker routes that constitute the Baltic Dirty Tanker Index. The vertical index represents WorldScale points, which is the main percentage system used to quote tanker freight rates.

Source: Author’s estimations.

In Table 5.2 we report basic statistics for freight returns on nine tanker routes and the BDTI reported by the Baltic Exchange. Basic statistics reported in Table 5.2 for freight returns clearly indicate a positive correlation between the size of tanker vessels and their four statistic moments, the larger the size of the tanker vessel the higher the daily mean return, and their volatility level and excess return. Most routes show signs of positive skewness, high kurtosis and departure from normality represented by the Jarque-Bera. There is also clear evidence of ARCH effects in freight returns, with different lag levels, Engle's ARCH (1982). While the positive/negative skewness, high kurtosis and the Jarque-Bera normality test clearly illustrate the non-normality of the distribution, the mean daily returns are quite close to zero, which support the zero mean assumption. There is clear evidence of volatility clustering in daily freight returns, where there are high freight volatility periods mixed with low freight volatility periods, which suggests the presence of heteroscedasticity, This confirms the presence of ARCH effects which is what the literature suggests (Engle, 1982).

Table 5.2: A summary of basic statistics for tanker freight rate returns

	RTD1	RTD2	RTD3	RTD4	RTD5	RTD6	RTD7	RTD8	RTD9	RBDTI
Mean	-0.000480	-0.000379	-0.000375	-0.000264	-0.000260	-0.000191	-0.000390	-0.000393	-0.000487	-0.000396
Std.D	0.043653	0.058885	0.054952	0.039586	0.047327	0.050416	0.053035	0.022907	0.066723	0.02288
Ske	-0.367760	0.161230	0.178120	0.114600	0.41752	1.3367	0.76119	-2.2027	0.61424	-1.8907
E-Kurt	18.95	25.92	11.97	11.11	6.61	13.98	15.51	52.56	11.72	35.38
Min	-0.529620	-0.709110	-0.501990	-0.342950	-0.35714	-0.37597	-0.49959	-0.39053	-0.51748	-0.38122
Max	0.262730	0.703470	0.399610	0.287430	0.28881	0.48027	0.427	0.20853	0.46239	0.12375
Norm. T	4937.8*	7110.2*	2961.1*	2723.5*	1265.1*	1791.7*	3397.9*	8949.3*	2512.5*	5625.8*
ADF(0)	-31.12†	-31.92†	-27.38†	-30.15†	-30.31†	-29.04†	-28.11†	-28.07†	-34.70†	-24.54†
ARCH(1-2)	14.1*	219.5*	41.0*	27.3*	30.3*	17.5*	17.2*	5.2*	46.5*	2.8589***
ARCH(1-5)	9.9*	90.2*	21.4*	10.9*	12.2*	8.7*	7.1*	2.2***	19.7*	1.3
ARCH(1-10)	5.1*	45.5*	12.3*	6.8*	6.9*	9.1*	7.2*	1.2	10.1*	0.68

Note Table 5.2: reports basic statistics on freight rate returns for nine different tanker routes and for the Baltic Dirty Tanker Index, a proxy for an average freight rate for the tanker market. Reported freight return statistics are mean, standard deviation, skewness, excess-kurtosis, minimum, maximum, normality test, ADF and ARCH tests. †, *, ** and ** refer to significance at any level, significance at 1%, 5% and 10%, respectively.

Source: Author’s estimations.

5.4.1. Value-at-risk for a portfolio of freight returns

As discussed in 5.3.1 value-at-risk measures administered on a portfolio of tanker freight returns is constructed in two steps. First, a variety of conditional variance models are estimated to assess the most suitable method to capture freight volatility within the tanker market. Second, a suitable assessment is made on the distribution of past returns. For the former step nine conditional variance models are estimated and for the latter three different assumptions are made on the distribution of returns.

Furthermore, it is argued in the literature that value-at-risk is not a coherent risk measure as it does not possess the sub-additively property. Thus, to convert a univariate VaR measure engineered in chapter four to a multivariate VaR measure to assess freight risk for a portfolio of freight returns, we convert each calculated VaR measure in percentages to their equivalent dollars per tonne of cargo and than estimate VaR for the portfolio using equations 5.3 and 5.4, respectively. The flat-rate values for the conversion and the constructed correlation matrix are reported in Tables 5.3 and 5.4, respectively. Furthermore, plots of calculated one-day VaR for portfolio of freight positions are illustrated in Appendix II.

Table 5.3: WorldScale flat-rates for 2008 and 2009

	TD3	TD4	TD5	TD7	TD9
2008	18.05	15.5	14.19	5.4	7.31
2009	25	21.71	19.63	6.3	9.86

Note Table 5.3: reports WorldScale flat rates for the years 2008 and 2009. These are dollars values for each transported tonne of cargo.

Source: Imarex and anonymous shipping brokers.

Table 5.4: Correlation matrix for freight returns

	TD3	TD4	TD5	TD7	TD9
TD3	1	0.431951	0.372149	0.133576	0.117143
TD4	0.431951	1	0.714011	0.080283	0.233756
TD5	0.372149	0.714011	1	0.209895	0.270872
TD7	0.133576	0.080283	0.209895	1	0.220321
TD9	0.117143	0.233756	0.270872	0.220321	1

Note Table 5.4: reports the correlation matrix of tanker freight returns used to calculate multivariate value-at-risk measure denoted by C in equation 5.4.

Source: Author's estimations.

Similar to the procedure of chapter four, value-at-risk measures are assessed by back-testing ex-post period of the sample. The results are reported in Table 5.5, where for each model the exceedencess, violation of estimated VaR relevant to actual returns based on T_0 and T_1 dummy variables, unconditional likelihood ratio, independent likelihood ratio and conditional likelihood ratio are reported subsequently in three panels. These panels report value-at-risk estimates based on a normal, non-normal and filtered historical simulation (FHS) specifications.

Empirical findings clearly announce the superiority of FHS based VaR models on normal and non-normal based VaR models, in estimating short-term freight risk. This is confirmed by the reduced number of exccedencess and violations of the value-at-risk measure to actual returns that are reported in Table 5.5. This is consistent with findings of chapter four and recent findings in the literature, see Kavussanos and Dimitrakopoulos (2007), Angelidis and Skiadopolous (2008), Nomikos *et al* (2007) and Abouarghoub and Biefang-Frisancho Mariscal (2011). Most importantly, VaR measure that accounts for distinct conditional variance states outperform all other models.

Table 5.5: Reports Back-Testing results for estimating value-at-risk for a portfolio of tanker freight returns

	HS		Risk Metrics		SGARCH		AGARCH		SGARCH-t-(d)		AGARCH-t(d)		AGARCH-t(d)-EVT		2-State-MS-CV	
	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%
Normal Value-at-Risk Models																
Exceedencess			11	18	14	25	15	32	12	27	15	35			6	16
T_0			451	438	445	436	446	433	449	437	446	426			457	446
T_1			10	23	16	25	15	28	12	24	15	35			4	15
Violation			2.22%	5.25%	3.60%	5.73%	3.36%	6.47%	2.67%	5.49%	3.36%	8.22%			0.88%	3.36%
LRuc			1.069†	2.562†	12.5***	0.169†	14.8***	1.050†	0.655†	0.041†	14.8***	5.66**			0.634†	0.557†
LRind			2.944*	22.1***	7.6***	14.7***	11.7***	15.6***	3.77*	3.29*	0.447†	8.8***			1.411†	0.151†
LRcc			4.011†	24.7***	20.1***	14.8***	26.5***	16.6***	3.123†	3.341†	15.3***	14.5***			1.610†	0.654†
Non-normal Value-at-Risk Models																
Exceedencess			10	22	11	32	12	38	11	40	9	41				
T_0			450	439	453	429	450	423	454	421	455	420				
T_1			11	22	8	32	11	38	7	40	6	41				
Violation			2.44%	5.01%	1.77%	7.46%	2.44%	8.98%	1.54%	9.50%	1.32%	9.76%				
LRuc			1.906†	0.0511†	0.088†	3.281	0.363	8.610	0.381	10.862	1.070	12.070				
LRind			2.755*	2.974*	4.42**	0.300†	30.7***	15.9***	3.565*	10.7***	2.944*	9.8***				
LRcc			0.849†	3.025†	4.340†	3.580†	31.1***	24.5***	3.945†	21.5***	4.013†	21.9***				
FHS Value-at-Risk Models																
Exceedencess	10	27	9	23	7	27	6	30	8	21	8	21	6	19		
T_0	450	434	450	438	455	434	455	431	455	440	455	443	456	444		
T_1	11	27	11	23	6	27	6	30	6	21	6	18	5	17		
Violation	2.44%	6.22%	2.44%	5.25%	1.32%	6.22%	1.32%	6.96%	1.32%	4.77%	1.32%	4.06%	1.10%	3.83%		
LRuc	0.085†	0.676†	0.655†	0.001†	0.362†	0.187†	0.368†	2.022†	0.029†	0.197†	0.029†	0.197†	0.027†	0.227†		
LRind	5.30**	26.5***	6.6***	8.4***	1.345†	3.97**	2.931*	0.019†	2.609†	3.752*	2.609†	1.678†	2.613†	0.124†		
LRcc	5.39**	27.2***	7.30**	8.49**	1.708†	4.160†	1.031†	2.042†	2.638†	3.950†	2.638†	1.875†	2.640†	0.352†		

Note Table 5.5: reports Back-Testing results for value-at-risk measures carried out on a portfolio of tanker freight returns. Reported results are for normal-value-at-risk, non-normal-value-at-risk and FHS-value-at-risk in three subsequent sections. These results are reported for different value-at-risk measure based on eight distinct conditional variance models. Statistical tests are unconditional, independent and conditional coverage of the interval forecasts under each approach for the portfolio under investigation, denoted by LRuc, LRind and LRcc, respectively. *, ** and *** denote significance at 10%, 5% and 1% level, respectively. The tests for LRuc and LRind are $x_1^{1\%}$ and $x_1^{5\%}$ for 1% VaR and 5% VaR, respectively. The tests for LRcc are $x_2^{1\%}$ and $x_2^{5\%}$ for 1% VaR and 5% VaR, respectively. Critical values for $x_1^{1\%}$, $x_1^{5\%}$, $x_1^{10\%} x_2^{1\%} x_2^{5\%} x_2^{10\%}$ are 6.63, 3.84, 2.7, 9.21, 5.99 and 4.6, respectively. If value of the likelihood ratio is larger than the critical value the Value-at-risk model is rejected at the significance level. † refers to acceptance of the null. In other words, the suitability of the model to measure VaR.

Significance levels for x^2 with one and two degrees of freedom.

		1df	2df
*	10%	2.705544	4.60517
**	5%	3.841459	5.991465
***	1%	6.634897	9.21034

Source: Author's estimations.

5.4.2. Principal component analysis

As discussed earlier PCA is a powerful decomposition statistical tool that is used to capture the characteristics of the volatility dynamics of a data set by deriving a new matrix that is an approximation of the correlation matrix of returns, which consists of fewer uncorrelated components with smaller dimension. Most empirical work suggests that for most portfolios two or three components could be sufficient to capture different patterns within a system of data, especially if these factors can account for a high percentage of the volatility dynamics of the return matrix.

The estimation process for a conditional variance PCA is of twofold. First, PC analysis that is carried out in the following steps; calculate the unconditional mean of the data set, calculate the PCA for the correlation matrix, calculate eigenvectors, calculate the correlation between PC and the variables and finally, estimate O-GARCH rotation matrix $Z_m=P_m L_m^{(1/2)}$ with $m=5$. The empirical results are reported in Table 5.6, where the output from the principal component analysis is reported in three sections. Panel A presents the eigenvalue, variance proportion and cumulative proportion for each estimated principal component. For example the first principal component (factor) explains more than 37 per cent of the portfolio variation and the first three factors together explain more than 66 per cent of the portfolio variation. The eigenvectors of the estimated PCA and their correlation with freight returns are reported in panels B and C, respectively. Furthermore, the impact of the eigenvectors of first five risk factors extracted through PCA on the portfolio of freight returns are illustrated in Figures 5.2.

Table 5.6: Principal component analysis results

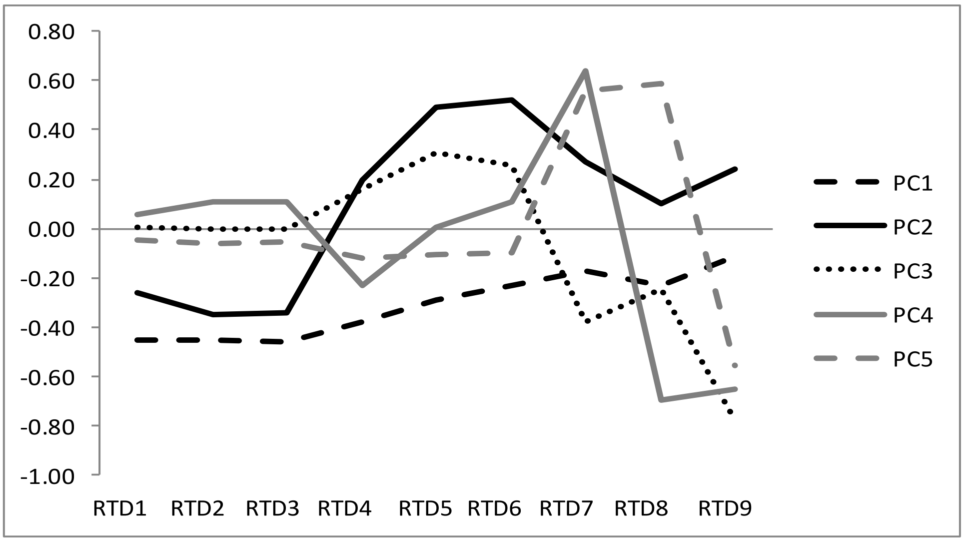
Panel A: Principle Components and Proportions					
	Comp	Eigen-V	Prop	Cumul	
	PC1	3.35090	0.37232	0.37232	
	PC2	1.64420	0.18269	0.55501	
	PC3	1.00380	0.11154	0.66655	
	PC4	0.91106	0.10123	0.76778	
	PC5	0.78690	0.08743	0.85521	
Panel B: Eigenvectors					
	PC1	PC2	PC3	PC4	PC5
RTD1	-0.45059	-0.26120	0.00678	0.05744	-0.04903
RTD2	-0.45165	-0.34657	-0.00063	0.11126	-0.05967
RTD3	-0.46373	-0.34350	-0.00298	0.10507	-0.05639
RTD4	-0.38027	0.19616	0.16274	-0.23500	-0.11938
RTD5	-0.28907	0.49243	0.30499	0.00642	-0.10249
RTD6	-0.22844	0.52188	0.25650	0.11031	-0.10203
RTD7	-0.17582	0.26742	-0.37990	0.63697	0.55512
RTD8	-0.23373	0.10188	-0.24638	-0.70020	0.58445
RTD9	-0.10971	0.24174	-0.78078	-0.65233	-0.55313

Panel C: PC- Freight Returns Correlation					
	PC1	PC2	PC3	PC4	PC5
RTD1	-0.82482	-0.33493	0.00680	0.05482	-0.04349
RTD2	-0.82677	-0.44440	-0.00063	0.10619	-0.05293
RTD3	-0.84889	-0.44045	-0.00298	0.10029	-0.05002
RTD4	-0.69610	0.25153	0.16305	-0.22430	-0.10590
RTD5	-0.52915	0.63143	0.30558	0.00613	-0.09092
RTD6	-0.41817	0.66919	0.25699	0.10529	-0.09051
RTD7	-0.32185	0.34291	-0.38063	0.60799	0.49243
RTD8	-0.42786	0.13064	-0.24685	-0.66834	0.51845
RTD9	-0.20082	0.30998	-0.78227	-0.09469	-0.49067

Note Table 5.1: reports principal component analyses results in three sections. Panel A presents the eigenvalue, variance proportion and cumulative proportion for each estimated principal component. The eigenvectors of the estimated PCA and their correlation with freight returns are reported in panels B and C, respectively. Furthermore, the impact of the eigenvectors of first five risk factors extracted through PCA on the portfolio of freight returns are illustrated in Figures 5.1.

Source: Author’s estimations.

Figure 5.2: Illustration of the eigenvectors extracted from principal component analysis on tanker freight rates



Note Figure 5.2: An illustration of the first five eigenvectors from principal components analysis on the portfolio of tanker freight rates. **Source:** Author's estimations.

Table 5.7: Conditional variance estimations of the principal component analysis

	PC1	PC2	PC3	PC4	PC5
			Symmetric GARCH		
α	0.397463 (3.6)†	0.236567 (2.4)*			0.253181 (5.9)†
β	0.424251 (2.5)*	0.603280 (2.9)†			0.432070 (4.3)†
ω	0.178286	0.160153			0.314749
$\alpha + \beta$	0.82	0.8399			0.6853
MLE	-3017.654	-3167.601			-3257.056
			Intigrated GARCH		
α	0.638715 (4.2)†			0.951796 (13.5)†	
β	0.361285			0.048204	
ω	0.181471 (3.1)†			0.471215 (4.6)†	
$\alpha + \beta$	1.00			1.00	
MLE	-2995.389			-3207.925	
			Aymmetric GARCH		
α	0.512007 (5.6)†				
β	0.412846 (2.7)†				
ω	0.18368				
δ	-0.217066 (-2.7)†				
$\alpha + \beta + \delta/2$	0.81632				
MLE	-3003.827				
			Fractional-Intigrated Symmetric GARCH		
α	0.568063 (2.5)*		0.781703 (5.5)†		0.791335 (10.12)†
β	0.494680 (1.9)**		0.865058 (10.9)†		0.896225 (30.3)†
ω	0.085301 (1.7)**		0.024014 (1.5)		0.015796 (2.3)*
d-Figarch	0.470578 (2.9)†		0.319747 (2.9)†		0.430915 (3.6)†
MLE	-2976.554		-3210.409		-3233.518

Note Table 5.7: presents conditional variance estimations for the first five estimated principal component analysis extracted from eigenvectors of a portfolio of tanker freight returns. Coefficients values along with their t-statistics are reported for the models that have the highest likelihood values and are chosen by model selection criteria. Furthermore, persistence and the maximum likelihood estimation are reported. †, * and ** refers to any significance level, 5 per cent and 10 percent significance level, respectively.

Source: Author's estimations.

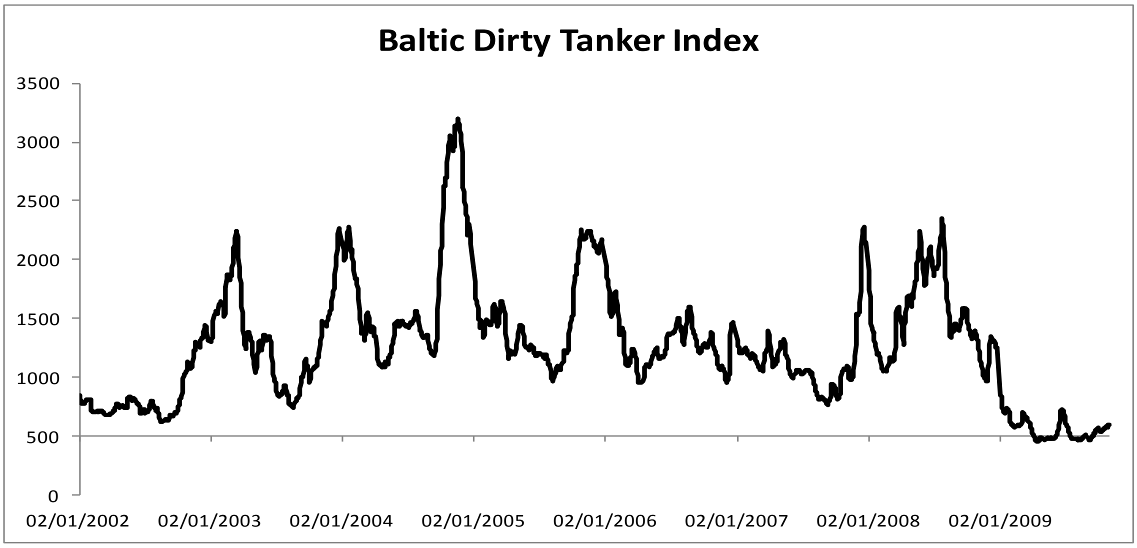
Second, ML estimation of the GARCH-type models suitable for the unobserved factors (PC) are reported in Table 5.7. Conditional variance estimations of uncorrelated risk factors clearly indicate the distinctive nature of volatility dynamics within shipping freight rate, as the most suitable model for the second moment of freight rate returns is conditional on the underlying risks that are associated with the vessel size and trade. From an empirical view, an integrated fractional conditional variance approach is the most suitable for the first, third and fifth estimated risk factors, while a symmetric and integrated conditional variance models are suitable for the second and forth estimated risk factors.

Furthermore, empirical findings of a principal component analysis indicate that tanker freight rates are associated with distinct risk factors that influence and shape the volatility dynamics of the freight markets. However, one important characteristic seems to have an influence on all of these risk factors is tanker segment (parcel size) and is clearly observed in panel B of Table 5.6 through eigenvalues that are grouped in three groups according to shipment size. These are group one TD1, TD2, TD3 and TD4, group two TD5 and TD6 and group three TD7, TD8 and TD9. Furthermore, the first three risk factors account for more than 66 per cent of variations in the portfolio of returns. First, a parallel shift in freight returns values, which is mainly the positive correlation between the size of the tanker and freight volatility. Second, twist in the movement of freight returns, finally, a bending effect evident in the third risk factor. In our view these are related respectively to overall size affect and changes in vessel size affect in respond to distinct volatility regime states.

5.4.3. The output of the two-state conditional freight-beta model analysed

The empirical work of chapter four along with findings of section 5.4.1 and 5.4.2 strongly suggest that freight risk is conditional on the volatility levels prevailing at the time and that a two-state distinct conditional variance framework is better suited to capture volatility dynamics within freight returns. Therefore, we develop a two-state conditional variance freight-beta returns model to measure freight risk sensitivity within a lower and higher market volatility states. First, the average return for the tanker market that is represented by the Baltic Dirty Tanker Index is used in our model as a proxy for tanker returns and is illustrated in Figure 5.3. Second, a two-state Markov-switching model is implemented to identify daily freight returns that belong to two distinctive states, lower and higher volatility states. The transitional and smoothing probabilities are illustrated in Figure 5.4, thus, creating a framework of two-dummy indicator function that is presented in section 5.3.3. Finally, based on the previous steps a conditional variance two-beta freight returns model is structured to assess the hypothesis of a distinct freight-beta measure.

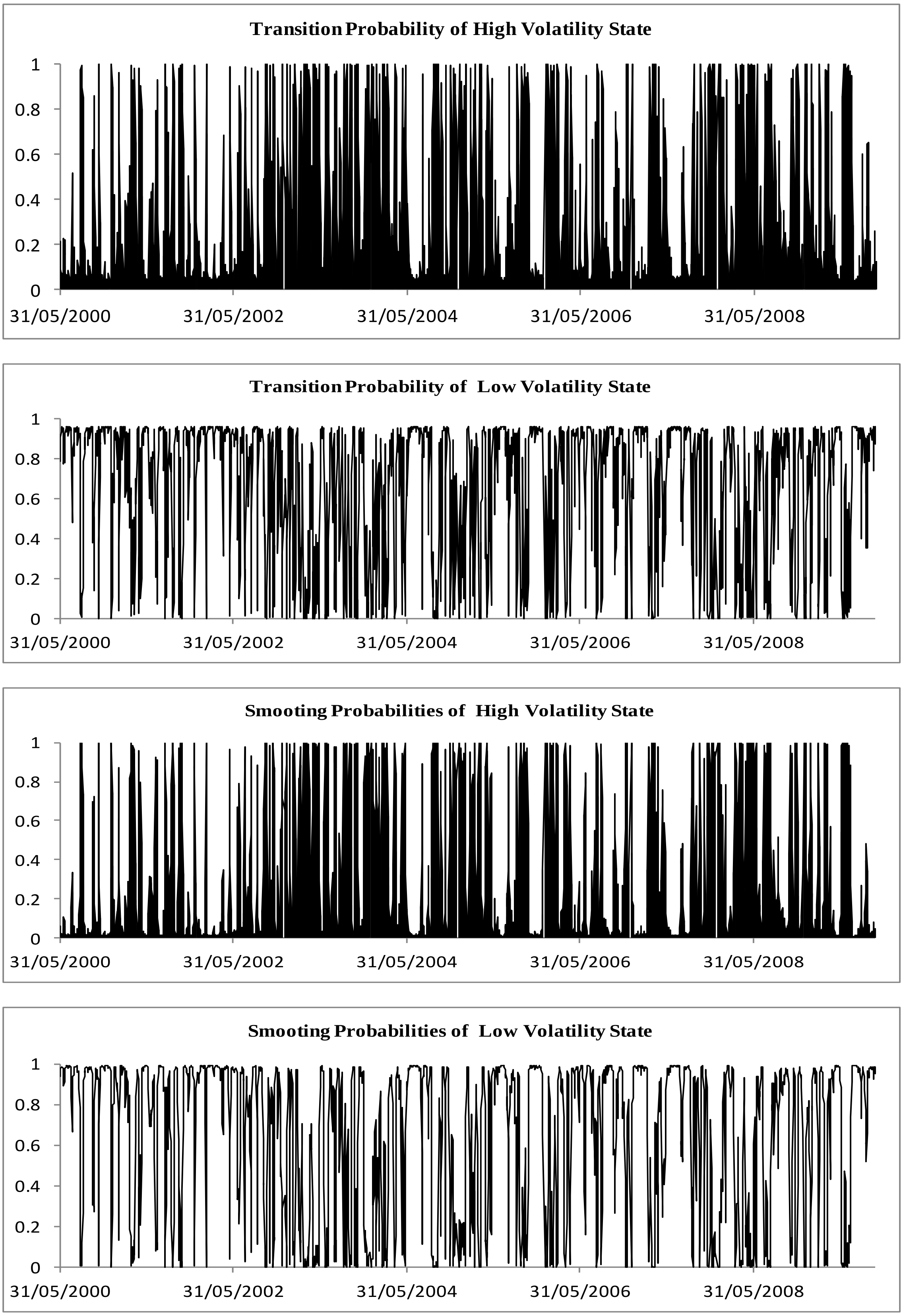
Figure 5.3: An illustration of average tanker freight rate price-levels expressed in a plot of the Baltic Dirty Tanker Index (BDTI)



Note Figure 5.3: is an illustration of average freight level price represented by the Baltic Dirty Tanker Index in an index point system.

Source: Author’s estimations.

Figure 5.4: Transitional and smoothing probabilities of the higher and lower freight volatility states



Note Figure 5.4: Presents an illustration of estimated transitional and smoothing probabilities of higher and lower volatility states for the Baltic Dirty Tanker Index. **Source:** Author’s estimations.

Table 5.8: Reports covariance and correlation matrix of the portfolio of freight returns

	RTD1	RTD2	RTD3	RTD4	RTD5	RTD6	RTD7	RTD8	RTD9	RBDTI
RTD1	**1**	0.001896	0.001881	0.000787	0.000457	0.000315	0.000361	0.000245	0.000208	0.000523
RTD2	0.737769	**1**	0.002993	0.000887	0.000488	0.000316	0.000422	0.000296	0.000199	0.000668
RTD3	0.784224	0.925096	**1**	0.000885	0.000484	0.000302	0.000422	0.000291	0.000205	0.000664
RTD4	0.455564	0.380665	0.406812	**1**	0.000932	0.000649	0.000304	0.000269	0.000365	0.000508
RTD5	0.221181	0.175281	0.186149	0.497544	**1**	0.001342	0.000572	0.000203	0.000373	0.000606
RTD6	0.142928	0.106346	0.108990	0.324989	0.562438	**1**	0.000608	0.000166	0.000441	0.000607
RTD7	0.155731	0.134975	0.144931	0.144881	0.227914	0.227485	**1**	0.000125	0.000580	0.000650
RTD8	0.245395	0.219690	0.230919	0.297034	0.186958	0.143464	0.102940	**1**	0.000205	0.000223
RTD9	0.071482	0.050638	0.056011	0.138198	0.118163	0.130968	0.164032	0.134269	**1**	0.000744
RBDTI	0.523363	0.495932	0.527897	0.561324	0.559745	0.526170	0.535771	0.425003	0.487266	**1**

Note Table 5.8: is the covariance and correlation matrix of tanker freight returns that constitute the portfolio under investigation, with upper-diagonal and below–diagonal report covariance and correlation of freight returns, respectively.

Source: Author's estimations.

The output of a conditional variance two-state beta freight return system is represented in two parts in Table 5.9. First, the top part, reports summary statistics of the unrestricted system of equation, this includes T (2361) the number of observations used in estimating the system and the number of parameters in all equations nk (9×3) where n represents the nine equations in the system and k represents the three parameters (including the constant) and expressed in equation 5.21 and is followed by the log-likelihood value. As explained in section 5.3.4, the highest attainable likelihood value for the system of equations is estimated by maximizing $\hat{\ell} = K_c - \frac{T}{2}\ln|\widehat{\Omega}|$ with $\widehat{\Omega}$ scaled by T, where K_c is a constant and is represented by $\frac{-Tn}{2}(1 + ln2\pi)$ which equals the value of -30151.02489. Thus, $\hat{\ell} = -30151.02489 - \frac{2361}{2}\ln|2.88550528 \times 10^{-27}| = 41989.44519$ and therefore, we report the log-likelihood, the omega and the $\frac{-Tn}{2}(1 + ln2\pi)$ values, along with $ln|R'R/T|$ which is paramount for calculating measures of the goodness of fit of the system. Furthermore, we report two measures of goodness of fit for our system based on the Likelihood-ratio and Lagrange multiplier principles Additionally, two F-tests are reported to test the null hypothesis that all estimated coefficients are zero and the significance of each column of the beta matrix in which results are highly significance for both tests, indicating the significance of beta's values in the system. In Table 5.9 end of the top panel the significance of each column of the beta matrix through an F-test on retained regressors, with abbreviations LVDTI and HVDTI read low volatility dirty tanker index and high volatility dirty tanker index, respectively. This classification is based on a two-state freight volatility regime indicator framework and is defined as a lower freight volatility state and higher freight volatility state.

Second, the bottom panel of the table reports outputs of each equation in the system. This part consists of eleven columns from left to right presenting tanker route, beta values for lower freight volatility state, relevant standard deviation, t-statistics and partial R^2, beta values for higher freight volatility state, relevant standard deviation, t-statistics and partial R^2. Furthermore, general restriction test for the joint significance of both estimated coefficient along their t-statistics and p-values. Additionally, in the bottom of the table we report general restriction tests for the whole system of equations for both distinct freight volatility states. All estimated coefficients of the unrestricted reduced form (URF) are reported along their t-values and significance levels output, while general restriction tests are reported along their probabilities levels in brackets. Furthermore, the correlations and covariance matrix for the portfolio is reported in Table 5.8.

The overall results reported in Table 5.9 indicate the validity of the implemented system through highly significance parameters and satisfying general restriction tests. Furthermore, these empirical findings postulate the inconsistency of tanker freight beta's values across distinct regime states, in which dynamic freight beta is mainly influenced by the size of the tanker and the changes in market conditions.

Furthermore, the hypothesis of a constant beta across different volatility states can not be rejected for only three tanker routes from nine in total, which clearly indicates the validity of a dynamic beta for tanker freight returns. Analysis of the results overwhelmingly suggests that all betas are positive and significant. This is an indication that the sensitivity of freight returns to market movement is conditional on the volatility state prevailing at the time, requiring shipping participants to re-examine and improve their risk management strategies.

In summary, results of conditional tanker freight betas provides a better freight risk insight, simply because sensitivity of tanker freight returns are better captured across distinct market conditions that are conditional on the prevailing volatility state at the time. There is a clear positive correlation between the size of a vessel and corresponding volatilities of earnings, in line with the maritime literature that recognises that larger vessel are more exposed to freight volatility in comparison to smaller vessels due to the latter ability to switch to different routes and cargos. Some tanker segments are more susceptible to market movements than others. For example, an owner of a VLCC or a Suezmax is exposed more to freight risk than an owner of an Aframax or a Panamax, due to the large loss in earnings levels during a higher volatility state in comparison to lower volatility state periods, simply because a vessel with a smaller parcel size is more flexible in adapting to demand and supply in freight services than a larger one.

Table 5.9: A conditional variance two-state beta freight return model

Multivariate CAPM

No. of Observations 2361
No. of Parameters 27
log-likelihood 41989.4452 -T/2log|Omega| 72140.4701
|Omega| 2.88550528e-027 log|Y'Y/T| -59.1625001
R^2(LR) 0.857384 R^2(LM) 0.0973278
F-test on regressors except unrestricted: F(18,4700) = 430.307 [0.0000] **
F-tests on retained regressors, F(9,2350) =
LVDTI 224.991 [0.000]** HVDTI 1310.28 [0.000]**
Constant U 0.104052 [1.000]

	LV-BDTI				HV-BDTI				General Ristericition Test	
	Coef 1	**Std.E**	**t-value**	**Partial R2**	**Coef 2**	**Std.E**	**t-value**	**Partial R2**	**Test**	**Obs Stat**
TD1	0.760988	0.083	9.19*	0.0346	1.044810	0.037	28.6*	0.2576	&2 -&1 = 0	9.8366 [0.0017]
TD2	1.11171†	0.114	9.75*	0.0388	1.30842†	0.050	26*	0.2231	&2 -&1 = 0	2.4925 [0.1144]
TD3	1.081230	0.104	10.4*	0.0438	1.304220	0.046	28.4*	0.2552	&2 -&1 = 0	3.8469 [0.0498]
TD4	0.788429	0.073	10.8 *	0.0472	1.006730	0.032	31.3*	0.2933	&2 -&1 = 0	7.4937 [0.0062]
TD5	1.17197†	0.087	13.4*	0.0708	1.15509†	0.039	29.9*	0.2754	&2 -&1 = 0	0.0312 [0.8599]
TD6	0.866732	0.095	9.09*	0.0338	1.216480	0.042	28.9*	0.2616	&2 -&1 = 0	11.250 [0.0008]
TD7	1.26945†	0.100	12.7*	0.0641	1.23647†	0.044	28.1*	0.2504	&2 -&1 = 0	0.0913 [0.7626]
TD8	0.229883	0.046	4.99*	0.0105	0.463599	0.020	22.8*	0.181	&2 -&1 = 0	21.569 [0.0000]
TD9	1.864550	0.130	14.4*	0.0807	1.334610	0.057	23.3*	0.1878	&2 -&1 = 0	14.001 [0.0002]
Joint Test										60.202 [0.0000]

Note Table 5.9: represents estimation and restriction tests results for a conditional volatility two-state beta freight return model. Results are reported in two panels. First part reports general statistic results for the model. These are number of observations, estimated parameters, log-likelihood estimation and measures of goodness of fit. Second part reports model coefficients estimations for both freight volatility states, a lower and higher volatility states along with general restriction tests. BDTI refers to Baltic Dirty Tanker Index. General restriction test examines the hypothesis of constant beta's across different state regimes and the joint test is testing the hypothesis of joint constant beta's across all routes. * refers to significance at any level and † refers to tanker routes that do not pass the test of the restriction test.

Source: Author's estimations.

Table 5.10: The correlation of the unrestricted reduced form (URF)

	Correlation of URF Residuals (standard deviations on diagonal)								
	TD1	**TD2**	**TD3**	**TD4**	**TD5**	**TD6**	**TD7**	**TD8**	**TD9**
TD1	0.0371	0.6459	0.7013	0.2266	-0.1016	-0.1881	-0.1732	0.0238	-0.2429
TD2	0.6459	0.0511	0.8993	0.1408	-0.1421	-0.2122	-0.1782	0.0083	-0.2503
TD3	0.7013	0.8993	0.0467	0.1553	-0.1553	-0.2372	-0.1922	0.0047	-0.2692
TD4	0.2266	0.1408	0.1553	0.0327	0.2680	0.0384	-0.2230	0.0732	-0.1837
TD5	-0.1016	-0.1421	-0.1553	0.2680	0.0392	0.3814	-0.1029	-0.0679	-0.2146
TD6	-0.1881	-0.2122	-0.2372	0.0384	0.3814	0.0428	-0.0755	-0.1115	-0.1645
TD7	-0.1732	-0.1782	-0.1922	-0.2230	-0.1029	-0.0755	0.0448	-0.1634	-0.1325
TD8	0.0238	0.0083	0.0047	0.0732	-0.0679	-0.1115	-0.1634	0.0207	-0.0854
TD9	-0.2429	-0.2503	-0.2692	-0.1837	-0.2146	-0.1645	-0.1325	-0.0854	0.0581
	Correlation Between Actual and Fitted								
	0.52624	0.49673	0.529	0.56323	0.55976	0.52943	0.5358	0.43363	0.49188

Note Table 5.10: represents correlation matrix of the unrestricted reduced form for residuals with standard deviations on diagonal. Furthermore, correlations between actual and fitted values are reported in the bottom of the table.

Source: Author's estimations.

5.5. Conclusion

The accuracy of value-at-risk measures for a portfolio of freight returns is conditional on the methodology used to estimate the volatility of the underlying asset. Thus, factors such as volatility clustering, non-normality, fat-tails and skewness that are associated with freight markets affect the accuracy of a value-at-risk measure. Therefore, empirical work in this chapter attempts to accommodate asymmetries of freight returns and time varying freight volatility in the structure of the proposed models.

Univariate value-at-risk measures are converted to a multivariate value-at-risk measure to estimate freight risk for a portfolio of freight returns. Empirical findings clearly indicate the superiority of a semi-parametric based VaR model to measure freight risk for a portfolio of freight returns, which is consistent with previous findings in chapter four and recent findings in the literature. However, a freight risk measure that is capable of adapting to changes in volatility dynamics outperforms any other models and provides a better insight into the dynamics of the freight supply curve.

Furthermore, uncorrelated risk factors are extracted from a portfolio of freight returns and modelled using an O-GARCH framework. Findings indicate that freight rates are associated with distinct risk factors that influence and shape the volatility dynamics of freight markets. However, one important characteristic seems to have an influence on all of these risk factors is tanker segment, influencing the three highest eigenvectors in different ways. In our view this is related to the changes in vessel size affect in respond to distinct volatility regime states.

Moreover, a two-state conditional freight-beta returns model is developed to measure freight risk sensitivity within lower and higher market volatility states. This provides a better freight risk insight, simply because sensitivity of tanker freight returns are better captured across distinct market conditions that are conditional on the prevailing volatility state at the time. Additionally, there is a clear positive correlation between the size of a vessel and corresponding volatilities of returns, in line with the maritime literature that recognises that larger vessel are more exposed to freight volatility in comparison to smaller vessels due to the latter ability to switch to different routes and cargos.

The variety of single- and multi-state conditional variance models used in chapter four to capture volatility dynamics within freight returns deals with freight returns for single routes in which empirical investigation indicates that a fitting framework to model the second moment of freight returns is conditional on tanker segment and is distinct across different routes. That is why for a portfolio of returns it is important that the number of estimated conditional variance models is reduced to uncorrelated principal component with a diagonal covariance matrix and at the same time to capture the characteristics of the portfolio. Therefore, empirical work in the previous chapter is extended in this chapter to a portfolio of freight returns, where the number of estimated conditional variance models for a system of tanker assets is reduced by adopting a principal component analysis (PCA) framework.

It is important to note that the assets that are used to construct this hypothetical portfolio can not be physically traded as one would normally trade financial assets, but they provide a useful insight into the physical risk exposure of shipping participants that are involved in shipping operations. Furthermore, the continuous developing freight derivative market provides shipping participants with the opportunity provided in financial markets.

Chapter Six

6. A Practical insight into freight risk management: A tanker freight derivatives professional case study

6.1. Introduction

In this thesis we use a variety of quantitative techniques in an attempt to explore different ways to improve measurement and management of freight shipping risk, which is the undesirable fluctuation on the revenue side for shipping practitioners. Therefore, it is paramount that we understand and explore current practices in freight markets to neutralise and exploit such risks. This insight into the practical techniques used by shipping practitioners to manage freight risk using derivatives should place us in a better position to improve our understanding of freight risk and therefore improve the quantitative techniques employed in this thesis. In other words, the objective of this chapter is to provide a practical insight into the structure and use of freight derivatives by shipping practitioners to mitigate and profit from freight risk, through constructing forward curves and assessing the usefulness of such a forecasting tool in managing freight risk and improving profitability. Therefore, directional accuracy and volatility of short- and long-term forward curves are measured for different tanker segments and compared against a general perception in the literature. Furthermore, a developed value-at-risk measure employed in chapter four is exploited in this chapter in order to assess the usefulness of such an empirical framework in improving market information. The empirical work in this chapter benefited most from attending a tanker freight derivatives professional trading course set by Imarex Academy part of the Imarex ASA group. The data and freight prices used in examples within this chapter are real market data and are based on real shipping scenarios. The rest of the chapter is organised as follows. Section 6.2 examines relevant literature and gives some background on the devolvement and the structure of freight derivatives market. Section 6.3 examines tanker freight rates measurements in worldscale points in comparison to Time-Charter-Equivalent. Section 6.4 explains and analysis the data used to constructed forward curves. Section 6.5 discusses and analyses the use of derivatives to mitigate freight risk through practical examples. Section 6.6 concludes the chapter.

6.2. Literature review

Shipping practitioners long before the introduction of freight derivatives recognised the importance of the use of different freight contracts to manage their freight risk exposure through hedging their physical position using period time-charter contracts[13] and Contracts of Affreightment (COA)[14]. According to Gray (1990) the need for a futures market to manage freight risk had been recognised by shipping practitioners as early as the 1960, but not until the 1980s was a form of a future freight market to be established, this is simply because of the non-storable nature of the underlying freight service, thus, the cost-of-carry principle dose not apply for a shipping service, as this is not a physical commodity that can be bought and stored for future delivery. This shortcoming was overcome by the introduction of a cash value settlement for a freight service at maturity, Alizadeh and Nomikos (2009). This innovation triggered the development of the Baltic International Freight Futures Exchange (BIFFEX), the first instrument to manage freight risk, which is a futures contract that was traded on the London Commodity Exchange and settled on the Baltic Freight Index (BFI). This daily freight index initially consisted of 13 voyage routes covering a variety of dry cargos such as Grain, Iron Ore, Barley, fertiliser and Coal, and was replaced in November 1999 by the Baltic Panamax Index (BPI) due to its poor performance. More details can be found in Alizadeh and Nomikos (2002). In this section we briefly discus the important developments over the years in freight markets focusing on the dirty tanker market and in particular the freight derivatives submarket.

6.2.1. Baltic Exchange market information

The Baltic Exchange is an independent source of maritime market information that reports daily prices of traded and settled physical and derivative freight contracts. In 1985 the Baltic Exchange published the first freight index the Baltic Freight Index (BFI) that initially consisted of 13 different voyage routes and was developed as the underlying asset to settle the new established Baltic International Freight Futures Exchange (BIFFEX) contract. However, due to structure changes in seaborne trade and changes to vessel specification that led to the devolvement of shipping markets over the years, the BFI was replaced by the Baltic Panamax Index (BPI) as the new underlying

[13] A vessel is hired for a specific period of time for a daily, monthly or annual payment. There are three types of period time-charter contracts, time-charter, trip-charter and consecutive voyage charter.

[14] An agreement by a ship-owner to shift quantities of specific type of cargo on a particular route or routes for a particular period of time and using vessels of the ship-owner's choice.

asset for shipping freight futures contract. This consisted of average weighted routes for a number of Panamax vessels on different routes. The Baltic Exchange also started to introduce other indexes that represented freight prices for different ship sizes and cargos.

Most importantly for this thesis, on the 27^{th} of January 1998 the Baltic Exchange started to publish daily tanker freight prices for five tanker routes representing different tanker segments. Furthermore, along the years the tanker information sector evolved significantly to include 17 dirty (crude oil) tanker routes covering all tanker sizes operating on different shipping routes, these routes also comprised the overall tanker freight movement represented by the Baltic Dirty Tanker Index (BDTI) and is constructed as an equally weighted average of the routes in Table 6.1. Details of the history of Baltic Exchange Indices including all the changes that have been implemented since their inception in 1985 are published by the Baltic Exchange (2007). For simplicity, shipping information reported by the Baltic Exchange can be divided in to four sectors.

1. Dry Market Information that is represented by the following indices: the Baltic Handysize Index (BHSI); the Baltic Supramax Index (BSI), the Baltic Panamax Index (BPI); the Baltic Capesize Index (BCI); the Baltic Dry Index (BDI) and the averages of BHSI, BSI, BPI and BCI.
2. Wet Market Information that is represented by the following indices: the Baltic Clean Tanker Index (BCTI); the Baltic Dirty Tanker Index (BDTI); the Baltic LPG Route (BLPG) and the Baltic Palm Oil Route (BPOIL).
3. Ship Value Information that is represented by the following indices: the Baltic Exchange S&P Assessments (BSPA) and Baltic Exchange Demolition Assessments (BDA)
4. FFA Market Information that is represented by the Baltic Freight Assessment BFA; the Forward Freight Agreements (FFAs) rates for wet and dry routes and FFA settlement prices.

As the main focus of this thesis is on the dirty tanker sector we examine this further in the following section.

6.2.2. Baltic Dirty Tanker Index (BDTI)

The BDTI is an index that tracks freight movements for crude oil and dirty oil products and is composed of 17 voyage-charter (spot) routes quoted in Worldscale (WS) points. This is represented in Table 6.1 with a description of the route and maximum amount of cargo in metric tonnes that can be transported on a specific route using a specific tanker size and for some routes the required temperature in Fahrenheit to maintain a particular type of cargo in its liquid form.

Table 6.1: Baltic Dirty Tanker Index (BDTI) route definitions

Route	Route Description	Cargo Description
TD1	MEG (Ras Tanura) to US Gulf (LOOP)	280,000 mt
TD2	MEG (Ras Tanura) to Singapore	260,000 mt
TD3	MEG (Ras Tanura) to Japan (Chiba)	260,000 mt
TD4	West Africa (bonny) to US Gulf (LOOP)	260,000 mt
TD5	West Africa (bonny) to USAC Gulf (Philadelphia)	130,000 mt
TD6	Black sea (Novorossiysk) to Mediterranean (Augusta)	135,000 mt
TD7	North Sea (Sullom Voe) to continent (Wilhelmshaven)	80,000 mt
TD8	Kuwait (Mena el Ahmadi) to Singapore	80,000 mt , crude/DPP 135F
TD9	Caribbean (Puerto la Cruz) to US Gulf (Corpus Christi)	70,000 mt
TD10D	Caribbean (Aruba) to USAC (New York)	50,000 mt fuel oil
TD11	Cross Mediterranean, Banias to Lavera	80,000 mt
TD12	ARA (Antwerp) US Gulf (Houston)	55,000 mt
TD14	SE Asia (Seria) to East Cost Ausralia (Sydeny)	80,000 mt NHC
TD15	West Africa (Bonny) to China (Niqpo)	260,000 mt NHC
TD16	Black Sea (Odesa) to Mediterranean (Augusta)	30,000 mt fuel oil 135F
TD17	Baltic (Primors) to UK or continental Europe (wilhelmshaven)	100,000 mt
TD18	Baltic (Tallinn) to UK or continental Europe (Rotterdam)	30,000 mt

Note Table 6.1: presents the definitions of the Baltic Dirty Tanker Index (BDTI) routes based on 2008. All routes are quoted in WorldScale points and cargoes are for the transportation of crude oil apart from TD10D and TD16 routes that are for fuel oil. LOOP stands for Louisiana oil port; NHC no heat crude; DPP dirty products.

Source: Baltic Exchange.

6.2.3. Forward freight agreements (FFAs) in the literature

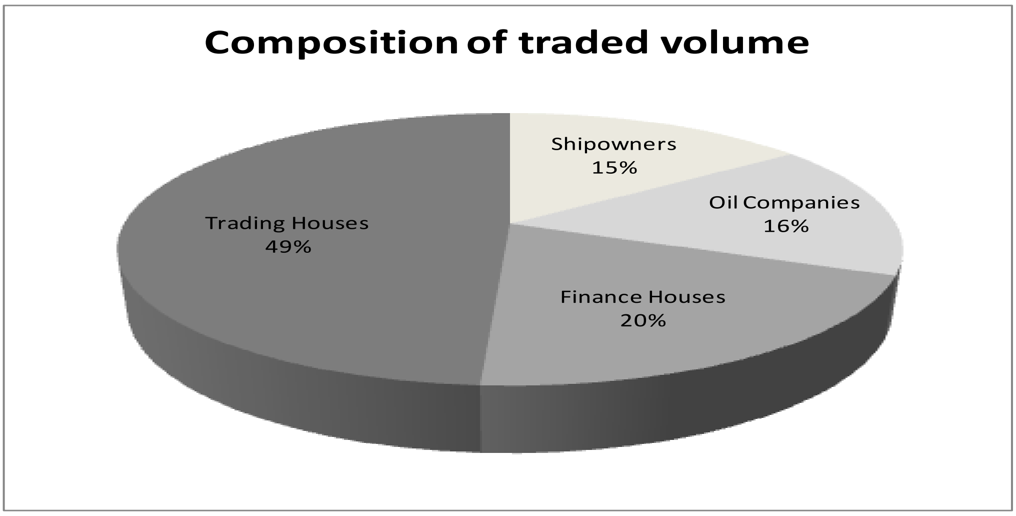
According to maritime economists such as Alizadeh and Nomikos (2009) the need for a new market to trade the forward value of a freight contract emerged primarily in response to shortcomings of the existing at the time structure to mange freight risk, which was based on the Baltic International Freight Futures Exchange (BIFFEX) contracts, and was established in the 1990s. Kavussanos and Nomikos (2000a) showed through their empirical work that the risk effectiveness of BIFFEX contracts varied from 4 per cent to 19.2 per cent across the different routes that constituted the underlying index, which is way below the 70 per cent average in risk reduction provided with similar instrument in other commodity markets. This poor performance was the primary reason for the decreased trading activities levels after 1996 until eventually the BIFFEX was delisted in April 2002. Moreover, the introduction of an over-the-counter forward instrument in the mid 1990s also added to the unpopularity of the future instrument. This Forward Freight Agreements (FFA) was cash settled against a single underlying shipping route or a basket of routes reducing the affect of basis risk that was evident in the BIFFEX market.

Therefore, since the establishment of Forward Freight Agreements (FFAs) in 2002 shipping practitioners found FFAs to be a more efficient hedging tool for freight risk, as it provided a better match to their physical exposure that was clearly reflected in an increase in trading activities. According to the Freight Investor Services, the shipping derivatives market in 2008 was worth US$125 billion[15] up from 50 billion in 2007, a 150 per cent annual increase[16]. This is mainly attributed to exceptionally high freight rates and volatility levels during 2007, the latter attracted new players such as investment banks and hedge funds that led to an increase in the use of freight derivatives to manage freight risk and speculate on market movements. Between 2007 and 2008 there were 40 per cent increase in such activities, thus, since July 2007 the Baltic Exchange and major international brokers started reporting on weekly bases the traded volumes of FFAs contracts. In comparison to the dry sector, the traded volume of FFA in the wet sector is considered to be much smaller, although it has been growing considerably in recent years. One important difference is that the percentage of cleared tanker FFAs through clearing houses is much larger than the percentage of dry FFAs that are cleared through clearing houses, this is an indication that shipping participants

[15] This valuation includes all shipping derivatives traded in 2008 not just FFAs.
[16] Financial times (2008) ‘Freight futures surge as funds seek refuge’, 24 February.

recognise that the significance of counterparty risk is much higher in the tanker sector. The Baltic Exchange reported in 2007 that total FFAs traded were 13,351 trades a volume of 374,870,440 mt with a market value of more than 6.7 billon dollars, an increase of nearly 5 per cent on 2006 and that nearly 50 per cent of total traded FFAs were cleared through a clearing house. Furthermore, Imarex report estimated composition of wet FFA trade volume and market participants for 2006. In general there are four types of market participants, ship-owners/ship-operators, that are natural sellers of FFAs, energy companies, that are natural buyers of FFAs and finally, trading houses and financial houses, that are speculators. Figures 6.1 and 6.2 clearly indicate that 70 per cent of traded FFAs are carried out by trading houses and finance houses even though they account for only 40 per cent of market participants as counterparties. On the other hand ship-owners that represent 45 per cent of market participants trade only 15 per cent of total FFAs traded. According to maritime economists this is an indication that most trades are for speculative purposes. For a detailed explanation of the structure, functioning, trading practices, documentation and type of contracts used in trading FFA contracts, see Alizadeh and Nomikos (2009).

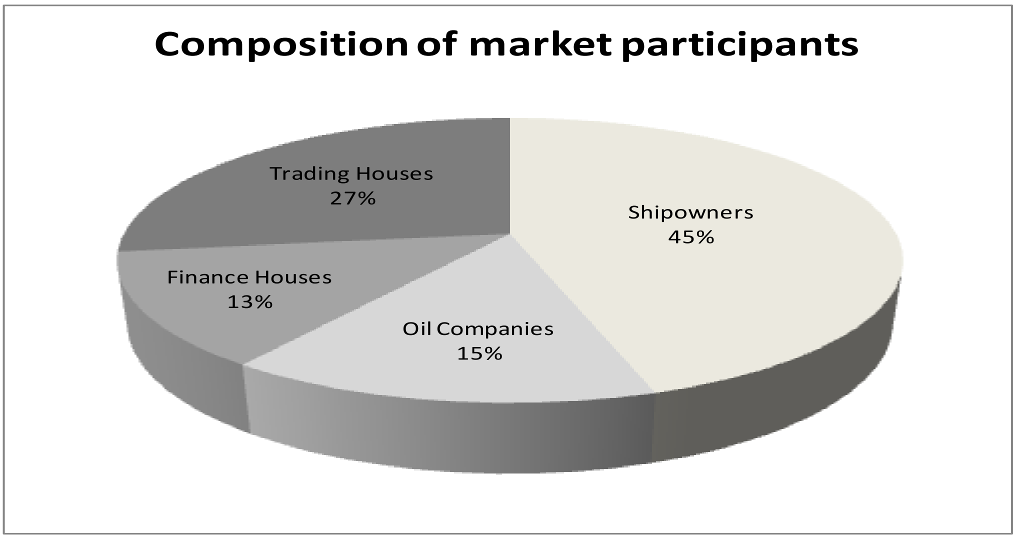
Figure 6.1: The composition of traded FFAs in the wet sector for 2006 by market participants



Note Figure 6.1: the composition of traded FFAs in the wet sector for 2006, represented through traded volume by market participants.

Source: Alizadeh and Nomikos (2009) based on estimated stats from Imarex.

Figure 6.2: The composition market participants in FFAs in the wet sector for 2006



Note Figure 6.2: the composition of market participants in FFAs wet sector for 2006.

Source: Alizadeh and Nomikos (2009) based on estimated stats from Imarex.

Furthermore, a forward freight agreement is an agreement between two counterparties to settle a freight rate, for a specified quantity of cargo (type of a vessel), for one basket of major shipping route(s) in the dry bulk or tanker markets at certain date in the future. The underlying asset of an FFA contract is a freight rate assessment for an underlying shipping route or basket of routes. The assessment of a freight rate is supplied by shipping information providers such as the Baltic Exchange and Platts. The settlement of FFAs is in cash and is based on the difference between the contract agreed price and the settlement price on the day. The calculation of the settlement price depends on the type of traded contract, while, the settlement price for individual routes in the dry sector for a voyage-charter contract is calculated as the average price of the route over the last seven trading days of a month, a settlement price for a time-charter contract for the same sector is calculated as the average price of the whole month. The use of an average freight value over a period of time as a settlement price is mainly to insure the integrity and non-involvement of any market manipulation. Alizadeh and Nomikos (2009) argue that the use of two different methods to assess the settlement price stems from the particularity use of FFAs as a risk management tool. For example, hedging a single voyage on individual routes, a high positive correlation between the hedging instrument and the underlying asset is needed, thus, a short averaging period is more efficient. Furthermore, ship-owners who operate number of vessels and are after hedging their monthly freight earnings using an instrument that tracks a basket of routes prefer a settlement price that is calculated based on an average month of daily earnings of a basket of routes, as it provides a better fit for their physical requirements. In general there are two issues to consider when using FFA contracts as a hedging instrument. First, the settlement risk which is the difference between the average rate used for the settlement of a FFA contract and the freight rate at which a vessel is fixed in the physical market, Alizadeh and Nomikos (2009) find that settlement risk is at its lowest when the hire date of a vessel is as close as possible to the seven-day average window used in the calculation of settlement rates in comparison to a vessel that was hired in the first half of a month. Second, the basis risk, that rises from the mismatch between the specification of an FFA contract and the exposure within the physical market. To minimise this effect, the choice of a FFA contract to hedge a physical freight exposure should be strongly correlated with the underlying physical exposure. Furthermore, a hedge ratio should be accurately calculated to the ratio of the size of the FFAs to sell/buy to the size of the exposure in the physical market.

Alizadeh and Nomikos (2009) examine tankers' most liquid FFAs routes for a period from March 2003 to December 2007 and compute in percentages the accuracy of constructed forward curves using FFAs to predict the future direction of spot freight rates, referring to this as the directional predictability of FFAs. They find that the directional accuracy of forward curves ranges from 60 percent to 80 per cent for short maturity contracts (current month, 1-mont, 2-month and 3-month) and is positively correlated with time to maturity. They suggest that the reason for the increase in directional accuracy as time maturity increases is possibly due to the reflection of tanker seasonality in forward rates recognised by shipping agents. They also examine FFAs volatility levels and find that FFAs long-maturity contracts have much lower volatilities level than short-maturity and spot contracts, suggesting that volatility is quite high close to spot values and decreases with time to maturity. This is known as the volatility term structure, which is consistent with the literature in regards to the fact that spot freight rates are mean reverting, and that volatility levels for FFA rates are greater for larger vessel than they are for smaller vessels, which is consistent with the characteristics of the underlying physical market.

6.2.4. Measurement of tanker freight rates

In general there are three different measures of freight rates. The two main ways to quote dry cargo freight rates are US dollars per ton and US dollars per day, which are two contrasting measures with different implications for freight risk and are associated with voyage-charter and time-charter contracts, respectively. Even though recently freight information providers started calculating tanker freight rates in similar ways, tanker freight rates are normally quoted in a more complex measure known as WorldScale points.

6.2.5. WorldScale

The tanker industry uses this freight rate index as a more convenient way of negotiating the freight rate per barrel of oil transported on many different routes, this system is used to compare tanker freight rates all over the world irrespective of the length of the voyage and its geographical location, hence, the corresponding flat-rate (WS100) is quoted in dollars per cargo tonne. For a detailed analysis of the WorldScale as a useful measure of tanker hire see Laulajainen (2007 and 2008).

The WorldScale index is published annually in a book and online, reporting for each tanker route the cost of transporting a tonne of cargo, which is referred to as the flat-rate or the WS100 per cent level. Charterers and ship-owners negotiate through their relevant brokers an agreed price that can be higher than the WS100 level or a fraction of the flat-rate. The calculations of these flat-rates are based on a standard vessel on a round voyage with standard characteristics and are revised annually by the WorldScale committee. For more details on the history development and structure of the WorldScale point system see Stopford (2009). Furthermore, current implemented flat-rates are available only for subscribers to the WorldScale association[17] and are only affordable by corporations not individuals. In Table 6.2 we report historical WorldScale flat-rates for the most popular and active tanker routes, these historical flat-rates are not available on any database, as far as we are aware this is the first publication of historical WorldScale flat-rates in an academic related document. The importance of knowing the WorldScale flat-rate for tanker routes is twofold. First, most historical empirical work in the literature studying tanker rates, examines freight rates that are measured in WorldScale points or Time-Charter-Equivalents (TCE)[18]. The only issue in the literature regarding the former is the possibility of jumps in the time series after flat-rates are adjusted at the start of every year. On the one hand, there is no evidence to suggest that this has a significant impact on academic empirical work as the change is transparent in new quoted freight rates and reflected in freight-return time-series used for analysing short- and long-term dynamics. On the other hand, the impact of the annual adjustments in flat-rates is evident in shipping operations and reflected in shipping agents' cash flow. See section 6.5.5 for a practical illustration. Therefore, these historical flat-rates can be used to convert a WorldScale time series to a time series that better represents the daily hire of one tonne of cargo in dollars. Second, a quoted tanker freight rate in dollars per tonne instead of WS points can be used to make an assessment of daily net earnings for different vessels operating on different routes, therefore, providing a useful assessment for a shipping agent's prospective cash flow. This conversion is computed through equations 6.1 to 6.5 using the assumption in Table 6.3 and illustrated in Figure 6.4 in comparison to WS points illustrated in Figure 6.3.

[17] http://www.worldscale.co.uk/

[18] Researchers in recent papers started to use TCE calculated and reported by Clarkson Intelligent Network as the bases for their analysis.

Table 6.2: Historical WorldScale flat-rates

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
TD3	12.62	12.31	12.15	13.11	13.39	15.16	17.72	18.05	25.00	18.72
TD5	9.87	9.74	9.44	10.16	10.36	11.79	13.93	14.19	19.63	14.60
TD7	3.47	3.50	3.71	4.00	4.45	4.74	5.09	5.40	6.30	5.59
TD8	7.46	7.35	7.28	7.78	7.92	9.04	10.61	10.83	14.93	11.06
TD9	5.10	5.02	4.97	5.33	5.49	6.16	7.18	7.31	9.86	7.86

Note Table 6.2: presents historical WorldScale flat rates for most active tanker routes. Values are reported in dollars per metric ton. For example in 2009 the flat rate for a VLCC tanker operating on the TD3 route is 25 dollars per metric ton. In other words, a quoted WorldScale of 60 per cent on TD3 in 2009 means that the charterer is offering the ship-owner (0.6×25) 15 dollars per ton of transported crude oil on the relevant route.

Source: Imarex and anonymous shipping brokers.

In Table 6.3 we present the assumptions used by market facilities such as Imarex to calculate a Time-Charter-Equivalent (TCE) for tanker freight rates. In simple terms, TCE is a conversion of the spot freight rate quoted in dollars per tonne into a daily hire rate for a particular voyage by deducting voyage costs from gross freight and dividing by the number of days in the voyage. Thus, WorldScale points for tanker freight rates are converted to TCE using equations 6.1 to 6.5 and the assumptions reported in Table 6.3. The columns from left to right report the route relevant to a specific tanker segment, maximum cargo capacity for each tanker segment, barrel factor used to convert WorldScale points to price per barrel units, the average cost of port dues, bunker cost in dollars, bunker consumption per day for each type of vessel, the broker commission for fixing the vessel, number of days in a round voyage and finally a measure of match between the relevant paper derivative and underlying asset. For example a round trip for a VLCC on TD3 route takes on average 45.5 days, assuming that there are 365 days per year, a VLCC can only make 365/45.5 or 8 roundtrips per year, which is equivalent to a 0.67 (8/12) roundtrip per month. In other wards, to hedge earnings for a VLCC that operates on a TD3 route for one month the appropriate match is a 67 per cent of one FFA contract. The reason for this is simply because that FFA contracts are traded and settled on monthly basis. Furthermore, the number of lots to trade is down to the transported amount of cargo. This is explained more in a practical example in section 6.5.6.

Table 6.3: Assumptions used by practitioners to convert WorldScale point to daily TCE for tankers

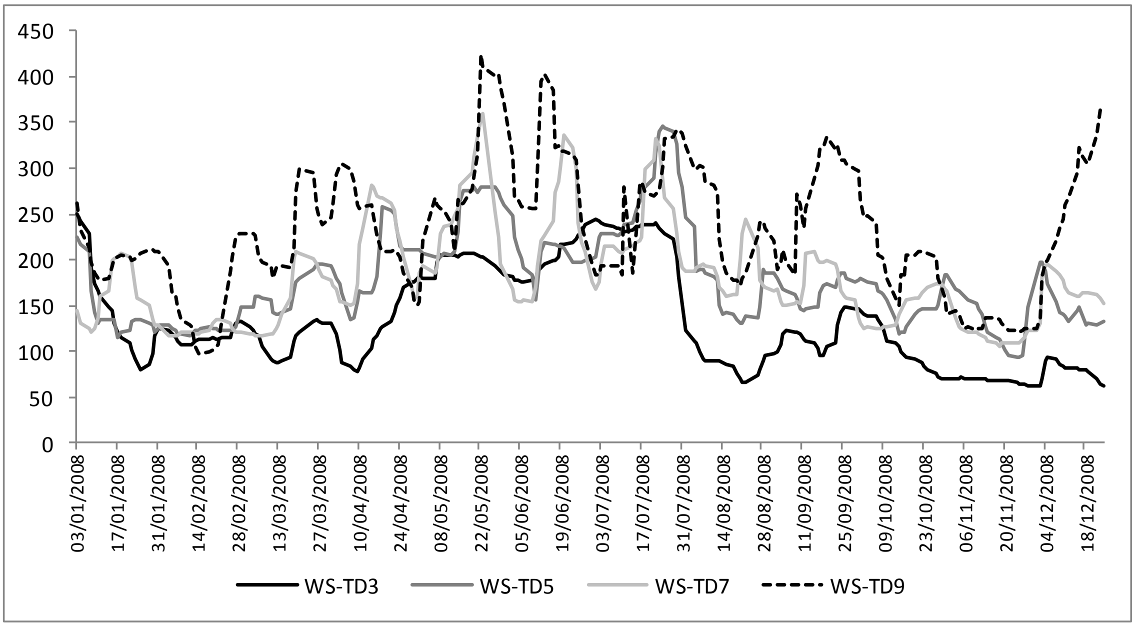
Route	Capacity	Barrel Factor	Port cost	Bunker ($)	Bunker cons. / day	Broker comm.	Voyage (days)	Paper match
TD3	260,000	7.15	155,000	481.5	90	2.50%	45.5	66.7%
TD5	130,000	7.49	64,000	457.0	55	2.50%	35	86.7%
TD7	80,000	7.55	225,000	450.3	51	2.50%	7.5	405.8%
TD8	80,000	6.4	133,000	481.5	51	2.50%	28	108.3%
TD9	70,000	7.19	89,500	457.0	51	2.50%	15	202.5%

Note Table 6.3: presents the assumptions used by market facilities such as Imarex to calculate a TCE for tanker freight rates. WorldScale points for tanker freight rates are converted to TCE using formulas and the above assumptions. The columns from left to right report the route relevant to a specific tanker segment, maximum cargo capacity for each tanker segment, barrel factor used to convert WorldScale points to price per barrel units, the average cost of port dues, bunker cost in dollars, bunker consumption per day for each type of vessel, the broker commission for fixing the vessel, number of days in a round voyage and finally a measure of match between the relevant paper derivative and underlying asset.

Source: Imarex assumptions.

To put the above in perspective, a VLCC ready to transport crude oil from the Arabian Gulf area to Japan (TD3 route) on the 3rd of January 2008 was fixed for 250.63 WS points. Based on historical data, this is equivalent to 205,303 dollars per day net earnings. On the 28th of November 2008, the same vessel operating on the same route was fixed for 61.81 WS points that is equivalent to 15,417 dollars per day net earnings. Thus, a drop in WS points by 75 per cent for TD3 corresponds to a drop in daily earnings of 92.5 per cent, a significant drop in a company cash flow and a useful measure for a shipping-owner especially if he is liable to banks through shipping loans.

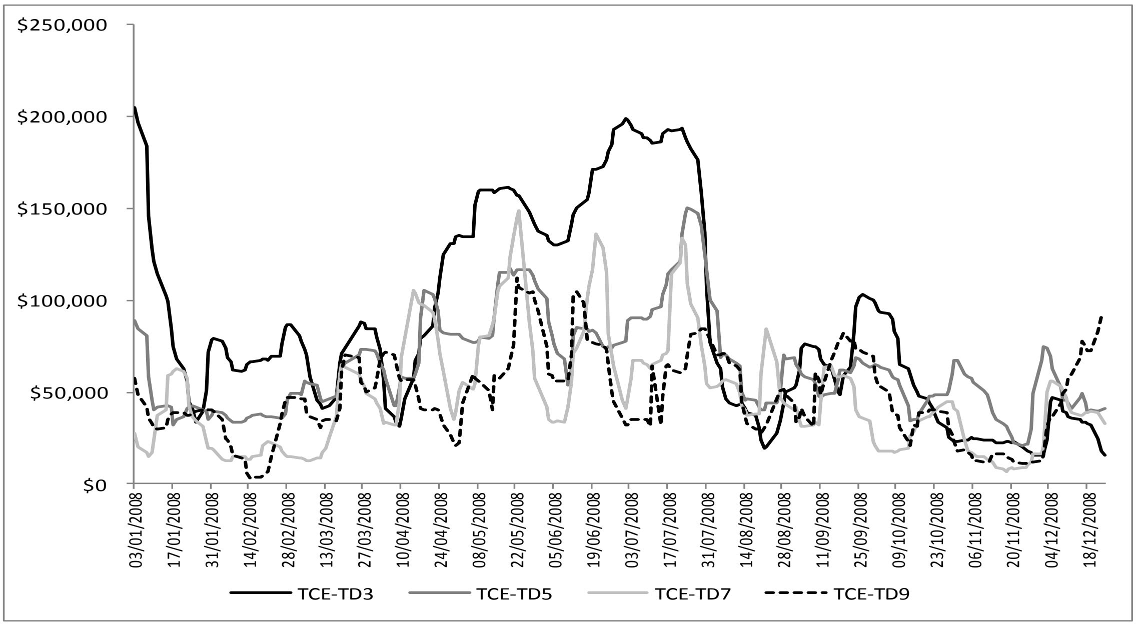
Figure 6.3: Freight rates in WorldScale points for different tanker segments



Note Figure 6.3: is an illustration of time series of freight rates quoted in WorldScale points for four major tanker segments operating on the four most popular routes.

Source: Author's estimations.

Figure 6.4: WorldScale point converted to Time-Charterer-Equivalents (TCE)



Note Figure 6.4: is an illustration of time series of daily tanker earnings. This is net daily earnings for different tanker segments after deducting all equivalent costs. The vertical axis represents tanker earnings in dollars.

Source: Author's estimations.

6.3. Forward freight agreements (FFAs) data

The data used in this chapter is provided by Imarex Academy and represent tanker FFAs prices that were traded on the Imarex exchange. Imarex trade different contract periods to better suit the requirement of shipping practitioners, these are one-month, two-month, three-month, four-month, five-month and six-month ahead FFAs. For example on the third of January 2008 the exchange traded a January, February, March, April, May, June and July FFAs contracts. All traded one-month contracts cease trading on the last week of the trading month and are used by Imarex to calculate one-quarter, two-quarter and three-quarter ahead FFAs, which are also traded on the exchange and most importantly used to structure forward curves to asses in the management of freight risk by providing a prospective of future spot tanker prices on different shipping routes for different vessel sizes. Therefore, we rollover these contracts to construct a current-month (CM), one-month (+1M), two-month (+2M), three-month (+3M), current-quarter (CQ), one-quarter (+1Q) and two-quarter (+2Q), time series’ that can be used to structure forward curves at any point of time to examine the usefulness of FFA contracts in management of freight risk. In Figures 6.5, 6.6, 6.7, 6.8, 6.9, 6.10, 6.11 and 6.12 rolled over short-term and long-term FFAs are illustrated subsequently, for VLCC, Suezmax, Aframax and Product vessels, respectively. In Table 6.4 we examine the different characteristics used by Imarex to construct their forward curves. First, one-month contracts are traded based on the bid and ask (demand and supply) set by market participants and are rolled over at the end of every month to construct a time-series of a one-month ahead forward curve, each lot is equivalent to 1000 metric tonnes and are cleared on this basis, the minimum traded lots aloud by the exchange is 5 lots (5000 mt). Second, quarter contracts are calculated each day as the average of consecutive three-month contracts with each lot equivalent to 3000 metric tonnes and rolled over by the end of each month. Finally, calendar contracts are calculated each day as the average of consecutive four-month contracts with each lot equivalent to 12000 metric tonnes and rolled over by the end of each month.

Table 6.4: Forward curves constructed by Imarex are based on the following:

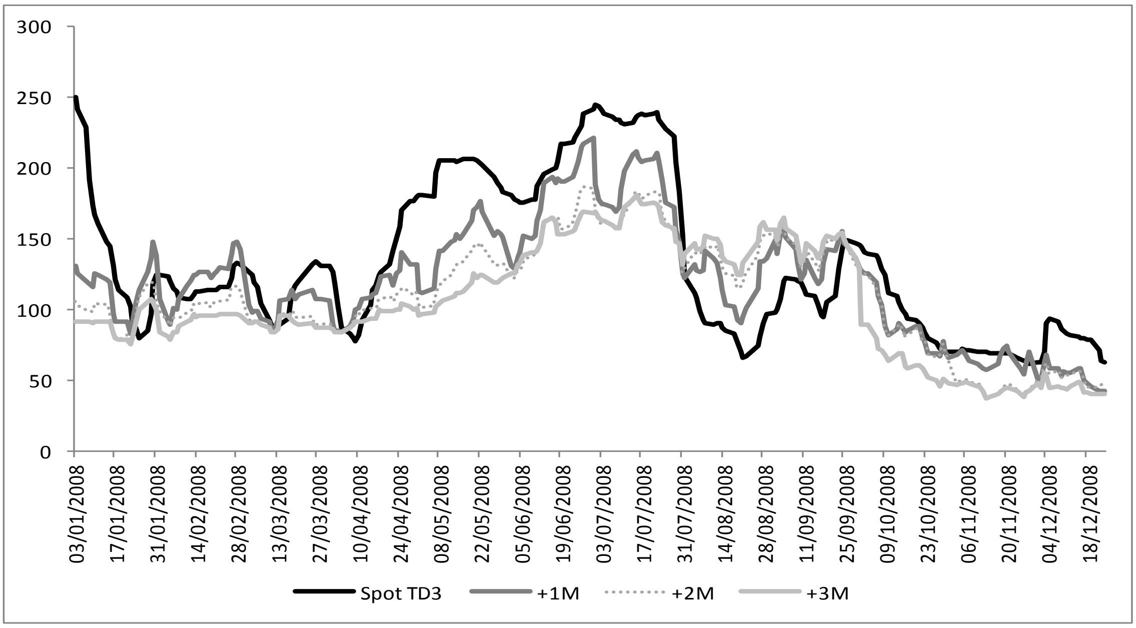
Position	period	Roll date	composition	OTC FFA	Cleared Future
1	Month	Last of month	Trade done/ bid-ask	1 lot=1000MT	1 lot =1000MT
2	Month	Last of month	Trade done/ bid-ask	1 lot=1000MT	1 lot =1000MT
3	Month	Last of month	Trade done/ bid-ask	1 lot=1000MT	1 lot =1000MT
4	Month	Last of month	Trade done/ bid-ask	1 lot=1000MT	1 lot =1000MT
5	Month	Last of month	Trade done/ bid-ask	1 lot=1000MT	1 lot =1000MT
6	Month	Last of month	Trade done/ bid-ask	1 lot=1000MT	1 lot =1000MT
1	Quarter	Last of 1st month	Avg of 3 months trades done/ bid-ask	1 lot p/m=3000MT	1 lot p/m=3000MT
2	Quarter	Last of 1st month	Avg of 3 months trades done/ bid-ask	1 lot p/m=3000MT	1 lot p/m=3000MT
3	Quarter	Last of 1st month	Avg of 3 months trades done/ bid-ask	1 lot p/m=3000MT	1 lot p/m=3000MT
4	Quarter	Last of 1st month	Avg of 3 months trades done/ bid-ask	1 lot p/m=3000MT	1 lot p/m=3000MT
1	Calendar	Last of 1st month	Avg of 4 quarters trades done/ bid-ask	1 lot p/y=12000MT	1 lot p/y=12000MT
2	Calendar	Last of 1st month	Avg of 4 quarters trades done/ bid-ask	1 lot p/y=12000MT	1 lot p/y=12000MT

Note Table 6.4: presents the characteristics that are used by Imarex to construct forward curves. This includes the number of month, quarter and calendar traded, the rolling date, the composition and amount of metric tonne for each lot.

Source: Imarex.

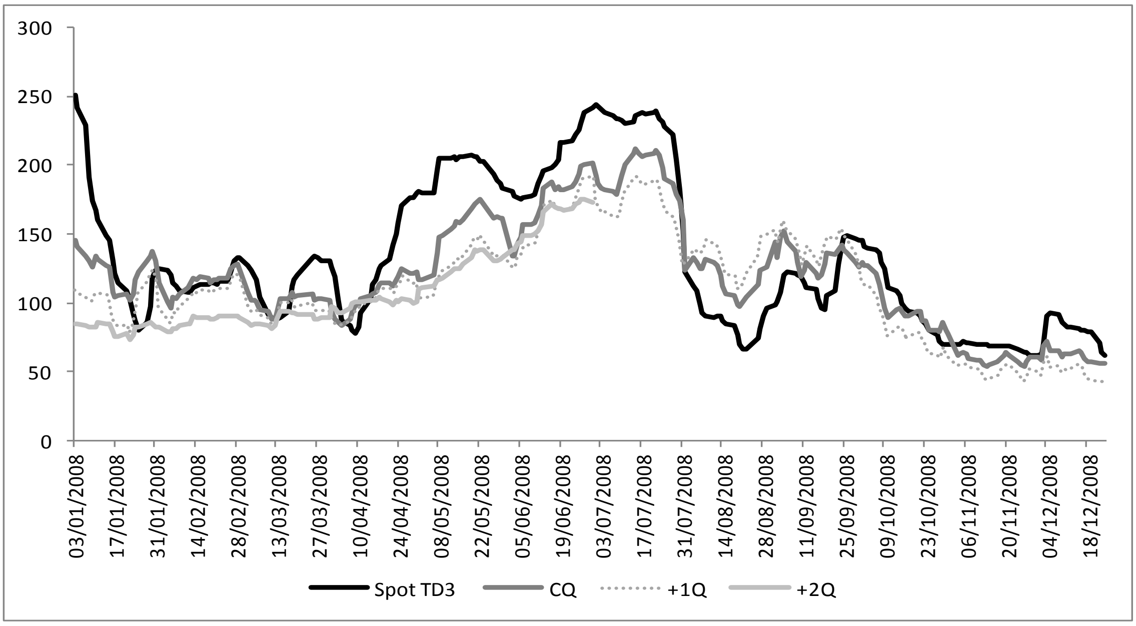
In the Figures below two types of forward curves are constructed using FFAs. First, short-term forward curves illustrated in Figures 6.5, 6.7, 6.9 and 6.11 using rolled over one-month, two-month and three-month FFA contracts and imposed on spot freight rates. Second, long-term forward curves illustrated in Figures 6.6, 6.8, 6.10 and 6.12 using rolled over current-quarter, one-quarter and two-quarter FFA contracts and imposed on spot freight rates. These constructed time-period forward curves for one-month, two-month, three-month and one-quarter for different tanker segments are plotted together to compare volatility levels between different time-period forward curves across different tanker sizes in Figures 6.13, 6.14, 6.15, and 6.16, respectively.

Figure 6.5: Forward Freight Agreements (FFAs) short-term contracts for TD3



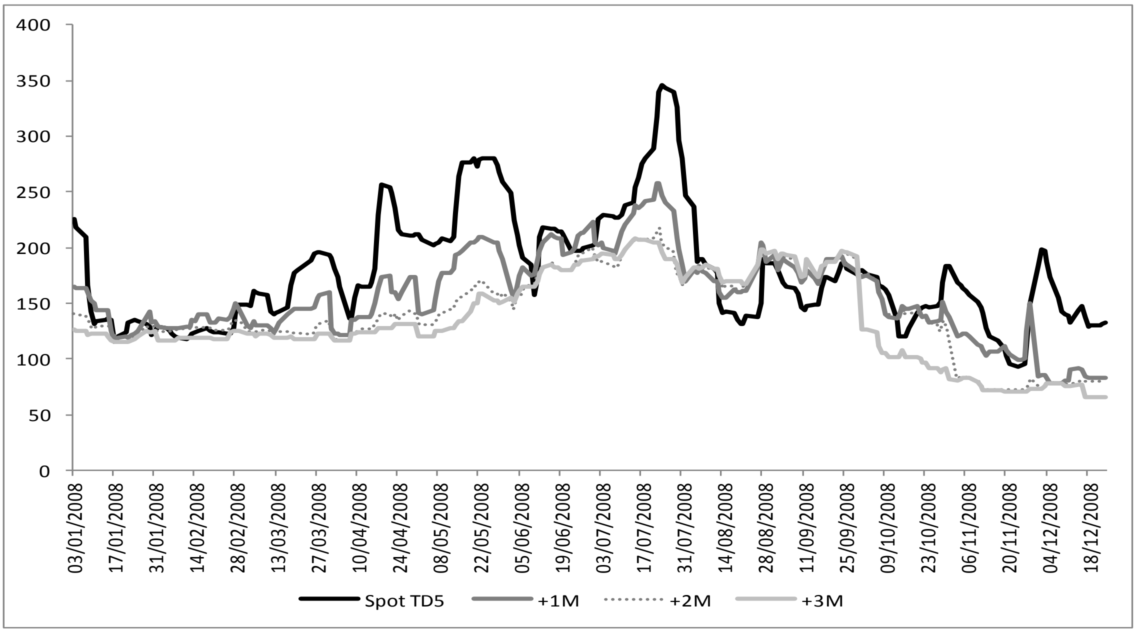
Note Figure 6.5: presents a comparison between short-term forward freight contracts for TD3 route imposed on TD3 spot rates. The vertical axes represent tanker freight prices in WorldScale for spot freight and one month, two month and three month forward tanker freight rates. **Source:** Author's estimations.

Figure 6.6: Forward Freight Agreements (FFAs) long-term contracts for TD3



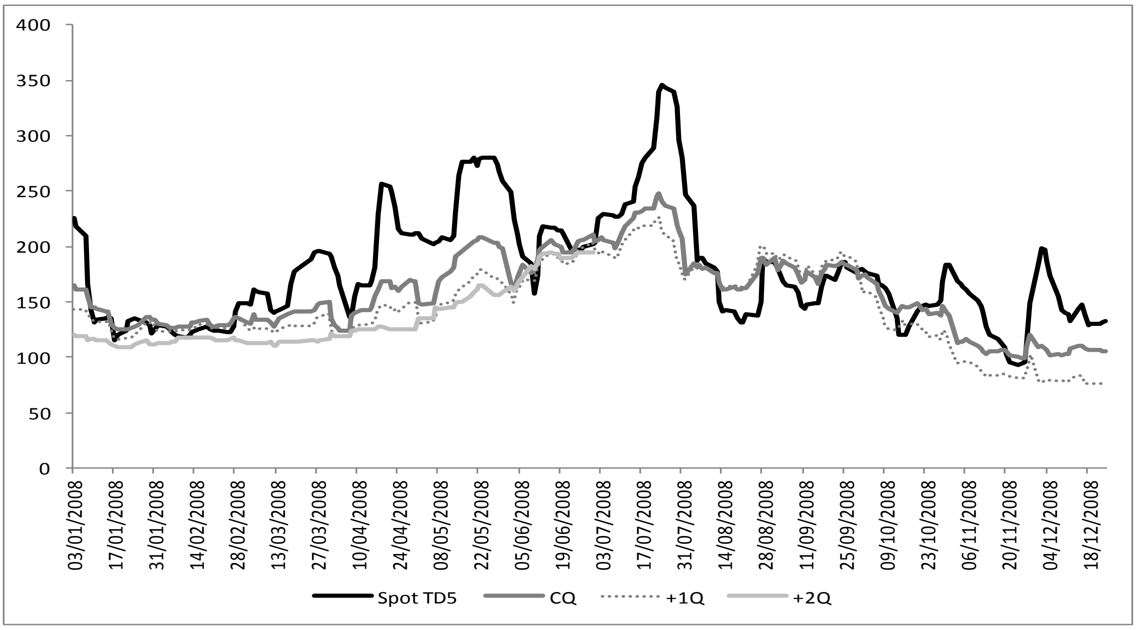
Note Figure 6.6: presents a comparison between long-term forward freight contracts for TD3 route imposed on TD3 spot rates. The vertical axes represent tanker freight prices in WorldScale for spot freight and one month, two month and three month forward tanker freight rates. **Source:** Author's estimations.

Figure 6.7: Forward Freight Agreements (FFAs) short-term contracts for TD5



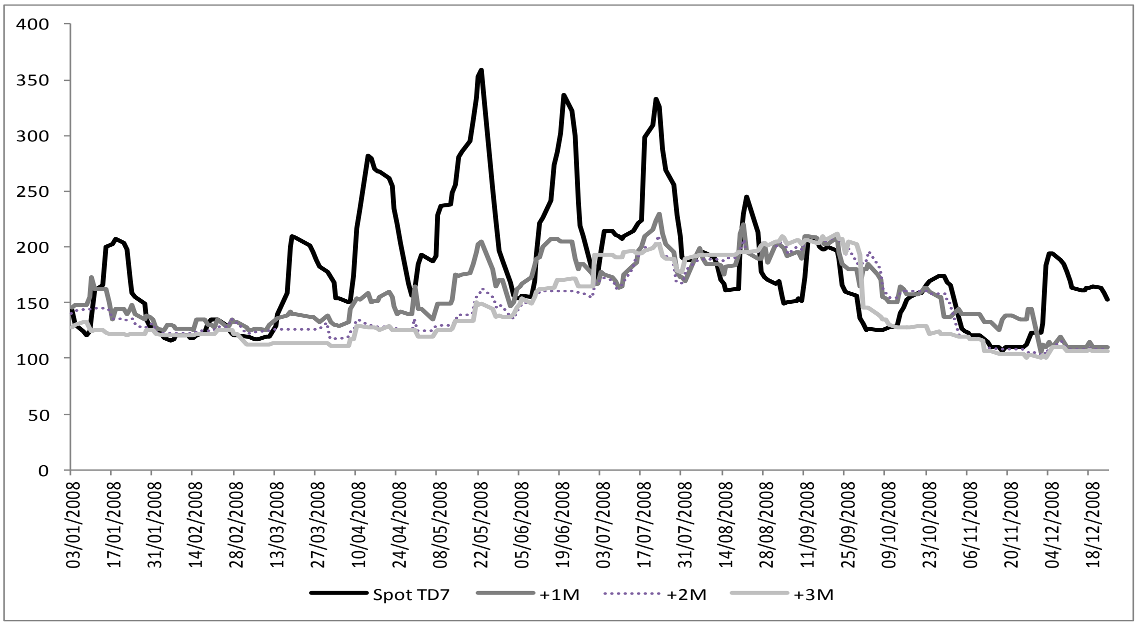
Note Figure 6.7: presents a comparison between short-term forward freight contracts for TD5 route imposed on TD5 spot rates. The vertical axes represent tanker freight prices in WorldScale for spot freight and one month, two month and three month forward tanker freight rates. **Source:** Author's estimations.

Figure 6.8: Forward Freight Agreements (FFAs) long-term contracts for TD5



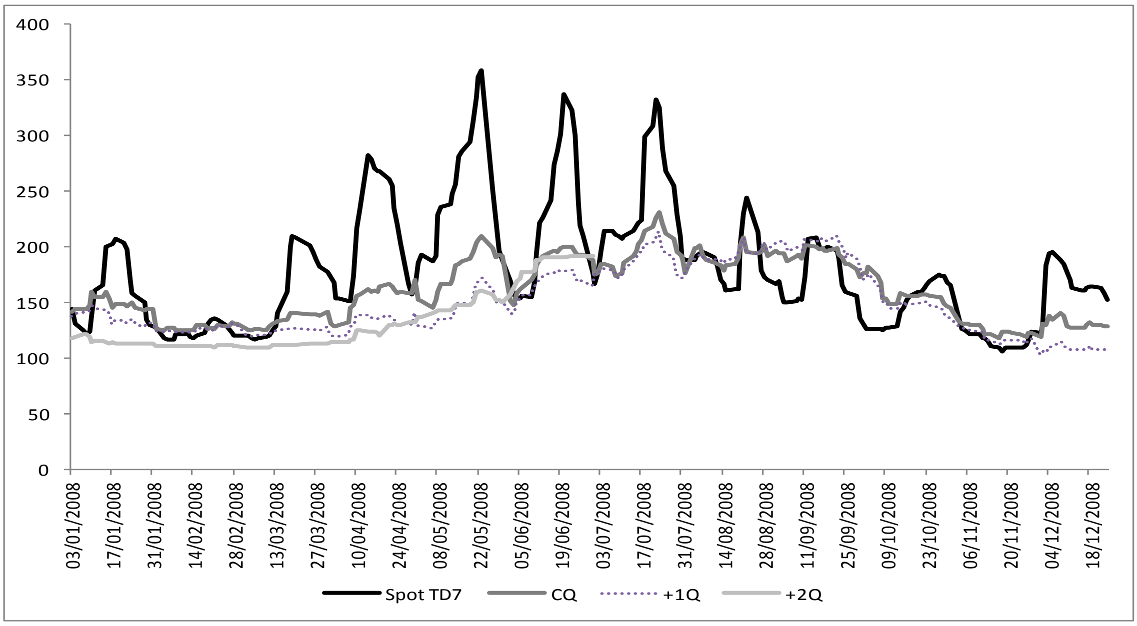
Note Figure 6.8: presents a comparison between long-term forward freight contracts for TD5 route imposed on TD5 spot rates. The vertical axes represent tanker freight prices in WorldScale for spot freight and one month, two month and three month forward tanker freight rates. **Source:** Author's estimations.

Figure 6.9: Forward Freight Agreements (FFAs) short-term contracts for TD7



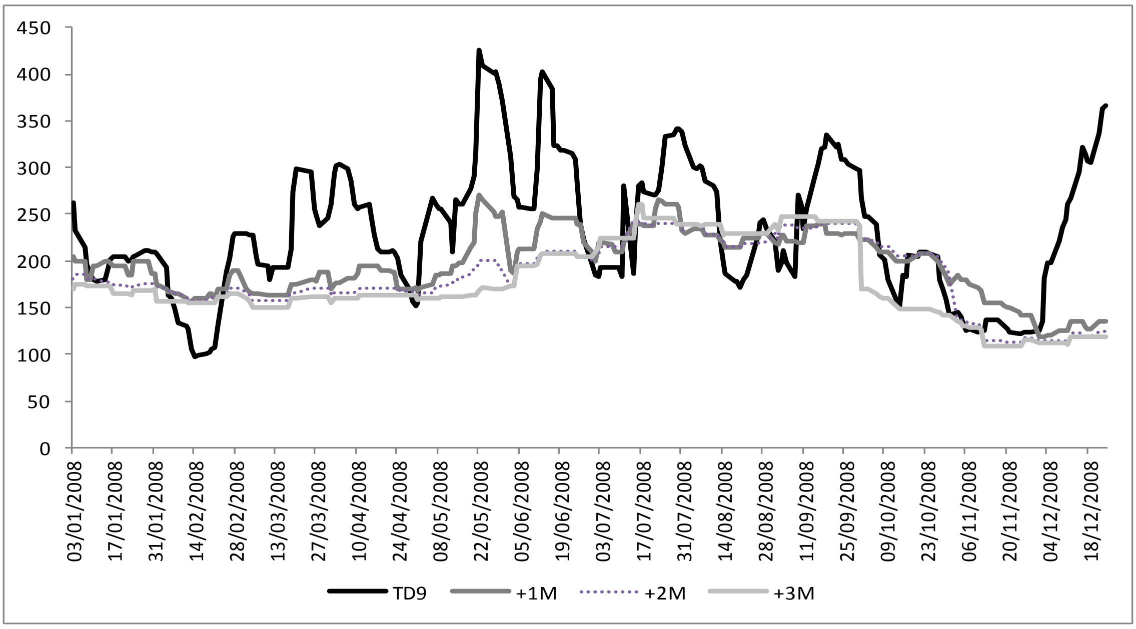
Note Figure 6.9: presents a comparison between short-term forward freight contracts for TD7 route imposed on TD7 spot rates. The vertical axes represent tanker freight prices in WorldScale for spot freight and one month, two month and three month forward tanker freight rates. **Source:** Author's estimations.

Figure 6.10: Forward Freight Agreements (FFAs) long-term contracts for TD7



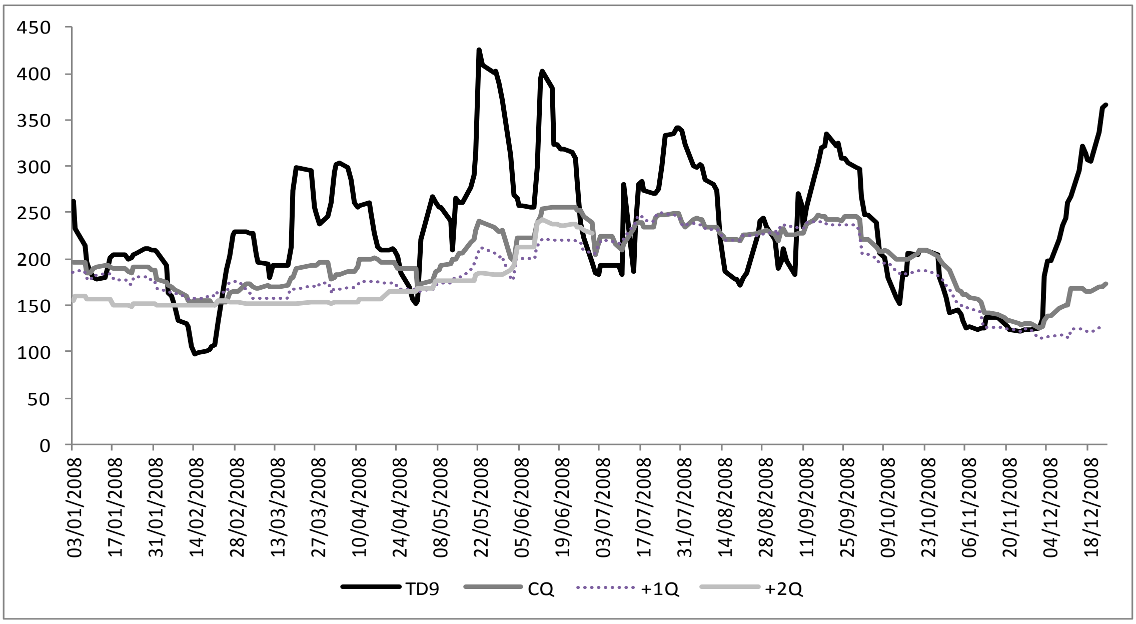
Note Figure 6.10: presents a comparison between long-term forward freight contracts for TD7 route imposed on TD7 spot rates. The vertical axes represent tanker freight prices in WorldScale for spot freight and one month, two month and three month forward tanker freight rates. **Source:** Author's estimations.

Figure 6.11: Forward Freight Agreements (FFAs) short-term contracts for TD9



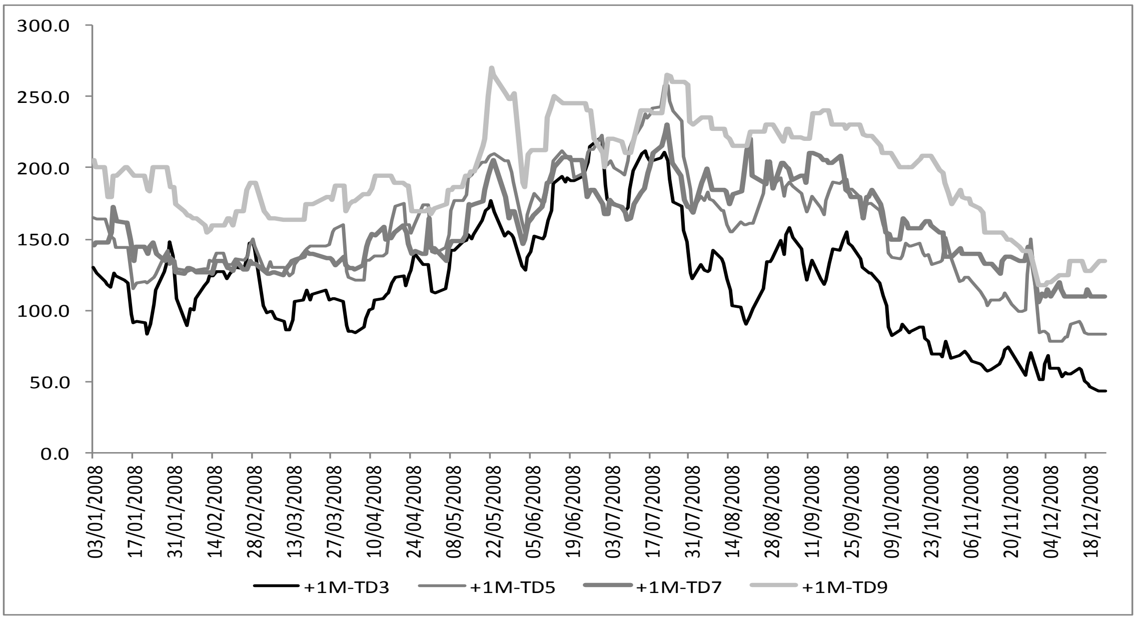
Note Figure 6.11: presents a comparison between short-term forward freight contracts for TD9 route imposed on TD9 spot rates. The vertical axes represent tanker freight prices in WorldScale for spot freight and one month, two month and three month forward tanker freight rates. **Source:** Author's estimations.

Figure 6.12: Forward Freight Agreements (FFAs) long-term contracts for TD9



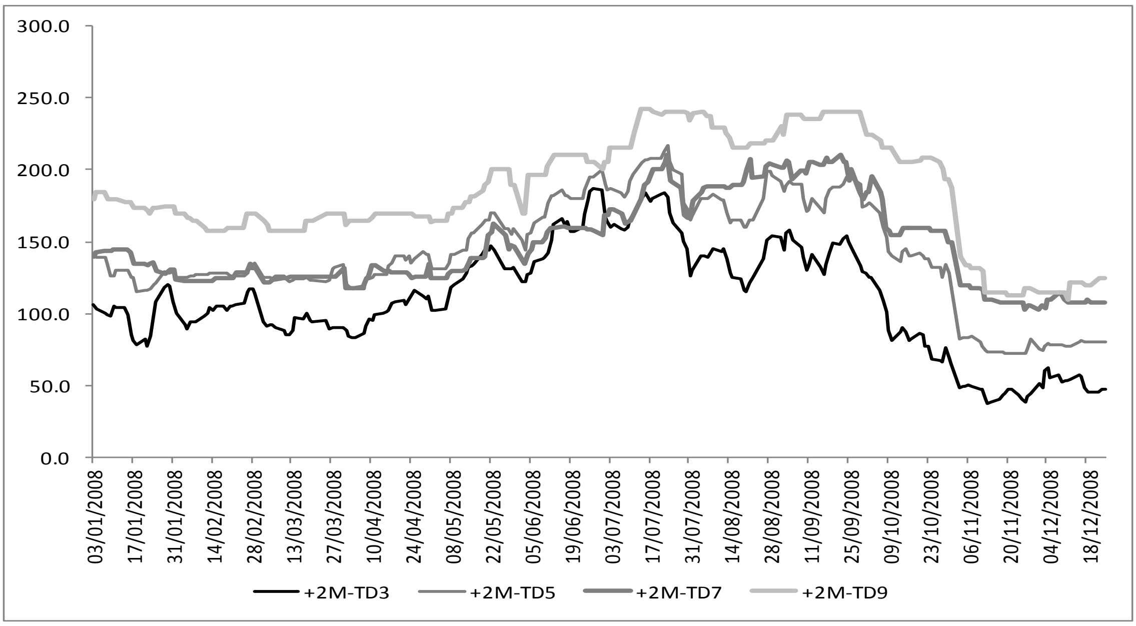
Note Figure 6.12: presents a comparison between long-term forward freight contracts for TD9 route imposed on TD9 spot rates. The vertical axes represent tanker freight prices in WorldScale for spot freight and one month, two month and three month forward tanker freight rates. **Source:** Author's estimations.

Figure 6.13: A comparison between one-month Forward Freight Agreements across tanker segments



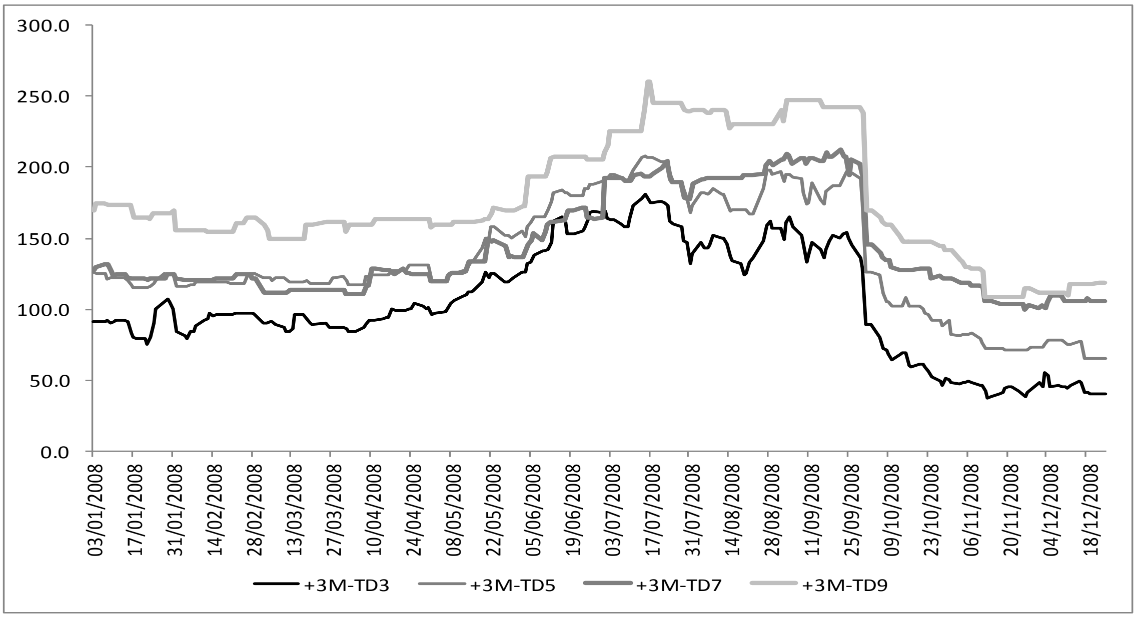
Note Figure 6.13: presents a comparison between one-month forward freight contracts across different tanker segments. The vertical axes represent tanker freight prices in WorldScale points. **Source:** Author's estimations.

Figure 6.14: A comparison between two-month Forward Freight Agreements across tanker segments



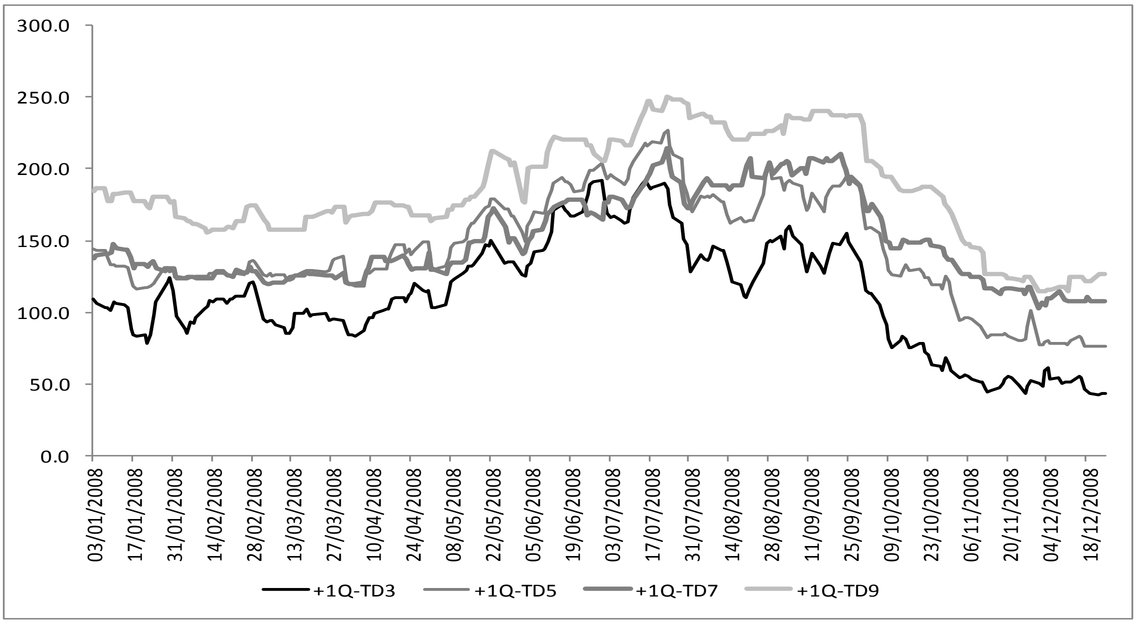
Note Figure 6.14: presents a comparison between two-month forward freight contracts across different tanker segments. The vertical axes represent tanker freight prices in WorldScale points. **Source:** Author's estimations.

Figure 6.15: A comparison between three-month Forward Freight Agreements across tanker segments



Note Figure 6.15: presents a comparison between three-month forward freight contracts across different tanker segments. The vertical axes represent tanker freight prices in WorldScale points. **Source:** Author's estimations.

Figure 6.16: A comparison between one-quarter Forward Freight Agreements across tanker segments



Note Figure 6.16: presents a comparison between one-quarter forward freight contracts across different tanker segments. The vertical axes represent tanker freight prices in WorldScale points. **Source:** Author's estimations.

Table 6.5: The accuracy of FFAs in predicting future spot freight rates for tankers

		CM	+1M	+2M	+3M	CQ	+1Q	+2Q
TD3	Accuracy	70% (18.5)†	54% (13.7)	41% (12.9)†	36% (10.9)†	55% (17.9)†	44% (13.0)†	46% (11.8)†
	Spec Risk	304%	321%	261%	266%	250%	274%	314%
TD5	Accuracy	69% (24.1)†	48% (14.0)	27% (12.9)†	23% (6.6)†	48% (16.2)†	33% (10.0)†	33% (8.0)†
	Spec Risk	239%	288%	266%	291%	247%	273%	347%
TD7	Accuracy	58% (17.5)†	28% (12.6)	11% (7.15)†	14% (7.3)†	33% (16.1)†	18% (9.7)†	26% (8.0)†
	Spec Risk	362%	242%	166%	215%	219%	199%	351%
TD9	Accuracy	45% (10.5)†	31% (14.1)	15% (9.8)†	11% (6.1)†	30% (12.9)†	19% (11.0)†	23% (7.6)†
	Spec Risk	529%	271%	184%	221%	290%	212%	367%

Note Table 6.5: reports the accuracy of FFAs in forecasting future spot prices along with a measure of risk for four tanker segments that represent the most popular traded tanker derivatives in freight markets. The accuracy measure is the estimated coefficient from a single regression equation, where FFAs and spot freights are the dependent and independent variables, respectively. The risk measure is the specific risk, which is measured by annualising the standard deviation of the regression residuals for the relevant tanker segment; $Specific\ Risk = \sigma_{\varepsilon_{seg}} \times \sqrt{250}$. Values in brackets are t-values form the regressions and † represents significance at any level.

Source: Author's estimations.

Furthermore, in Table 6.5 we report the accuracy of our constructed forward curves in predicting future spot freight rates, in short- and long-term periods, along with a risk measure for the 2008 period. The short-term forward curves are represented by one-month, two-month and three-month constructed forward curves that are constructed from one-month, two-month and three-month rolled over FFA contracts. First, assuming stationary and using a univariate regression equation, where FFA and spot freight rates are the dependent and independent variables, respectively, we report the estimated beta coefficient from the regression alongside its *t*-values in brackets. Second, the annualised risk measure reported in the above table is the specific risk, which is an indication of volatility levels in the residuals of the regression. The above illustrations and reported results in Table 6.5 clearly indicate the poor performance of FFA forward curves in predicting and assessing future spot freight rates, excluding current-month forward curves that ranged from 70 per cent to 45 per cent across tanker segments. In other words, during 2008 period FFA contracts could only be used to forecast spot freight prices for a couple of weeks ahead and the accuracy level of such forecasts depended on the size of the underlying vessel. This is due to the recent financial turmoil and is a clear reflection of the effect of the large percentage of trading and finance houses relative to shipping risk mangers, resulting in high levels of speculative trading in tanker futures markets. Alizadeh and Nomikos (2009) examine the directional accuracy of short-term forward curves for a period from March 2003 to December 2007 and conclude that the directional accuracy is at reasonable levels for short maturities and increases with time to maturity from 60 per cent up to nearly 80 per cent, suggesting that the three-month forward curve is the most accurate in forecasting future spot freight rates for the most liquid traded routes. Furthermore, they also examine volatility levels for these constructed forward curves and find that volatility is much higher in comparison to other financial and commodity markets and that it decreases with time to maturity.

6.4. An insight into market practice in trading FFAs

Forward freight agreements (FFAs) are traded either over the counter or through a hybrid exchange. In general, trades take place either on the basis of a principle to principle contract between two counterparties or through one of the clearing freight service houses, such as the London Clearing House (LCH. Clearnet), the Singapore Exchange (SGX) Asia Clear Service, the Norwegian Futures and Options Clearing House (NOS) and the New York Mercantile Exchange (NYMEX). For more details and examples of the standard contract forms that are used in practice see Alizadeh and Nomikos (2009). Furthermore, most recently, shipping practitioners recognising the impact of counterparty risk on their open positions, have tended to increase their use of hybrid exchanges to trade FFAs to neutralise their counterpart risk exposure. The most popular and largest is the International Maritime Exchange (Imarex), where they provide a trading screen for practitioners to trade standardised contracts, which are cleared through NOS.

6.4.1. A general rule of thumb

A physical freight contract is the underlying asset for an FFA contract, in which the latter is used to manage freight risk exposure. Similar to hedging financial contracts, the main objective of a freight hedge is to neutralise the risk of a freight price movement. However, this is subject to the freight derivative contract matching the value and corresponding to the timing of the physical exposure. In general the following is considered to be a rule of thumb for FFAs counterparts.

- If you are LONG physical freight: you SELL the FFA (SHORT FFA)

  This neutralises the effect of falling freight prices

- If you are SHORT physical freight: you BUY the FFA (LONG FFA)

  This neutralises the effect of rising freight prices

6.4.2. Four principles for freight hedging

In general there are four principles for hedging freight risk and are explained in the following table.

Table 6.6: A description of the four principles of hedging freight risk

No	Contract principles	Description
1	Direction	Physical position: short, neutral and long.
2	Period	Freight price risk exposure period and when the physical position is neutralised.
3	volume	The right number of FFA contracts to match the physical risk exposure.
4	Time to exit	Close the FFA position or wait for maturity.

Note Table 6.6: presents the four important principles of hedging freight risk. **Source:** Author.

6.4.3. Basic hedging position: physical long vs short principle

On the one hand, a ship-owner before letting (fixing) his vessel is long physical and once he's vessel is hired he is neutral, thus, a short FFA position protects a ship-owner that is long physical from falling markets. On the other hand, a cargo-owner before hiring a vessel to transport his cargo is considered to be short physical and once he fixes a vessel he is neutral, thus, a long FFA position protects charters/oil refiners that are short physical from rising markets. Table 6.7 presents examples of different shipping participants and their normal hedging positions.

Table 6.7: Basic hedging positions for shipping practitioners

No	Long physical freight (ship-owner require a cargo)	Short physical freight (cargo-owner require a ship)
1	Ship owners.	Charterers and oil refiners.
2	Trading companies with excess tonnage.	Trading houses.
3	CIF[19] buyers of cargo.	FOB[20] buyers of cargo.

Note Table 6.7: presents examples of normal hedging positions for different shipping practitioners. CIF stands for cost, insurance and freight and FOB stands for free on board[21]. **Source:** Author.

[19] CIF stands for cost, insurance and freight, this means that the paid price of any goods by the importer includes payment of insurance and transporting freight, which is arranged by the exporter.

[20] FOB stands for free on board, this means that the paid price of any goods does not include any insurance and transportation costs from the loading port to the discharging port, which is the responsibility of the importer to make the required arrangements.

Moreover, a hedging position for shipping practitioners changes over time from being exposed to freight risk to neutral depending on their physical position relative to the paper one. In the following table we explain this for the two main counterparts in an FFA contract, ship-owners and charterers.

Table 6.8: The different stages for shipping agents before, during and after hedging

	Ship-owner	**Cargo-owner (charterer)**
Before fixing	Long physical freight	Short physical freight
Paper strategy	Short paper freight	Long paper freight
After fixing	Neutral physical freight	Neutral physical freight
Closing position	Buy back paper hedge	Sell out paper hedge
Reason 1	A long physical freight position and a short paper position, cancel each other	A short physical freight position and a long paper position, cancel each other
Reason 2	If market raise (high freight prices) the ship-owner gains from his physical position that is off-set by his losses on his paper position.	If market rise (high freight prices) the cargo-owner pays more to hire a vessel but this is off-set by his gain on his paper position.

Note Table 6.8: explains the different positions of shipping agents before, during and after hedging their risk exposure.

Source: Imarex.

[21] These are known as the International Commercial terms (Incoterms).

6.4.4. The usefulness of converting WorldScale points to metric measures

As mentioned earlier, shipping agents negotiate tanker freight rates in WorldScale points, as it is easy to compare freight rates across different routes and vessel sizes using the WS point system. However, freight rates in WS points are easily converted to dollars per tonne or to dollars per barrel, so that expected revenue and cost for a particular voyage can be calculated by ship-owners and charterers, respectively. These conversions are done using the following formulas.

First, to convert WS point to dollars per tonne

$$\$\ per\ metric\ ton\ (\$/MT) = \frac{WS \times flat\ rate}{100} \tag{6.1}$$

Second, to convert WS point to dollars per oil barrel

$$\$\ per\ barrel\ (bbl) = \frac{WS \times flat\ rate}{100 \times barrel\ factor} \tag{6.2}$$

Third, total revenue or cost of a particular voyage is calculated using

$$Total\ freight\ revenue = \frac{WS}{100} \times flat\ rate \times cargo\ size\ (ton) \times 97.5\% \tag{6.3}$$

Furthermore, once total revenue of a particular voyage is calculated, net profits can be calculated by deducting voyage costs, which in general are bunker cost and port dues. Bunker cost is calculated as following.

$$Bunker\ cost = daily\ bunker\ consumption \times bunker\ price\ per\ metric\ ton \times voyage\ days \tag{6.4}$$

As discussed earlier tanker freight rates are quoted in WS points that are easily converted to their equivalent dollars per tonne rates, because these measure are not easily comparable to time-charter rates for tanker vessels, where the latter is quoted in dollars per day (the cost of hiring a particular vessels for one day). For example a ship-owner can be faced with numerous fixtures for his vessel, some quoted in WS points (spot market) and other in time-charter rates (time-charter market in dollars per day). Therefore, shipping practitioners tend to calculate a Time-Charter-Equivalent for spot fixtures to be easily comparable against time-charter once using the following formula.

$$Time\ Charter\ Equivalent\ per\ day\ (TCE) = \quad (total\ freight\ revenue - port\ costs - bunker\ cost)/(voyage\ days)$$

(6.5)

To put these formulas in perspective we continue the following calculations, for example, assuming that a ship-owner of a VLCC tanker has been quoted a WS78 to transport 260,000 mt of crude oil from Middle East gulf (Ras Tanura) to Japan (Chiba), on the TD3 route. With the following particulars:

Flat rate: $18.72/ton for 2010

Barrel factor: 7.15

Port cost: $155,000

Bunker cost $475 per metric ton

Bunker consumption: 90 ton per day

Voyage duration (round trip): 45.5 days

Thus, a WS 78 is equivalent to

$$\$\ per\ metric\ ton\ \left(\frac{\$}{MT}\right) = \frac{78 \times 18.72}{100} = \$14.6/ton$$

and

$$\$\ per\ barrel\ (bbl) = \frac{78 \times 18.72}{100 \times 7.15} = \$2.0/bbl$$

Thus,

$$Total\ freight\ revenue = \frac{78}{100} \times 18.72 \times 260{,}000 \times 97.5\% = 3{,}701{,}505\ dollars$$

$$Bunker\ cost\ = 475 \times 90 \times 45.5\ = 1{,}945{,}125\ dollars$$

$$Time\ Charter\ Equivalent\ per\ day\ (TCE) = \frac{3{,}701{,}505 - 155{,}000 - 1{,}945{,}125}{45.5}$$
$$= \$35{,}195/day$$

Therefore, a WS78 quote for a TD3 route is equivalent to 14.6 dollars per ton according to 2010 flat-rate and excluding voyage costs this is equivalent to a daily net income for the ship-owner of 35,195 dollars per day.

6.4.5. Adjusted flat rate settlements (AFRS)

As mentioned earlier WorldScale flat-rates are adjusted at the start of every year changing the settlement value for FFAs contracts, which affects the revenue and the cost for a ship-owner and a charterer, respectively, if a contract is settled during this period. Thus, using practical examples we illustrate these effects.

First, an AFRS example for a closed position:

An Imarex trader buys 10 lots of TD3FEB10 at WS63 in 1st of September 2009. On the 1st of December 2009 he sells the same contract for WS69.5 (close position). The prevailing flat rate during 2009 is \$25. On the 1st of January 2010 the worldscale association adjusts the flat rate for TD3 to \$18.72.

Thus,

Trade value: $10 \times 1000 \times 25 \times \left(\frac{WS63}{100}\right) = \$157{,}500$

Market value: $10 \times 1000 \times 25 \times \left(\frac{WS69.5}{100}\right) = \$173{,}750$

Therefore, his trading position is neutral and profit before adjustment is \$16,250

NOS calculations for AFRS

New trade value: $10 \times 1000 \times 18.72 \times \left(\frac{WS63}{100}\right) = \$117{,}936$

New market value: $10 \times 1000 \times 18.72 \times \left(\frac{WS69.5}{100}\right) = \$130{,}104$

Therefore, adjusted profit is $12,168 and AFRS is $4,082, which is deducted from buyer and paid to seller.

Second, an AFRS example for an open position:

An Imarex trader buys 10 lots of TD3FEB10 at WS63 in 1st of September 2009. On the 31st of December 2009 the closing price was WS69.5. The prevailing flat rate during 2009 is $25. On the 1st of January 2010 the worldscale association adjusts the flat rate for TD3 to $18.72.

Thus,

Original trade value: $10 \times 1000 \times 25 \times \left(\frac{WS63}{100}\right) = \$157{,}500$

Original market value: $10 \times 1000 \times 25 \times \left(\frac{WS69.75}{100}\right) = \$174{,}375$

Original mark to market is $174,375-$157,500=$16,875.

New trade value: $10 \times 1000 \times 18.72 \times \left(\frac{WS63}{100}\right) = \$117{,}936$

New market value: $10 \times 1000 \times 18.72 \times \left(\frac{WS69.75}{100}\right) = \$130{,}572$

New mark to market is $130,572-$117,936=$12,636.

Therefore, AFRS is $4,239, which is deducted from buyer and paid to seller.

6.4.6. Trading dirty tanker FFAs and the usefulness of forward curves (FC)

The three main challenges facing shipping agents in using FFAs to mange freight risk is the choice of number of lots to trade (traded volume), the right time to open a position and the right time to close the position. Thus, an important challenge for ship/cargo owners using FFAs to mitigate freight risk is to match a paper position to a physical exposure, thus, adjusting the volume of a traded paper to a voyage that is longer/shorter than a month. For example if a VLCC owner is concerned that freight prices will drop in the near future and that finding employment for his vessel will be challenging, he should consider selling FFAs, so if freight prices drop he will buy the required contracts to close the position at a lower price and make a profit that compensates for the loss on the physical position. The challenge is finding the exact number of contracts and time to hedge. To put this in perspective, let’s assume that a ship-owner has to deliver his vessel for its annual dry-dock in Japan and is looking for a cargo to load from the Arabian Gulf (TD3 Route). He believes that freight rates are at the downside and wishes to neutralise his freight risk exposure. As discussed earlier, once the vessel is fixed the position is neutralised. In other words, a ship-owner is only exposed to freight risk for the period before fixing. The other challenge is the exact amount of paper contracts to sell. Assuming the following voyage particulars:

Ras Tanura (AG) to Yosu (Japan)	
Distance one way	6206 Nautical Miles
Laden speed	14 knots
Ballast speed	15 knots
Days in port	4 days
Sea margin	2.5%
Flat rate	$16.55/t
Cargo size	260,000 mt

First, we need to calculate the number of days for the round trip.

Outbound trip: from Ras Tanura to Yosu

$$number\ of\ days = \frac{Distance}{Speed \times 24hrs} \times (sea\ margin\ of\ 2.5\%) = \frac{6206NM}{14knots \times 24hrs} \times 1.025 = 18.9 \cong 19\ days$$

Inward trip: from Yosu to Ras Tanura

$$number\ of\ days = \frac{Distance}{Speed \times 24hrs} \times (sea\ margin\ of\ 2.5\%)$$

$$= \frac{6206NM}{15knots \times 24hrs} \times 1.025 = 17.7 \cong 17.5\ days$$

If total days in port are 4 days, thus, the total of voyage days is 40.5 days. Therefore, a round trip takes 40.5 days, assuming that there are 365 days per year, a VLCC can only make 365/40.5 or 9 roundtrips per year, thus, a 0.75 (9/12) roundtrip per month. In other wards, for a VLCC that is operating on a TD3 route the ratio of a round trip to one-month (the length of an FFA contracts) is equivalent to 0.75.

Second, we calculate flat rate differences:

The volume to be traded $= Cargo\ size\ \times \left(\frac{roundtrips}{month}\right) \times \frac{physical flat\ rate}{paper\ flat\ rate}$

$$= 260{,}000 \times 0.75\ \frac{16.55}{18.72} = 172{,}395 \cong 170{,}000\ tonnes$$

The volume is rounded to the nearest 5000 tonnes as the smallest tradable volume is 5k tonnes. Thus, the number of lots to sell is 170 lots (170,000/1000). However, the exact percentage to hedge is the ship-owner's, in practical terms ship-owners normally hedge a percentage of their physical position to benefit from any movement in the market, this is based on their market perspective, company policy, experience, time charter position and risk exposure.

In contrast to ship-owners, charterers hedge the full amount of cargo, not a monthly equivalent, in an attempt to trade the same value on paper as their physical lifting. Thus, they consider freight as a lump sum cost incurred at point of fixing and are not concerned in smoothing their freight cost over the course of the voyage. For charterers the underlying exposure is on the day/period of fixing not on day/period of loading.

Furthermore, we examine a hedging strategy for a charterer based on two different scenarios and compare this with the usefulness of forward curves to improve earnings. First, an example of a gain, a refinery located in Japan has to buy crude in July for the normal busy period in August, they expect that the cargo will be loaded in June with a Laycan[22] 20-30 days, so that they receive the crude in August.

Particulars: A VLCC vessel is fixed on the 19th of June and starts loading on the 15th of July from Ras Tanura, with an expectation of delivery around the 4th of August.

The charterer buys FFA TD3Jun on May 11th at WS84

Required size:

$$260{,}000 \times \frac{\$13.51}{\$15.16} = 231{,}701 \cong 230{,}000\ tonnes$$

Value in US dollars:

$$230{,}000 \times \$15.16 \times \frac{WS84}{100} = 2{,}928{,}912\ dollars$$

The charterer fixes a VLCC on the 19th of June at WS120

Value in US dollars:

$$260{,}000 \times \$13.51 \times \frac{WS120}{100} = 4{,}215{,}120\ dollars$$

The charterer closes his FFA position by selling out FFA TD3Jun position at WS110

Value in US dollars:

$$230{,}000 \times \$15.16 \times \frac{WS110}{100} = 3{,}835{,}480\ dollars$$

The charter receives the difference of 906,568 dollars, thus, his net freight cost is 3,308,552 dollars saving the refinery 21.5% on freight cost, in comparison to unhedged position.

Second an example of a loss, the charterer buys FFA TD3Jun on May 11th at WS84

[22] Laycan is a ship chartering term which stands for number of days for commencement and cancelling of a charterparty. It specifies the earliest date on which the vessel can present itself for loading and the latest date after which the charter can opt to cancel the charter party.

Required size:

$$260{,}000 \times \frac{\$15.98}{\$17.72} = 234{,}469 \cong 235{,}000\ tonnes$$

Value in US dollars:

$$235{,}000 \times \$17.72 \times \frac{WS84}{100} = 3{,}497{,}928\ dollars$$

The charterer fixes a VLCC on the 19th of June at WS70

Value in US dollars:

$$260{,}000 \times \$15.98 \times \frac{WS70}{100} = 2{,}908{,}360\ dollars$$

The charterer closes his FFA position by selling out FFA TD3Jun position at WS72

Value in US dollars:

$$235{,}000 \times \$17.72 \times \frac{WS72}{100} = 2{,}998{,}224\ dollars$$

The charter has to pay the difference of 449,704 dollars, thus, his net freight cost is 2,908,360 dollars with a forgone potential saving for the refinery of 15.5% on freight cost, if the position remained unhedged.

However, it is important to examine forward freight curves at the time before the charter had bought FFAs and asses the usefulness of such a tool in managing risk and improving profitability. First, the example in 2006, the tanker FFA market on the 11-May suggest that freight rates are at the upside in the near future, suggesting the usefulness of hedging to protect against rising freight rates, supporting the charter actions in the first part of the previous example. This is illustrated in the constructed forward curves in Table 6.9 and Figure 6.17.

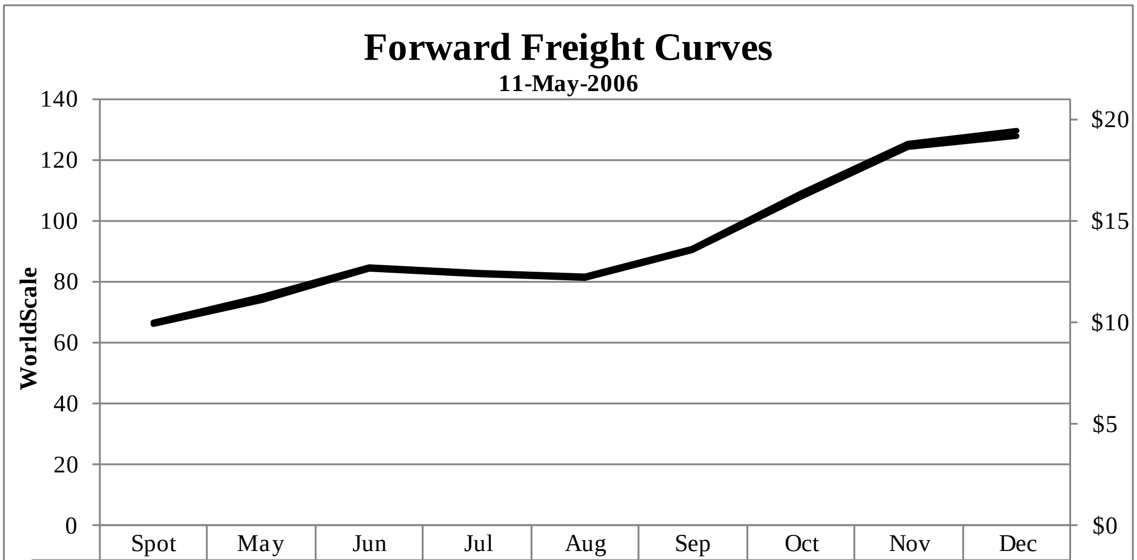
Table 6.9: The characteristics of the different contracts that construct the FC on the 11-May-2006

	WS	$/MT	Total Revenue	Bunker Cost	Net profit	TCE
Spot	65.8	$10.0	$2,528,733	$1,971,743	$401,991	$8,835
May	74	$11.2	$2,843,864	$1,971,743	$808,122	$17,761
Jun	84	$12.7	$3,228,170	$1,971,743	$1,031,428	$22,669
Jul	82	$12.4	$3,151,309	$1,971,743	$1,046,567	$23,001
Aug	81	$12.3	$3,112,879	$1,971,743	$1,051,636	$23,113
Sep	90	$13.6	$3,458,754	$1,971,743	$1,487,012	$32,682
Oct	108	$16.4	$4,150,505	$1,971,743	$2,178,762	$47,885
Nov	124	$18.8	$4,765,394	$1,971,743	$2,793,652	$61,399
Dec	128	$19.4	$4,919,117	$1,971,743	$2,947,374	$64,777

Note Table 6.9: report the different characteristics of the different contracts that construct the forward curve illustrated in Figure 6.17. These are freight rates measured in WS points, freight rates measured in dollars per metric tonne, a calculation of possible total revenue based on assumptions in Table 6.3, bunker cost for that particular vessel (VLCC) for the total voyage and a measure of total possible net profit and a Time-charter-Equivalents (TCE) for a ship-owner based on this fixture and previous particulars.

Source: Author's estimations.

Figure 6.17: Forward freight curve constructed on the 11-May-2006



	Spot	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
WS	65.8	74	84	82	81	90	108	124	128
$/MT	$10.0	$11.2	$12.7	$12.4	$12.3	$13.6	$16.4	$18.8	$19.4
TCE	$8,835	$17,761	$22,669	$23,001	$23,113	$32,682	$47,885	$61,399	$64,777

Note Figure 6.17: illustrates a constructed forward curve on the 11-May-2006 for TD3 route. Left and right axis represent freight rates in WS point and dollars per tonne, respectively. The first two rows in the below table presents the value of spot and each FFA contract on the 11-May2006 in WS points and dollars per tonne, respectively. The last row presents a time-charter-equivalent for spot and each FFA contract. **Source:** Author's estimations.

Second, for the example set in 2007, the below constructed forward curves illustrate a slacks freight rate in the near future, strongly suggesting that freight rates are on the downside and that an agent with a short physical position should not hedge to benefit from dropping freight rates. This is illustrated in the constructed forward curves in Table 6.10 and Figure 6.18.

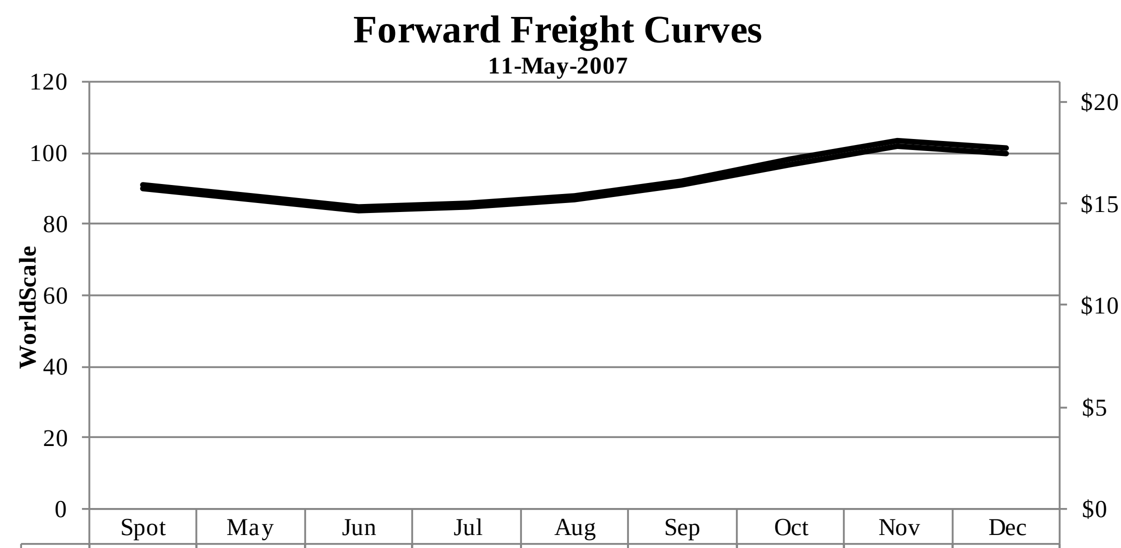
Table 6.10: The characteristics of the different contracts that construct the FC on the 11-May-2007

	WS	$/MT	Total Revenue	Bunker Cost	Net profit	TCE
Spot	90	$15.9	$4,042,818	$1,971,743	$2,071,076	$45,518
May	87	$15.4	$3,908,057	$1,971,743	$1,936,315	$42,556
Jun	84	$14.9	$3,773,297	$1,971,743	$1,801,554	$39,595
Jul	85	$15.1	$3,818,217	$1,971,743	$1,846,475	$40,582
Aug	87	$15.4	$3,908,057	$1,971,743	$1,936,315	$42,556
Sep	91	$16.1	$4,087,738	$1,971,743	$2,115,996	$46,505
Oct	97	$17.2	$4,357,259	$1,971,743	$2,385,517	$52,429
Nov	102	$18.1	$4,581,860	$1,971,743	$2,610,118	$57,365
Dec	100	$17.7	$4,492,020	$1,971,743	$2,520,278	$55,391

Note Table 6.10: report the different characteristics of the different contracts that construct the forward curve illustrated in Figure 6.18. These are freight rates measured in WS points, freight rates measured in dollars per metric tonne, a calculation of possible total revenue based on assumptions in Table 6.3, bunker cost for that particular vessel (VLCC) for the total voyage and a measure of total possible net profit and a Time-charter-Equivalents (TCE) for a ship-owner based on this fixture and previous particulars.

Source: Author’s estimations.

Figure 6.18: Forward freight curve constructed on the 11-May-2007



	Spot	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
WS	90	87	84	85	87	91	97	102	100
$/MT	$15.9	$15.4	$14.9	$15.1	$15.4	$16.1	$17.2	$18.1	$17.7
TCE	$45,518	$42,556	$39,595	$40,582	$42,556	$46,505	$52,429	$57,365	$55,391

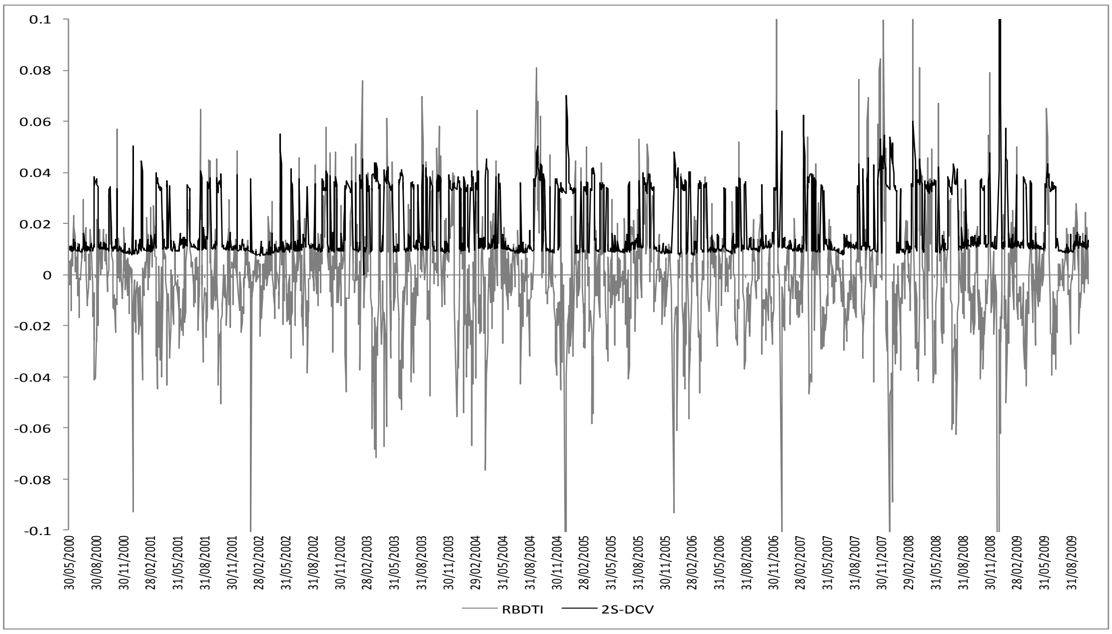
Note Figure 6.18: illustrates a constructed forward curve on the 11-May-2007 for TD3 route. Left and right axis represent freight rates in WS point and dollars per tonne, respectively. The first two rows in the below table presents the value of spot and each FFA contract on the 11-May2007 in WS points and dollars per tonne, respectively. The last row presents a time-charter-equivalent for spot and each FFA contract.

Source: Author's estimations.

6.4.7. Trading dirty tanker FFAs and the usefulness of value-at-risk forecasts

In the previous section we discussed the usefulness of forward freight curves combined with the use of derivatives to mitigate freight risk, using practical examples. In this section we implement the empirical approach outlined in section 4.3.5.6 to asses the usefulness of a developed value-at-risk framework in improving freight market information. This empirical framework is applied to the VLCC tanker market where worldscale (WS) values are converted to their equivalent dollars per ton for a better assessment of changes in freight levels. In Figure 6.19 tanker freight returns are compared across estimated one-day two-state Markov-switching distinctive conditional volatilities to illustrate the ability of the proposed framework in chapter four to capture the dynamics of the freight market. Most importantly, in Figure 6.20, one-day forecasts of 1%VaR and 5%VaR estimates based on the above mentioned framework are plotted against negative returns for the period from 2005 to 2007, which covers the examples in the previous section. It is important to note that the term period freight forecast that is based on estimated and scaled VaR measures used in this section refers to the maximum possible drop in freight rates for the holding period and a significance level (α).

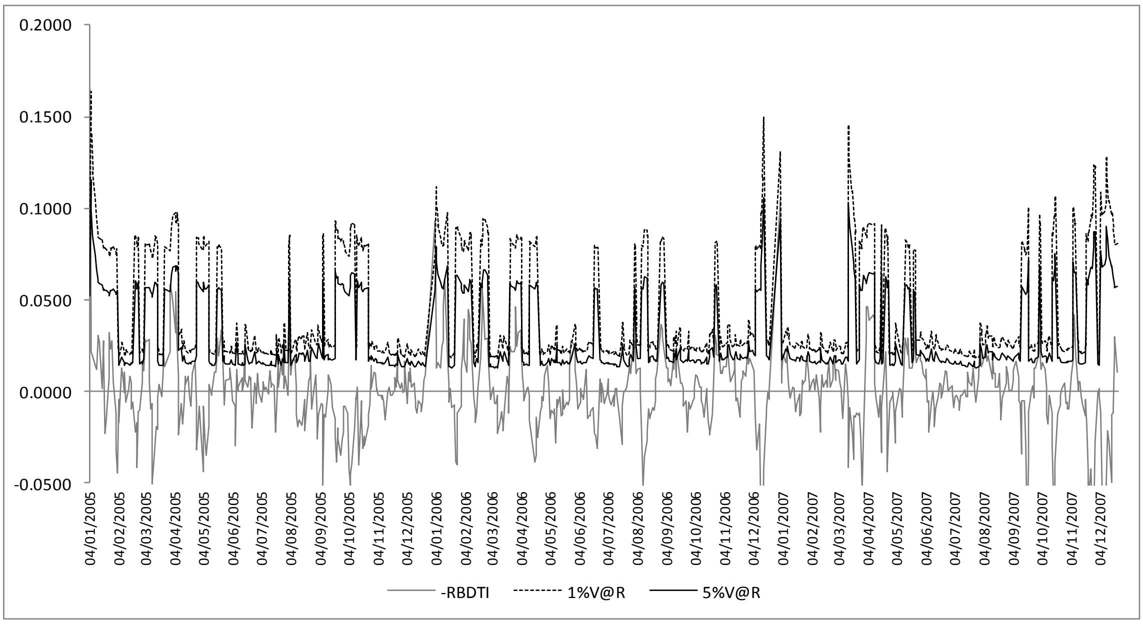
Figure 6.19: Tanker freight returns vs. estimated 1-day two-state markov-switching distinctive conditional volatilities



Note Figure 6.19: illustrates estimated daily (one-day ahead) two-states Markov-switching conditional volatilities for a portfolio of tanker freight returns imposed on actual daily returns (R) on the Baltic Dirty Tanker Index (BDTI). This graph of regime dependent volatilities is estimated for out-sample sample period from 02-01-2008 to 30-10-2009.

Source: Author's estimations.

Figure 6.20: Actual observed negative returns vs. estimated and forecasted 1–day value-at-risk



Note Figure 6.20: presents illustrations of 1-day ahead value-at-risk forecasts imposed on actual negative returns (-R) on the Baltic Dirty Tanker Index (BDTI). Daily value-at-risk estimates are measured for 1 per cent and 5 per cent significance levels for out-sample sample period from 04-01-2005 to 04-12-2007. **Source:** Author's estimations.

In Table 6.11 we compile all available freight market information and estimated short-term and long-term risk measures in one table for the specific dates used in the previous examples; these are worldscale rates, quoted spot and forward freight rates in worldscale and dollars per ton; average value-at-risk[23] and value-at-risk estimates that are based on the two-state Markov-switching distinctive conditional variance model proposed and estimated in chapter four, in percentages and dollars terms.

It is important to stress that reported one-day VaR values on a specific day are estimates of the possible maximum loss with a certain probability level, thus, the emphasis is on the level of possible drop in freight rate on a specific route for a certain holding period, which is problematic as estimated VaR values in this thesis is for one-day ahead, this problem is overcome by scaling one-day VaR to 30 days, which is the length of FFA contracts. In Table 6.11 one-day estimated VaR for freight returns is reported in percentages (%VaR) and in dollars per ton (VaR), where the following equation is used for conversion.

$$(fr_t^{WS} \times WSFL) \times \%VaR_{t+h}^{\alpha} = VaR_{t+h}^{\alpha} \tag{6.5}$$

fr_t^{WS} is spot freight rate at time *t* in WS and $\%VaR_{t+h}^{\alpha}$ is estimated VaR at time *t*+*h* in percentages with α significance level, and VaR_{t+h}^{α} is converted $\%VaR_{t+h}^{\alpha}$ to dollars per ton. Thus, the one day freight forecast in dollars per ton is calculated as:

$$one - day\ ahead\ freight\ forecast(fr_{t+1}^{\$/ton}) = fr_t^{\$/ton} - VaR_{t+h}^{\alpha} \tag{6.6}$$

On the same note, the one-month freight forecast is calculated as:

$$one - month\ ahead\ freight\ forecast(fr_{t+30}^{\$/ton}) = fr_t^{\$/ton} - \left(VaR_{t+h}^{\alpha} \times \sqrt{30}\right) \tag{6.7}$$

and the possible change in one-day freight forecast is calculated:

$$one - month\ ahead\ freight\ percentage\ forecast\left(\Delta fr_{t+30}^{\frac{\$}{ton}}\right) = \left(fr_{t+30}^{\$/ton} / fr_t^{\$/ton}\right) - 1$$

(6.7)

[23] Averages of value-at-risk reported in table 6.11 represent average VaR for all estimated models for route TD3.

In simple terms the term $VaR_{t+h}^{\alpha} \xrightarrow{yields}$ is the maximum possible loss in money terms (dollars) for each transported tonne of cargo in the next *h* period for a significance level (α).

Table 6.11: Value-at-Risk as an assessment of short-term and long-term freight rate risk

WS Flat Rate	Spot TD3		FFA TD3 June	
11/05/2006	WS	$/ton	WS	$/ton
$15.16	65.8%	$9.98	84.0%	$12.73
11/05/2007	WS	$/ton	WS	$/ton
$17.72	90.0%	$15.95	84.0%	$14.88
11/05/2006	**Normal Value-at-Risk**			
	Average V@R		**2-State-MS-CV**	
	1%	**5%**	**1%**	**5%**
1 Day %V@R	7.29%	4.39%	2.15%	1.52%
1 Day V@R	$0.73	$0.44	$0.21	$0.15
1 Day Fr $/ton	$9.25	$9.54	$9.76	$9.82
30 Day V@R	$3.99	$2.40	$1.17	$0.83
30 Day Fr $/ton	$5.99	$7.58	$8.80	$9.14
% 30 day loss	-40%	-24%	-12%	-8%
11/05/2007	**Normal Value-at-Risk**			
	Average V@R		**2-State-MS-CV**	
	1%	**5%**	**1%**	**5%**
1 Day %V@R	9.81%	5.46%	3.61%	2.55%
1 Day V@R	$1.56	$0.87	$0.58	$0.41
1 Day Fr $/ton	$14.38	$15.08	$15.37	$15.54
30 Day V@R	$8.57	$4.77	$3.15	$2.23
30 Day Fr $/ton	$7.38	$11.18	$12.79	$13.72
% 30 day loss	-54%	-30%	-20%	-14%

Note Table 6.11: presents the use of value-at-risk as an assessment of short-term and long-term freight rate risk. The table consists of three sections, the first part report flat-rate values spot and FFA freight rates for the TD3 route for years 2006 and 2007. The second and third part of the table report one-day value-at-risk in percentages' (%V@R) and dollar per ton (V@R), 30-day value-at-risk in percentages' (%V@R) and dollar per ton (V@R) and a forecast of one-month percentage loss in freight rate, for years 2006 and 2007.

Source: Author's estimations.

In Table 6.11 we report estimates of short-term and long-term freight risk based on one-day and one-month value-at-risk calculations, respectively, for one per cent and five per cent significance levels. The objective of introducing such calculations is to improve market information for shipping practitioners. In simple terms, one-day ahead VaR is estimated on a specific day and compared against a threshold percentage (average

VaR)[24], so that, if calculated VaR[25] is above/below the threshold, the recommendation is that freight rates are likely to drop/increase, thus, the ship practitioner should adjust his risk strategy accordingly. For the purpose of this study, we calculated the following thresholds (value-at-risk averages) 44 per cent, 27 per cent, 16 per cent and 11 per cent, for 1% average VaR, 5% average VaR, 1% 2-state-MS-CV and 5% 2-state-MS-CV, respectively. To put this in perspective, in the 2006 example, forward freight curves, illustrated in Figure 6.17, suggests that freight rates are at the upside, TD3 spot rate is 9.98 dollars per ton and TD3June06 is 12.73 dollars per ton, postulating a contango market condition, this is supported by our low one-day VaR estimates reported in percentages and dollars per ton, for both average VaR and 2-state-MS-CV estimations. In more details, on the 11th of May 2006 the cost of transporting one ton of crude oil on the TD3 route was 9.98[26] dollars per ton and the one-month ahead FFA contract was 12.73 dollars per ton suggesting a bullish market perception, which can been seen as a recommendation to hedge/unhedge using FFAs for charterers/ship-owners. From a different perspective, a risk estimate based on an average VaR measure suggests a maximum drop in freight rate by 3.99 dollars per ton, forecasting a freight rate of 5.99 dollars per ton ($9.98-$3.99) in a 30-day period, with a 99 per cent confidence level. This postulates a 40[27] percent drop in freight rates in a period of 30-days, which is below the threshold of 44 per cent. On the same note, our improved VaR measure based on a two-state Markov-switching conditional-variance framework suggests a maximum drop in freight rate by 1.17 dollars per ton, forecasting a freight rate of 8.80 dollars per ton ($9.98-$1.17) in a 30-day period, with a 99 per cent confidence level. This postulates a 12 percent drop in freight rates in a period of 30-days, which is below the threshold of 16 per cent. For both estimates the forecast is that the maximum possible drop in freight rate for the holding (30-days) period with a certain significance level, is below the threshold. Thus, the recommendation is that freight rates are likely to increase rather than decrease in a month period.

Similarly for the other example, on the 11th of May 2007 the cost of transporting one ton of crude oil on the TD3 route was 15.95 dollars per ton and the one-month ahead FFA contract was 14.88 dollars per ton, suggesting a sluggish market perception,

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[24] For illustration purposes we used an average VaR measure up to the day of the assessment for the estimated model on route TD3. This is different to reported averages of VaR in Table 6.11. The latter is an average risk value for all estimated models on route TD3. This should be investigated further in future research to include different shipping routes and periods.

[25] VaR estimates are reported in positive values in this thesis.

[26] Calculated using equation 6.1.

[27] This is calculated as $((5.99/9.98)-1)\times 100$.

which can been seen as a recommendation to unhedge/hedge using FFAs for charterers/ship-owners. From a different perspective, a risk estimate based on an average VaR measure suggests a maximum drop in freight rate by 8.57 dollars per ton, forecasting a freight rate of 7.38 dollars per ton (\$15.95-\$8.57) in a 30-day period, with a 99 per cent confidence level. This postulates a 54 percent drop in freight rates in a period of 30-days, which is above the threshold of 44 per cent. On the same note, our improved VaR measure based on a two-state Markov-switching conditional-variance framework suggests a maximum drop in freight rate by 3.15 dollars per ton, forecasting a freight rate of 12.79 dollars per ton (\$15.95-\$3.15) in a 30-day period, with a 99 per cent confidence level. This suggests a 20 percent drop in freight rates in a period of 30-days, which is above the threshold of 16 per cent. For both estimates the forecast is that the maximum possible drop in freight rate for the holding (30-days) period with a certain significance level, is above the threshold. Thus, the recommendation is that freight rates are likely to decrease rather than increase in a month period. Furthermore, the underlining empirical work for the improved VaR method (2S-MS-CV), that is presented in chapter four, postulates that during both assessment periods (11^{th}-May-2006 and 2007) freight returns were classified to belong to the lower-volatility-state, where freight rates and volatility levels are generally low, which is an indication of an elastic freight supply, as argued in this thesis.

6.5. Conclusion

In this chapter we recognise the importance of understanding the current implemented practices by shipping practitioners to mitigate and exploit fluctuations in their revenues, through the use of freight derivative markets. Therefore, directional accuracy and volatilities of short- and long-term constructed forward curves are measured across different tanker segments and compared against a general perception in the literature. On the one hand, findings indicate that there is reasonable evidence to support the usefulness of short-term forward curves that are constructed form FFAs as a forecasting tool to manage short-term freight risk. However, the accuracy of such methods is controversial and is down to the implemented techniques, especially in depressed markets when they are much needed. On the other hand, illustrations and analysis for constructed FFAs during the 2008 period clearly indicate the poor performance of FFA long-term forward curves. In other wards, during 2008 period FFA contracts could only be used to forecast spot freight prices for couple of weeks ahead and the accuracy level of such forecasts dependent largely on the size of the underlying vessel. This is due to the recent financial turmoil and clear reflection of the affect of large percentage of trading and finance houses relevant to ship-owners and cargo-owners, which resulted in speculative trading in tanker futures markets.

Furthermore, directional accuracy and volatility levels of short-term and long-term forward curves are examined for 2008, a period of extreme volatility and high FFAs trading levels, where results are in contrast to the general perception in the literature. First, the directional accuracy of short-and long-term forward curves, during the 2008 period, had decreased with time to maturity instead of increasing. Second, volatility levels for sort- and long-term forward curves, during the 2008 period, provide mixed results as they remain extremely high for all contracts. These are in reflection to the turbulence in the derivative market during the financial turmoil. Thus, it is our strong believe that the best way to improve freight risk management is to utilise all available information at the time, this means the need to combine the use of derivative markets and empirical quantitative methods to arrive to a better freight risk assessment.

Therefore, we exploit the empirical work carried out in chapter four in this chapter by estimating short-term and long-term value-at-risk measures for spot freight rates and assess their capabilities to aid shipping practitioners to mitigate risk. Arguably enough, a scaled average value-at-risk estimate combined with forward curve information can be very useful for shipping participants to make a decision regarding their short-term risk strategy. However, a value-at-risk estimate which is based on a framework that accounts for the distinctive nature of freight dynamics, in other words, is capable to adopt to frequent changes in freight rates, when they switch forward and backward between the elastic and inelastic parts of the supply curve, is a much more useful tool for freight risk assessment, that provides a better insight into freight market information. It is our opinion that this framework can be developed further to forecast long-term freight risk across different shipping sectors.

Chapter Seven

7. The Dynamics of tanker freight cycles: The financial crisis case

7.1. Introduction

Few disagree with a matured concept in maritime literature that shipping freight price levels are demand driven by the underlying transported commodity. For the shipping tanker market the main driving force behind freight price changes is changes in global demand levels for crude oil and petroleum products. Moreover, the most recent prolonged strength in oil prices has been attributed in the literature to a structural change in price levels. This if true, can have important implications for tanker freight rates. Therefore, it's of interest to investigate the hypotheses of a significant structural break in tanker freight price levels, that is caused exogenously and whether it is homogenous across all tanker segments, in particular pre and during the most recent financial crisis.

Furthermore, the concept of modelling shipping freight rates using supply and demand models has been widely explored in maritime literature. On the one hand, these models provide useful long-term perspectives for shipping participations. On the other hand, these models are limited in describing the short-run shifts in freight rates. One can argue that the short-run adjustments in tanker freight price levels are mainly caused locally by changes in the availability of tanker services relevant to the required transport levels at one time. While long-run adjustments in tanker freight price levels are mainly caused globally by changes in aggregated demand levels for crude oil and petroleum products in the global economy. This is a further incentive to research the existence of structural breaks within tanker freight market and whether they are caused endogenously or exogenously, respectively. Additionally, a visual inspection of tanker freight price levels across all tanker segments postulate the existence of a significant homogenous structural change post-2000. This is consistent with the idea that the recent strength in the prices of the underlying transported commodity by tanker vessels is better explained by the structural school of thought.

Motivated by the above, a Markov-switching regime framework is employed to investigate a postulate of twofold. First to examine the hypotheses of a significant homogenous structural shift within freight tanker earnings, which is caused by a significant structural change in oil price levels, and had triggered a prolonged period of shipping expansion, referred to in this thesis as the super-boom-cycle. Second to estimate conditional freight limitations, distinguishing between a ship-owner and cargo-owner markets, in particular pre and during the most recent financial crisis. Thus, we investigate freight dynamics within a conditional freight limitation framework, postulating that freight dynamics are better explained through a state dependence structure. This framework consists of three discrete states (s_1, s_2, s_3) that represents (a) a ship-owner's market regime state, characterised by a higher mean and an extreme volatility level, (b) a transitional regime state, characterised by a moderate mean and a volatility level (c) a cargo-owner's market regime state, characterised by a smaller mean and lower volatility level, these are referred to as expansion, transitional and contraction states, respectively. This framework is adequately evaluated and examined. In our opinion this concept of conditional freight limitations is essential to distinguish between a period that is largely controlled by ship-owners and a period that is largely controlled by cargo-owners (charterers) in a perfect competitive environment, which can improve risk management tourniquets for shipping agents. In this thesis the former is referred to as an expansion period while the latter is referred to as a contraction period. Thus, this thesis defines up and down market movements as shipping agent controlled. Moreover, empirical estimates are examined against Alizadeh and Nomikos (2011) definitions of freight dynamics during backwardation and contango market conditions.

This concept of structuring a framework that estimates dynamic freight thresholds can help to improve the performance of the main shipping agents; ship-owners, charterers and shipbrokers, in forecasting and managing freight risk exposure, Thus, fitting well with the rest of thesis. Additionally, this provides us with the foundations to investigate whether the freight risk-return relationship vary, in the next chapter, depending on volatilities changes and market conditions particularly pre and during the most recent shipping economic boom that was ended by the financial crises.

The rest of the chapter is organised as follows. Section 7.2 examines relevant literature. Section 7.3 presents the employed methodological framework. Section 7.4 discusses empirical findings and analyse the reported results. Section 7.5 provides a summery of the chapter. Section 7.6 concludes the chapter.

7.2. Literature review

The literature section is organised as follows. First, we examine relevant research that motivated the work in this chapter, trying to link all the ideas that had influenced the employed framework, in section 7.2.1. Second, we further examine more evidence from the literature that supports investigating the asymmetries of freight rate dynamics within a distinct regime state framework, in section 7.2.2. Third, shipping business cycles in maritime literature is discussed, in section 7.2.3. As the employed framework in this chapter investigates expansions and contractions within an estimated super boom cycle its paramount that we review the relevant literature for shipping business cycles. Fourthly, the controversial issue of stationarity of freight price-levels is examined, in section 7.2.4. Finally, we discuss different structural break tests employed in the literature, in section 7.2.5.

7.2.1. Three blocks

This chapter is motivated by the importance of shipping services being demand driven, the hypothesis of shipping agents influencing expansions and contraction phases and the usefulness of a multi-state Markov regime-switching model in capturing conditional freight limitations. First, the recent strength in tanker freight prices has been attributed to the increase in demand for crude oil and petroleum products by developing economies, in particular India and China. The price dynamics of this energy commodity is influenced by numerous factors such as production, refining, marketing and transportation costs. A report by Poten and Partners[28] a shipbroker, points out that there is clear evidence of the effect of high oil prices in larger tanker segments, for example, in VLCC, Suezmax and Aframax markets, for more details see Poulakidas and Joutz (2009). Researchers attribute this recent prolonged strength in oil prices from 2003 to 2007 to either a structural or a cyclical change, creating an interesting debate between two schools of thoughts, the cyclical school and the structural school. This concept is highlighted in the work of Stevens (2005) where he examines the particulars of the oil market and its influence over the policy structure. He argues that prices in the oil markets has exhibited an upward shift that will last up until 2014, indicating that recent strengths in oil prices are better explained by the structural school of thought. This is crucial for the tanker freight market, as the link between the two industries is well

[28] Poten and Partners (2004), A midsummer night's dream, Report 24, July, New York.

documented in the literature. For example Poulakidas and Joutz (2009) argue a consistency in price increase between tanker freight rates and oil prices. Additionally, numerous researchers find evidence of strong positive correlation between the price of a commodity and its relevant transportation cost. The above motivates us to examine endogenous and exogenous structure breaks within the tanker freight markets. The former being short-run adjustments in freight prices to changes in demand and supply for tanker services, while the latter is the long-run adjustments in freight prices influenced by changes in aggregated demand levels for crude oil and petroleum products in the global economy.

Second, in general, fluctuations in freight price levels in the short-term/long-term for a specific shipping route are dictated by temporarily/prolonged imbalances between the demand for transporting a specific cargo and the supply of available and suitable tonnage at one time. For example Goulielmous and Psifia (2007) define the freight market as a system that can be neither described as stable nor unstable, suggesting that freight markets exhibits short-run (local) randomness linked with a long-run (global) stability. Even though, freight rate levels are demand driven and influenced by micro- and macro-economical variables, the main influence on freight cost in the short run is the immediate availability of vessels to meet demand to transport cargo on a specific rout that causes spicks and slacks in freight price levels. Therefore, in simple terms, we can safely assume that demand for shipping services is driven by cargo-owners, while supply for shipping services is driven by ship-owners; these two counterparts are linked through shipping brokers, thus, equipped with an established network of shipping agents and market intelligence, shipbrokers facilitate an agreement between ship-owners and charterers. Furthermore, it is reasonable to suppose that charterers and ship-owners prefer a lower freight rate and a higher freight rate, respectively. Therefore, assuming shipping agents are profit maximizers, in solely controlled markets by ship-owners, freight rates will be at their highest; while in solely controlled markets by charterers, freight rates will be at their lowest.

Following from above, Tvedt (2011) formulates an interesting theoretical model to derive the freight rate equilibrium. The model suggests the possibility of a unique freight rate for each stable match of tonnage and cargo, using limited market agent properties; shipowner is characterised by the distance of his vessel from the loading area; cargo owner is characterised by the cost of waiting to load cargo; and the broker is characterised by his ambition to maximise expected commissions. Thus, restating the concept that prevailing freight rates are the result of negotiations between ship-owners and charters, most importantly, he expostulate that the compromises between the two parties are restricted by assuming an upper and a lower freight rate limit, these upper and lower freight rates are a result of either the ship-owner solely or the charterer solely setting freight price levels, respectively, this is due to periods of extremely unbalanced supply and demand of shipping services. Based on this argument, a simple empirical way to estimate upper/lower freight limitations is by adding/subtracting the variation (standard deviation) to/from a mean of a time series of a particular shipping freight route, this simple description can be used to account for upper and lower unconditional freight levels. However, to empirically estimate upper and lower freight rate levels during different market conditions, the need to account for market dynamics is paramount. This study recognizes the importance of studying the dynamics of conditional freight limitations, to distinguish between a ship-owner market and a charterer market, thus, proposing an empirical framework that enables shipping practitioners to extract dynamic thresholds from prevailing freight rates. In addition, proposing the use of this method to empirically estimate the dynamic freight restriction described in Tvedt's (2011) theoretical framework. Furthermore, this concept of using dynamic thresholds can improve the performance of the main shipping agents; ship-owners, charterers and shipbrokers, in forecasting and managing freight risk exposure.

Third, in general the modelling of spot freight rates can be classified to belonging to one of two schools of thoughts, either to old school or new school of maritime economics. According to Adland and Strandenes (2007), the increased interest in freight market research has developed these two distinct approaches. First, in the classical literature, freight rates are modelled in the traditional supply/demand equilibrium framework. This approach requires estimating a large number of variables, which is difficult to asses and result in weak econometric relationships. For example see Koopmans (1939); Zannetos (1996); Eriksen and Norman (1976); Beenstock and Vergottis (1989); Evans (1994) and Alizadeh and Talley (2011). Second, disregarding any information that is not embedded in current freight rates and attempting to model the high volatile and stochastic nature of the freight market, prices are modelled directly in a univariate stochastic framework. For example see Bjerksund and Ekern (1995); Tvedt (1997); Adland and Cullinane (2005); and Abouarghoub and Biefang-Frisancho Mariscal (2011). The former is either using statics models of demand and supply or through dynamic econometric models, in either case large number of variables need to be considered, while in the latter external information such as the size and age of the current fleet or activities within second-hand and scrapping markets are ignored. The interest in this chapter as it is in the whole thesis is focused on extracting information embedded in current and past freight rates by stochastically modelling freight rates directly.

Furthermore, the study of asymmetry of business cycles within different markets has been examined in the literature using a variety of linear and nonlinear models, whereby expansion and contraction phases of business cycles are modelled. In the literature a materialized argument is that linear structure is incapable of capturing asymmetries of business cycles in comparison to nonlinear structures, which is flexible and capable of determining different combinations of expansion and contraction periods. For example an early work by Kontolemis (1997) suggests that the economy behaves differently during expansion and recession periods of the business cycle, and later work by Simpson *et al* (2001) attributes the recent interest in using nonlinear models to the capability of these models to distinguishing between expansion and contraction phases within a business cycle, allowing different relationships to apply over these phases. In this chapter we use a Markov-switching regime model that is capable of combining the pros of both methods, capturing different freight earnings averages depending on the prevailing state of the market (regime state). Therefore, allowing the mean of a regression model to differ between contractions and expansions (for example in a two regime state). In addition to estimating the transitional probability of shifting from one regime state to another, capturing different behaviours within market regime states and thus, classifying tanker freights being in recession or boom at the time. Thus, estimating results from a two-state Markov regime-switching model applied to a postulated stationary period of freight earnings will yield averages of freights during expansions and contractions periods along with their volatility ranges and transitional probabilities.

7.2.2. Asymmetries within distinct tanker freight states

An important argument within this chapter is that freight dynamic asymmetry is better captured by a state dependence framework. Thus, assuming that freight earnings, switch between two distinct states; higher freight earning state and lower freight earning state, and that a multi-state Markov regime-switching model is suitable to capture these characteristics, then its reasonable to investigate if the hypotheses of a conditional freight limitations within freight markets is influenced by shipping agents. These expansions (higher earning state) and contractions (lower earning state) are used in our analysis as indications of upward and downward market movements, respectively, and are conditional on markets largely controlled by ship-owners and cargo-owners, respectively. Additionally, we enclose a third-state to distinguish between the previous two distinct states, capturing the trough stage in shipping cycles, and as a base to measure expansions and contractions stages within the super boom cycle.

This chapter investigates the above by embracing the structural school of thought. The justification of this is twofold. First, as discussed earlier, it is an embraced fact in maritime literature that demand for tanker freights is driven by demand for crude oil and petroleum products. Therefore, it is reasonable to assume that any structure changes in the oil market will impact on the tanker freight market, with recent research in oil markets pointing in this direction it’s important to investigate any evidence of structural change within the tanker freight market. For example, Stevens (2005) categorises the recent strength in oil prices to belong to either one of two schools of thoughts, the cyclical school or the structural school, the former indicates that high oil prices are unstable and that they will eventually return to low previous levels, whereas the latter argues that current high oil prices are here to remain due to a permanent (long period) structural price shift, concluding that the evidence suggest the structural school of thought. As the link between the oil market and the tanker freight market is evident, it’s paramount that we investigate the latter for structural change. Second, a visual inspection of tanker freight price levels across all tanker segments clearly indicates the existence of a significant homogenous structural change post-2000. This is consistent with Stevens (2005) conclusion that the recent strength in the prices of the underlying transported commodity by tanker vessels is better explained by the structural school of thought.

Furthermore, our analysis of freight dynamics is based on assuming that freight earnings switch between distinct regime states influenced by shipping agents. In a more recent theoretical study, Tvedt (2011) argues through a hypothetical framework that short-run freight equilibrium can be derived based on limited market indicators. His rational is based on three main market agents; the cargo-owner (charterer), the ship-owner and the shipbroker, and consists of an assignment model based on two sided matching theory (see Roth and Sotomayor, 1992a, 1992b) and a description of the shipbroker behaviour. On the one hand, demand (cargo) and supply (tonnage) are characterised by the charterer's time preference and the ship-owner's vessel's distance from the loading area, respectively. On the other hand, shipbrokers are characterised by their ambition to maximise their commission. Most importantly, he suggests a set of equilibriums (set of stable matches of tonnage to cargo) by restricting freight rates to a maximum upper freight rate level and a minimum lower freight rate level, based on the concept of who has the upper hand in negotiations; the ship-owner or the cargo-owner, respectively. Moreover, Tvedt argues that a shipbroker's perception of the market and incentive to maximise commission can be used to assign a unique freight rate to each match of cargo to tonnage.

Furthermore, modelling of the US business cycle using a discrete-state Markov process to account for structure change, by Hamilton (1989) and thereafter an extended version by Hamilton and Susmel (1994) inspired research of a wide range of variations of the topic within financial and economic literature. Thus, the popularity of switching regime models is well documented in the literature, see Angelidis and Benos (2004) and references within. Timmermann (2000) argues that 2-state Markov regime-switching models are better equipped in describing financial markets rather than non-switching ones, due to the non-zero skewness embraced by switching regime means, and the better capture of excess kurtosis by regime volatilities. Perez-Quiros and Timmermann (2001) find that mixture models outperform single state models in predicting third and fourth moments. Doornik and Hendry (2009a) argue that estimating different means along with their dynamic behaviour better describe a series, highlighting the possibility of a third state to better capture these dynamics.

Moreover, empirical results are examined against the characteristics of backwardated and contango markets. Alizadeh and Nomikos (2011) start their study with the suggestion that spot and time-charter shipping rates are related through the expectations hypothesis of the term structure. For more details see Kavussanos and Alizadeh (2002a). Based on this argument, they assume that time-charter rates are in fact a form of forward freight rates, arguing that term structures in freight markets is defined better by being in a backwardation or contango states[29]. Thus, they construct

[29] Contango and Backwardation describe the shape of the forward curve. Contango is a condition where forward prices exceed spot prices, so the forward curve is upward sloping. Backwardation is the opposite condition, where spot prices exceed forward prices, and the forward curve slopes downward. In oil markets, the prevailing condition may reflect immediate supply and demand. If crude oil prices are in contango, this may indicate immediately available supply. Backwardation can

multiple forward freight curves at different points in time by comparing spot and time charter rates with different durations, to study backwardations and contango terms. They investigate the relationship between the dynamics of these term structures and time-varying volatility of shipping freights rates using an EGARCH-X framework, stating that the importance of an accurate volatility measure for measuring VaR applications and risk management is the motivation for their study.

Furthermore, as the framework is built on two important assumptions. The assumption of stationarity and the significance of the structural-breaks identified within, we review in the next subsection the relevant literature for shipping cycles, stationarity and structural-breaks.

indicate an immediate shortage. For example a potential war tends to drive the oil market into backwardation.

7.2.3. Shipping market cycles

Martin Stopford (2009) identifies three typical shipping cycles. The first type is a long term cycle with an average of 60 years. According to Stopford the behaviour of freight rates in the long term are driven by technology development and social and political changes, his analysis is based on the early work of Braudel, (1982). The second type is a short term cycle or business cycle, with an average duration of between three and twelve years from peak to peak, these cycles are superimposed on the long term trend, this phenomenon is best explained by the periodicity theory, using Overstones's phases that are used to identify different stages in modern shipping cycles, were cycles are of unequal length, for more details see Schumpeter (1954). The final type is the seasonal cycle, which occurs within the year, for example, regular fluctuations in tanker freight rates during the year caused by stocking up of oil for periods of peak demand in the winter period. Kirkaldy (1914) defines shipping cycles as a succession of prosperous and lean periods, which play an important roll in separating winners from losers, several lean years, are followed by a series of prosperous years, thus, suggesting that the interaction of demand and supply in addition to the development of ocean transport, have shaped the fluctuating prosperity of the shipping industry. Nerlove *et al* (1995), argue that markets cycles are unique phenomena that should be analysed using decomposition techniques. Cournot (1927) stresses the importance of distinguishing between long term and short term (business cycles) trends. The main focus in this chapter is to analyse expansion and contraction phases within the second type, the shipping business cycles. Thus, this study identifies a supper boom cycle post-2000 and investigates freight dynamics within it.

According to Martin Stopford shipping business cycle consists of four stages, a trough stage, followed by a recovery stage, leading to a peak stage, followed by stage of collapse. He suggests that this consists of a trade boom accompanied with a short shipping boom during which there is over ordering of new builds, followed by a prolonged slump. Thus, he views shipping market cycles with a Darwinian purpose, creating an environment in which weak shipping companies are forced out and strong ones survive and prosper, creating efficient shipping markets, Stopford (2009).

Fayle (1933) suggested that booms and busts of the world economy combined with random events trigger the build up of shipping cycles and that a short boom is usually followed by a prolonged slump, pointing out that shortage of ships cause high freight rates attracting new investors, this leads to an increase in shipping capacity. Therefore, tramp shipping is characterised by wide fluctuations in demand for freight, speculator ship-owners and disproportion between supply and demand. Cufley (1972) argues that because of the uncertainty within cycles, forecasting freight rates are an impossible task and that underlying trends might be more predictable. While, Hampton (1991) suggests that shipping markets are influenced by the way investors behave and that they do not act rationally causing over reaction of markets to price signals. In respect of shipping cycles, Kirkaldy focused on competition within ship-owners, while Fayle was more concerned with the mechanism of the cycle.

Stopford defines risk in the context of shipping cycles as the "*measurable liability for any financial loss arising from unforeseen imbalances between the supply and demand for sea transport*", Stopford (2009, p.101). Thus, ship-owners and cargo owners are on the opposite sides of the shipping risk distribution, suggesting that the main risk takers in the shipping industry are equity holders and that adjustment of supply and demand is mainly influenced by cargo holders. He concludes by pointing out the importance of studying the effect of freight volatility on shipping cycles as shipping cycles lie at the hearth of shipping risk, Stopford (2009).

Stopford (2009) inspected 266 years of freight rates, distinguishing between insignificant fluctuations and major peaks and troughs, leading him to identify 22 cycles with an unconditional average of 10.4-years, arguing that average shipping cycles had dropped from 14.9-years to 8-years during the last 3 centuries. In his analysis shipping cycles are measured from peak to peak, with a trough phase in between, these visual identified major peaks are confirmed by shipping brokers' reports. Relevant to this study, he identifies two 5-year periods from 1998 to 2002 and from 2003 to 2007 representing a trough phase and an expansion phase, respectively. Moreover, he names the period from 1947 to 2007 as the bulk era[30], arguing that during this era 8 cycles had occurred, with only two cycles that can be identified as long cycles with periods of 14-year and 15-year, taking place from 1956 to 1969 and from 1988 to 2002, respectively, with the remaining 6 cycles averaging 5 years. During these cycles averages of peaks and troughs were of 3 years and 5 years, respectively. Thus, indicating that favourable times in shipping are short lasting in comparison to hard times. In a comparison with

[30] For more details see Stopford (2009, Table 3, p.106).

this chapter analysis, we postulate that a shipping cycle consists of two distinct phases separated by a transitional phase, an expansion phase and a contraction phase. Looking at Stopford's analysis of shipping cycles, his recovery stage and peak stage can be seen as our expansion phase and his collapse stage as our contraction phase, while the troughs stage in his analysis is our transitional state. We will show that the trough phase is a crucial stage, not only it indicates when good times had ended and that bad times had started, it is the period of slack in freight rates where the management and operation of vessels is most crucial, as margins are tight and employment is scars. The more efficient the management of operations during this period the more impact it has in contraction periods, where employment is scarcer and option of either laying-up or scrapping of vessels is considered.

Stopford's technical approach is a simple one in comparison to Goulielmos (2009 and 2010) that applies Chaos theory to maritime economics using a non-parametric rescaled analysis and V-statistic to examine and measure shipping cycles. Primarily rechecking the validity of the theory of random-walk in shipping, Goulielmos concludes that the index of dry cargo freight rates, for a sample from 1998-2008 does not follow a random-walk process. Moreover, he measures the duration of short shipping cycle forecasting the end of the cycle using a non-linear method. He argues that Stopford was specific with the main developments in shipping identifying economies of scale due to technology, without explaining the causes of the cycles. For example, two identified long cycles by Stopford from 1869 to 1914 and from 1945 to 1995 are explained by steam vessels replacing sail vessels and development in cargo-handling technology in bulk and linear shipping, respectively. Moreover, Goulielmos (2009 and 2010) investigates, the Bulk era identified by Stopford, by examining dry cargo freights for a sample from 1947 to 2007 and concludes that shipping cycle durations are a mix of 10-year and 20-year periods. Hence he forecasts that the shipping markets will recover from the 2006 crisis around 2016 or 2026. Similar to Goulielmos we apply a non-linear framework based on a multi-state Markov-switching regime model to analyse freight rates asymmetries during distinct markets. Even though there is an attempt to estimate the length of the most recent shipping cycle, referred to in this study as a super boom cycle, the main objective of our framework is to characterise different market condition through their corresponding market states (lower earning state, transitional-state and higher earning state). In other words, investigate freight sensitivity to market dynamics.

From a practical perspective Randers and Göluke (2007) argue that they have been successful in forecasting turning points in freight rates and market sentiment in shipping markets 1-4 years ahead of time, providing a useful perspective for global shipping markets. Their forecasting framework is based on a postulate that freight rates are influenced by two dominant balancing feedback loops; a fleet utilization adjustment loop and a capacity (fleet size) adjustment loop, arguing that long-term cycles are determined endogenously. Thus, their dynamic hypothesis is constructed around the postulate that a 4-year cycle (capacity utilization) is superimposed on a longer cycle of 20-years (capacity adjustment). The short cycle is mainly influenced by ship-owners utilizing their current fleet according to prevailing market conditions at the time, these are management decisions regarding their fleet, such as vessel speed adjustment, part-loading or full-loading and laying-up or not. While the long cycle is a result of an excess in the order-book of new built in good times, in contrast to fewer orders in bad time. Therefore, they argue that an endogenous short business cycle of 4-years characterise the shipping market in contrast to the more general view that transport demand is the main force behind shipping business cycles. Whereas, Taylor (1976, 1982) assumes that freight rates are determined exogenously through random effects and global wars independent of supply and demand. Furthermore, they view the shipping market as one entity, their argument is twofold. Firstly, they argue that the strong degree of substitutability of cargos among different tanker routes, explains the strong positive correlation in freights among all segments. Secondly, they suggest that shipping finance providers are indifferent to specific trade or route, generating a market sentiment influencing freight levels.

Goulielmos and Psifia (2006 and 2007) argue that time-charter and spot dry cargo freight rates are not random as they find evidence of long-term memory and non-linear dependence. Thus, their findings are aligned with maritime literature that freight rates are not identically and independently distributed (iid), for example Kavussanos and Alizadeh (2002b). Thus, a general consent that shipping cycles are not symmetrical prevails, as argued by Goulielmos (2009), in affiliation with the early work of Koopmans (1939).

Stopford's shipping market model for forecasting demand and supply activities within shipping markets can be found in Stopford (2009). While a traditional econometric method for modelling shipping freight rates can be found in Wijnolst and Wergeland (1997). Stopford (2009) argues that the decline in world trade that trailed the great crash of 1929 plunged the shipping industry into a major depression until 1937, following similar analysis; he identifies a boom period from 2003 to 2007 that was triggered by the global boom derived by China's increased demand of energy and raw material, Stopford (2009).

In summary, a general argument that a long term 20-year and a short term 4-year for average durations of shipping business, for long term and short term, respectively, prevails in maritime empirical literature. In addition, empirical and technical studies agree that these averages seam to decrease with time creating the uniqueness of each shipping cycle.

The argument of Randers and Göluke (2007) is of interest to us, especially for the tanker segment, as they argue that shipping markets are characterised endogenously through adjustments in fleet capacity and utilization and suggest that the shipping market is one entity, with practitioners indifferent between specific routes. Therefore, they argue that an endogenous short business cycle of 4-years characterises the shipping market in contrast to the view that transport demand is the main force behind shipping business cycles. On the one hand, in this chapter we examine the evidence of a single homogenous structural shift within tanker markets especially during the two identified periods in the literature from 1998 to 2002 and from 2003 to 2007. On the other hand, our framework examines if this is caused exogenously or endogenously. Furthermore, it is clear that freight markets exhibit clear clusters and that understanding shipping cycles is important in improving vessels performances and operations. In other wards, understanding shipping cycles will improve techniques of managing freight risk.

7.2.4. Stationarity of freight rates

The shipping industry consists of four main markets that integrate together prevailing perfect competitive freight market conditions. A more used phrase in many maritime economics studies is that freight markets in bulk shipping are usually held as textbook examples of perfectly competitive markets, for example see Adland and strandens (2007). This phrase has been used as early as Norman (1979) and is based on an extensive study conducted by Zannetos (1966) that showed that oil markets are highly concentrated and is perfectly competitive. These findings remain valid to this day despite the dramatic changes of the seventies, Dimitrios and Zacharioudakis (2012).

Details can be found in Norman, (1979) and Stopford, (2009). The latter uses a demand and supply model to analyse freight market cycles and to explain the mechanisms which determine freight rates. From an economic perspective he views each shipping cycle as being unique.

In the shipping sector sea transport is traded in freight markets with spot and derivative markets being subdivisions, where activities within these markets influence demand and supply of vessels in second-hand and new-build markets, with the latter exhibiting a time lag in the speed of adjusting to excess in demand for transport, due to delays between orders and delivers of vessels. This causes high persistence of freight rates, more details can be found in Adland and Cullinane (2006). Therefore, perfect competitive conditions in shipping markets imply that freight rates below operating levels coincide with oversupply of vessels and that high freight coincide with undersupply of vessels. Oversupply and undersupply of the number of employed vessels is adjusted to equilibrium through activities within the scrap and new-build markets, respectively. Furthermore, freight price level is determined through the interaction of demand and supply of shipping services, when freight rates are at low (unemployed) levels, supply of freight is very elastic, this becomes very inelastic at high (employed) freight levels, in addition, if freight earnings are below breakeven levels the owner has the option of laying-up or scrapping his vessel. Freight elasticity is extensively discussed in Koopmans (1939), Zannetos, (1966), Devanney, (1973) and Norman and Wergeland, (1981).

Most importantly, perfect competitive conditions prevail in shipping freight markets, where freight rates are considered to revert to a long run mean. This concept is widely accepted in maritime literature, for more details see; (Zannetos, 1966; Strandenes, 1984; Tvedt, 1997; Adland and Cullinane, 2005; Koekebakker, S. *et al* 2006). Thus, according to maritime economic *theory* freight prices cannot exhibit an explosive behaviour implied by a non-stationary process. By contrast, most maritime *empirical* studies conclude that freight rates are non-stationary. Koekebakker, S. *et al* (2006) argue that these findings are due to the weak power of the statistical tests, while, Adland and Cullinane (2006) explain the difficulties in rejecting a non-stationary hypothesis, and conclude that the spot freight rate process is globally mean reverting as implied by economic theory, and over all stationary. Furthermore, Goulielmos and Psifia (2007) investigate weather voyage (spot) and time charter freight rates are normally distributed and nonlinear dependence, employing the (BDS) test developed by

Brock, Dechert and Scheinkman, (Brock *et al* 1987), where they conclude that freight indices are not random and identically and independently distributed, in addition to being nonlinear dependence. Thus, pointing out the unsuitability of linear and traditional models to model freight distributions and capture dynamics within freight data.

7.2.5. Structural change and testing for structural breaks

Badillo, D. *et al* (1999) argue that endogenous structural break tests are superior to exogenous tests in identifying turning points (structural breaks) in commodity price cycles. Their argument is based on investigating the distortions that can occur in identifying structural trends and breaks in international commodity prices when employing exogenous in comparison to endogenous break tests. They conclude that an endogenous approach better determines the timing within commodity prices cycles and also the leads and lags between commodity prices cycles and leading macroeconomic variables. For example they found that the impact of the 1973 and 1978 oil crisis are better pronounced in commodity prices by using endogenous break tests and that this provides a better perspective of the influence of commodity prices on inflation and related policy adjustments. They examine monthly prices for twenty different international commodity markets, including crude oil prices, where they study the superiority of endogenous test over exogenous test in identifying structural trends and breaks in commodity prices series', their conclusion emphasize the importance of endogenous break selection. Thus, if structural breaks exist within freight rates and can be determined endogenously, will be strong evidence of freight rates fluctuating around a mean rather than follow an explosive behaviour.

In the literature there are numerous tests for the stationarity of time series with and with out structural breaks. Perron (1989) argues that the Dickey-Fuller procedure is biased in accepting the null hypothesis of a unit root for a time series with structural breaks and that this biased is more pronounced as the magnitude of the break increases. Perron (1989) developed a procedure to test a time series with a one-time structural break for the presence of unit root. Perron argues that most macroeconomic variables appear to be trend stationary coupled with structural breaks, suggesting that most of these variables experienced a one time fall in the mean caused by an exogenous shock after the 1929 financial crisis and a slow down in growth after the 1973 oil crisis.

Therefore, his framework allows a single change in the intercept of the trend function after 1929 and a single change in the slop of the trend function after 1973. Perron's analysis is based on the assumption of only one break point occurring in a time series and the choice of this break point is based on the smallest t-statistic among all possible break points, for testing the null hypothesis of a unit root. In other words, these tests results do not rollout the possible existing of more than one breakpoint, they just point out the most significant of all. Furthermore, suggesting that Dickey-Fuller framework is not adequate to test for unit root in the presence of structural breaks and that the test statistics are biased towards the non-rejection of a non-stationary, Perron (1989)[31].

One shortcoming of Perron's procedure is that the test is based on a known time-break; this is a serious drawback as the point of structural break in most studies is the point of investigation, as it is in this thesis. Improving on his previous work, Perron modifies his unit root test to test for an unknown structural break, Perron (1997). This improved procedure to test a time series for unit root in the presence of one unknown structural break does not rollout the presence of more than one structural break. Therefore, this test in our analysis is used to investigate the most significant structural shift in a time series.

[31] Peron (1989) test is a modified version of the dickey fuller test for unit root, with a single known break. The null hypothesis of a unit root is different to the DF as it includes dummy variables and the alternative hypothesis is a broken-trend stationary. In other words, this is a unit root process with a one time jump in the level of the sequence, while under the alternative hypothesis the series is trend stationary with a one time jump in the intercept. Perron (1997) test is similar to the previous structural apart from the jump, which is unknown. Thus, the date for the break point is estimated within the test rather than a required input in the previous test.

7.3. Methodological framework

In this thesis the investigation of the dynamics of tanker freight earnings and returns before and during the financial crisis is discussed in two chapters, 7 and 8, respectively. The former inspects freight earning level-prices[32] and consists of four stages; while the latter inspects freight earning returns and consists of two stages. This is illustrated in diagram 7.1.

The framework in this chapter is of four stages. Stage one examines the stationarity of the data[33]. This is vital as the further three stages depend on the postulate that freight earnings (level-prices) are satisfactorily conditional stationary. Stage 2, part one, a multi-state Markov-switching regime model is implemented to inspect and estimate the asymmetry in the dynamics of tanker freight earnings pre and post-2000, and to inspect the homogeneity of an observed structural shift in freight earnings post-2000 across tanker segments. In this chapter we investigate the possibility of these structural breaks being consistent across all tanker segments and hence are exogenously caused in line with the recent literature. Additionally, we attempt to empirically estimate the start of this global freight shift that coincides with the most recent shipping boom. In stage 2, part two, a three-state Markov-switching regime model is implemented after we have identified an exogenous structural-break for all five data sets, with three-state parameters, to capture endogenous structural-breaks (turning points) and to provide a framework to identify expansion and contraction phases within this super boom cycle. This is to estimate conditional freight limitations to distinguish between a ship-owner and cargo-owner markets. In stage three, the significance of these structural-breaks is examined through exogenous and endogenous tests. In stage four, expansions and contractions phases are constructed based on an assumption of a conditional freight limitation framework, influenced by shipping agents.

In summary the use of a Markov-switching regime model is motivated by the postulate of freight rates switching between two distinct earning states, which differ in their dynamics. A ship-owner's market characterised by higher freight and volatility levels and a cargo-owner market characterised by lower freight rates and volatilities levels. Furthermore, the inclusion of a third state identified as a transitional state, aims

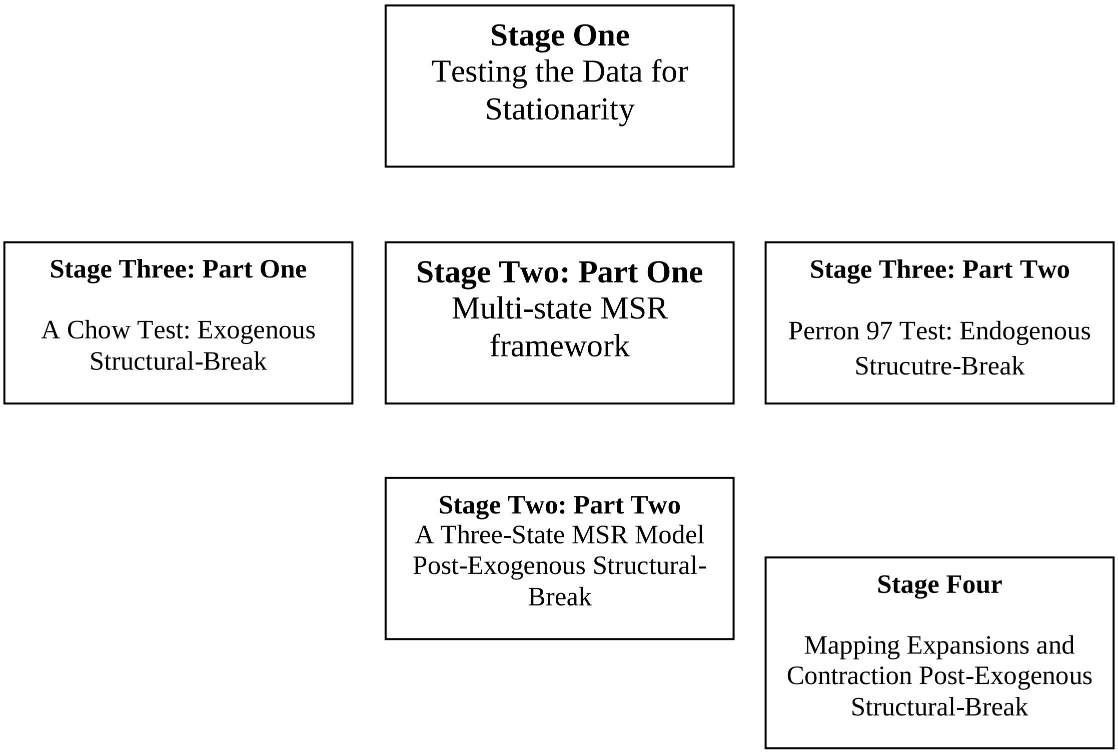
[32] In this chapter freight rates that we examine is a measure of daily earnings for ship-owners in the relevant tanker sector. In an attempt to distinguish between the data examined in this chapter and the rest of the thesis we use the term freight earnings. These daily freight earnings are examined in their price levels form in this chapter and in their returns form in the next chapter.

[33] In this chapter we examine stationarity of freight level prices not freight returns as the latter is well examined in chapter 8.

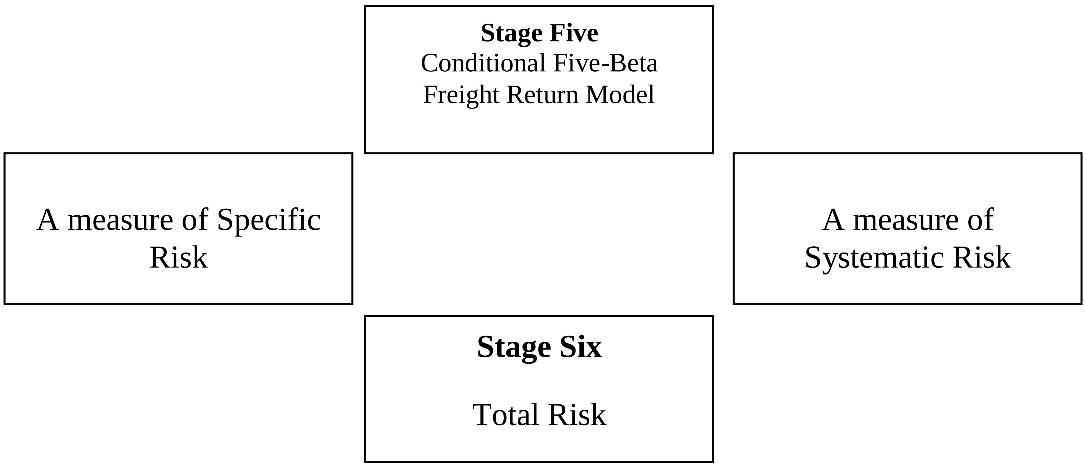
to capture the slack period in freight rates between the two markets, known in maritime literature as the trough stage (a phase of a shipping cycle). Thus, this transitional state is used as a base for measuring phases (from trough to trough) and to distinguish between expansions and contraction for the post-exogenous structural-break period. This four-stage framework is explained in more details in the following sections.

Diagram 7.1: An illustration of the applied framework in chapters 7 and 8

<u>Chapter 7: Freight Level-Price</u>



<u>Chapter 8: Freight Returns</u>



Note diagram 7.1: illustration is divided to two parts, one part maps steps applied to freight earning price-levels and the second part maps steps applied to freight earning returns, see text above. **Source:** Author.

7.3.1. First stage: examining the stationarity of freight earnings

A Markov-switching framework requires the stationarity of the variables used. Therefore, testing freight earnings for unit-root is of importance. An augmented Dickey-Fuller (ADF) test for linear unit-root against linear stationarity is provided by a *t*-statistic for an estimated β in:

$$\Delta f_t = \alpha + d_t + \beta_0 f_{t-1} + \sum_{i=1}^{k} \beta_i \Delta f_{t-i} + u_t \quad (7.1)$$

This is a one-tailed *t*-test, such that the null hypothesis is $H_0: \beta_0 = 0$ and the alternative null is $H_1: \beta_0 < 0$. Where f_t refers to tanker freight earnings (price-level) at time *t*, Δ symbol is the lag operator so that $\Delta f_t = f_t - f_{t-1}$, α is a constant, d_t is a drift and u_t is white noise. The ADF test is determent by computing the *t*-statistic, $t_{stat} = \beta_0 / Se_{\beta_0}$. The purpose of additional lags *k* is to reduce autocorrelation within the residuals. Where β_0 coefficient is estimated by OLS and *Se* refers to the estimated standard deviation. The selection of the appropriate lag length is based on a minimization of the Schwartz information criterion. Critical values are derived from the response surfaces in MacKinnon (1991). Unconditional, reported results in the empirical section support the stationarity of tanker spot freight rates, aligned with maritime economic theory. The results can be found in section 7.4.5, Table 7.3.

7.3.2. Second stage: a multi-state Markov-switching framework

Markov-switching models were originally introduced by Hamilton (1988, 1989) and since then, there have been used in a wide range of contributions, including Engle and Hamilton (1990), Hamilton and Susmel (1994), Hamilton and Lin (1996), and Gray (1996). These models introduce state dependence within their estimated variables, allowing the mean and variance to differ between expansions and contractions, capturing market dynamics, upward and downward movements. For a recent overview of regime switching models see Teräsvirta (2006). The use of such a framework in our analysis was motivated by inspecting a simple plot of the data, where a significant jump in the mean and volatility of tanker earning levels is visible post-2000, across all tanker segments. Implementing this procedure across different tanker segments examines the homogeneity of a significant structural break and the asymmetry of freight earnings dynamics pre and post-2000. Moreover, this framework is used to investigate the hypothesis of sate dependence within freight earnings, by capturing expansions and contractions phases within the super boom cycle, which distinguishes between the dynamics of a ship-owner's and a cargo-owner's markets, respectively. Therefore, our multi-state Markov-switching regime framework is twofold.

7.3.2.1. Investigating the postulate of a homogenous exogenous shift within the data

First, we apply the following regime switching model for the full data sample, empirically capturing the observed exogenous structural-break, identifying empirically the start of the shipping boom that coincides with the most recent prolonged economical trade boom. This is expressed as:

$$\begin{bmatrix} Regime1: y_t = \mu_1 + \epsilon_{1t} & \epsilon_{1t} \sim N[0, \sigma_1^2] \\ Regime2: y_t = \mu_2 + \epsilon_{2t} & \epsilon_{2t} \sim N[0, \sigma_2^2] \\ Regime3: y_t = \mu_3 + \epsilon_{3t} & \epsilon_{3t} \sim N[0, \sigma_3^2] \end{bmatrix} \quad (7.2)$$

Where the specification within each estimated state is linear and the resulting time-series model is non-linear. Moreover, regimes are arbitrary and the mean can be expressed as a function of s_t:

$$\mu(s_t) = \begin{bmatrix} \mu_1 \text{ } if \text{ } s_t = 1 & (Low\ earning\ State\ Pre - ExSB) \\ \mu_2 \text{ } if \text{ } s_t = 2 & (High\ earning\ State\ Pre - ExSB) \\ \mu_3 \text{ } if \text{ } s_t = 3 & (Boom\ shift\ Post - ExSB) \end{bmatrix} \quad (7.3)$$

where *ExSB* represents the estimated exogenous structural-break and the unobserved random variable s_t follows a Markov chain, defined by transition probabilities between the *N* states:

$$p_{i|j} = P[s_{t+1} = i | s_t = j] \qquad i,j = 0,1, \ldots N-1. \quad (7.4)$$

The probability of moving from state *j* in one period to state *j* in the next depends only on the previous state, where the system sums to unity such that; $\sum_{i=0}^{N-1} p_{i|j} = 1$and the full matrix of transition probabilities is $P = (p_{i|j})$. An exception is made for Suezmax segment where we find that a four regime is more appropriate, the additional state is identified as a transitional period between the low and high earning states pre-2000. The results are discussed in section 7.4.6, Table 7.4 and illustrated in Figures 7.3, 7.4, 7.5 and 7.6.

7.3.2.2. Identifying turning-points post-exogenous structural break (during the shipping super boom-period)

Second, we examine the post exogenous-break period with a three-state Markov-switching regime model. Trials of several MSR models have been undertaken by the author with numerous states, the choice of a tree-state prevails empirically. This is expressed as:

$$\begin{bmatrix} Regime4: y_{t+PExSB} = \mu_4 + \epsilon_{4t} & \epsilon_{4t} \sim N[0, \sigma_4^2] \\ Regime5: y_{t+PExSB} = \mu_5 + \epsilon_{5t} & \epsilon_{5t} \sim N[0, \sigma_5^2] \\ Regime6: y_{t+PExSB} = \mu_6 + \epsilon_{6t} & \epsilon_{6t} \sim N[0, \sigma_6^2] \end{bmatrix} \tag{7.5}$$

where *PExSB* is post the exogenous structural-break of 2000 and the mean is expressed as a function of s_t:

$$\mu(s_t) = \begin{bmatrix} \mu_4 \; if \; s_t = 4 & (Contraction\ State) \\ \mu_5 \; if \; s_t = 5 & (Transitional\ State) \\ \mu_6 \; if \; s_t = 6 & (Expansion\ State) \end{bmatrix} \tag{7.6}$$

This section postulates that a multi-state Markov-switching regime framework is useful for testing the hypothesis of consistent and significant structural shifts within freight earnings, across different tanker segments. Assuming that freight level earnings are stationary and do fluctuate between two distinct regime states, lower freight earning state and higher freight earning state, we carryout a three-state MSR analysis on four different tanker segments. The inclusion of a third state aims to distinguish between the two distinct states. The results are discussed in section 7.4.8, Table 7.5 and illustrated in Figure 7.7.

In summary, this approach identifies a consistent and clear departure in the dynamics of freight earning post the second quarter of the year 2000, for all tanker markets. Furthermore, findings indicate three significant impacts on tanker earnings post-2000 causing structural breaks that are consistent across all tanker segments. These coincide with an increase in shipping finance innovation and developments in the shipping industry, a global boom in trade and the financial crisis, respectively. The significance of these structural-breaks is tested in the following subsection.

7.3.3. Third stage: investigating and testing the significance of structural breaks within freight earnings

A multi-state Markov-switching regime framework is implemented to test the hypothesis of consistent and significant structural shift, in freight earnings, across different tanker segments, a more detailed methodology is provided in the methodology chapter.

Assuming that freight level earnings are stationary and do fluctuate between two distinct regime states, lower and higher earning state regimes, we carryout a three-state MSR analysis on four different tanker segments. The inclusion of a third state aims to capture any significant structural shift in earning levels. This approach identifies a consistent and clear departure in the dynamics of freight earnings after the second quarter of the year 2000, for all tanker markets. Therefore, a Chow (1960) test is implemented to examine the significance of such structural breaks.

The applied model in earlier stage empirically identifies exogenous structural-breaks for all tanker freight segments within the data sample under investigation. These time-breaks are used to split each time series to two time-periods, pre- and post-2000 boom-period. The most resent economical boom. A Chow (1960) test is implemented to examine the significance of such structural breaks. Thus, we estimate three regressions as following:

Pre-2000 $$y_t = \alpha_1 + b_1 y_{t-1} + \varepsilon_{1t} \quad where \ \ (t = 1,2, \dots, T_{bp}) \tag{7.7}$$

Post-2000 $$y_t = \alpha_2 + b_2 y_{t-1} + \varepsilon_{2t} \quad where \ \ (t = T_{bp} + 1, \dots, T) \tag{7.8}$$

Full sample $$y_t = \alpha + b y_{t-1} + \varepsilon_t \quad where \ \ (t = 1,2, \dots, T) \tag{7.9}$$

The final regression assumes no change in the intercept and slope coefficient, contrary to the previous two. By estimating the above we obtain the unrestricted sum of squares, which is computed as following: $RSS_{UR} = RSS_1 + RSS_2 \ with \ df = (n_1 + n_2 - 2k)$. A Chow test tests the null hypotheses of no structural change against the alternative of a structural change, by computing an *f* ratio, that follows an *F* distribution with *k* and $(n_1 + n_2 - 2k)$degrees of freedom in the following form:

$$F = \frac{(RSS_R - RSS_{UR})/k}{RSS_{UR}/(n_1 + n_2 - 2k)} \sim F_{[k,(n_1 + n_2 - 2k)]} \tag{7.10}$$

where:

RSS_R is restricted residual sum of squares obtained by estimating 7.9.

RSS_{UR} is unrestricted residual sum of squares obtained by estimating 7.7 and 7.8.

k is number of parameters estimated.

$n_1$is number of observations used in regression 7.7.

$n_2$is number of observations used in regression 7.8.

$T_{bp}$is the time of the estimated structural-break point.

T is the last observation in the sample.

The test is concluded by comparing the computed value of the *f* ratio with the critical values from the *F* tables. The null hypothesis of parameter stability is rejected if the formal exceeds the latter at the chosen level of significance. There are two drawbacks associated with this test. The first one, is that this procedure is build on the assumption that the break point is known, the second one, is that the errors variances in the examined two-periods are the same. The former is overcome by estimating the time-break empirically, while the later is tested by the following *f* test:

$$F = \frac{\hat{\sigma}_1^2}{\hat{\sigma}_2^2} \sim F_{(n_1-k),(n_2-k)} \tag{7.11}$$

where:

$\hat{\sigma}_1^2$ is the unbiased estimator of the variance for regression 7.7 and is computes as:

$$\hat{\sigma}_1^2 = \frac{RSS_1}{n_1 - k} \tag{7.12}$$

$\hat{\sigma}_2^2$ is the unbiased estimator of the variance for regression 7.8 and is computes as:

$$\hat{\sigma}_2^2 = \frac{RSS_2}{n_2 - k} \tag{7.13}$$

The above ratio follows the *F* distribution with $(n_1 - k)$ and $(n_2 - k)$degrees of freedom in the numerator and denominator, respectively. By convention the larger estimated variance is always in the numerator. The null hypothesis of consistent variance is rejected if the value of the computed *f* ratio is larger than the value of the critical value at the chosen significance level. The rejection of the previous test can be used as an indication of the unsuitability of the Chow test for the sample data. We find a distinctive structural shift in freight earnings, referred to in this study as a super boom-cycle. The results can be found in section 7.4.5, Table 7.3.

Furthermore, Perron (1997) test in our analysis is used to investigate the most significant structural shift in a time series. The optimal break date T_b is chosen by minimizing the *t*-statistic for testing $\beta_0 = 1$, in the following regression:

$$\Delta f_t = \alpha + \theta DU_t + \delta D(T_b)_t + \beta d_t + \gamma DT_t + \beta_0 f_{t-1} + \sum_{i=1}^{k} \beta_i \Delta f_{t-i} + u_t \qquad (7.14)$$

where both a change in intercept and the slop is allowed at time T_b. The test is performed using the *t*-statistic for the null hypothesis that $\beta_0 = 1$ and include dummy variables that take value of one as; $D(T_b)_t = 1$ if $t = (T_b + 1)$, $DU_t = 1$ if $(t > T_b)$ and $DT_t = 1$ if $(t > T_b)t$. The number of lags for *k* is selected on a general to specific recursive procedure based on the t-statistic on the coefficient associated with the last lag in the estimated autoregression, for details see, Perron (1997).

Testing freight earnings for significant structural breaks by implement the above test on the whole sample identifying the most significant break point in the series, this revels a significant upward structural shift in earning levels that is consistent across all tanker routes. Therefore, we repeat the procedure starting from the identified time break to investigate the boom period for any structural breaks.

In other wards, a Perron (1997) unknown endogenous time break test is carried out on the identified boom-cycle and once a time break has been identified another test is carried out starting from this point. Findings indicate three significant events had a significant impact on tanker earnings causing structural breaks that are consistent across all tanker segments. These coincide with an increase in shipping finance innovation and developments in the shipping industry, a global boom in trade and the financial crisis, respectively. The results can be found in section 7.4.5, Table 7.3.

7.3.4. Fourth stage: identifying expansions and contractions within the boom period

A three-state Markov switching regime framework is used to identify expansions and contractions periods within the ten year boom-cycle. Even though freight markets exhibit extreme volatility levels, the transition between a low and high occurs through a third state. This is confirmed with a zero or low value for the transitional probability between the two regimes, this is a clear indication that using a transitional state is valid. This can be vital for making management decisions in regards of comparing types of charter contract and the use of derivatives for reducing risk exposure. This approach identifies eight periods of expansions and contractions within the super-boom cycle. These phases are used to analyse and study the relationship between returns and volatilities during expansion and contraction freight markets. The results can be found in section 7.4.8, Tables 7.6 and 7.7 and are illustrated in Figures 7.8, 7.9 and 7.10.

7.4. Empirical findings

In this section we present empirical analysis and findings, starting with the impact of oil seaborne trade on tanker freight prices. Furthermore, we describe and statistically analyse the data sample used in this chapter, in doing so, we express freight earnings in multiple regime states pre and post a significant structural shift, in regards to different market forces derived by shipping agents.

7.4.1. Oil seaborne trade

Shipping is the main medium for transporting the majority of world traded goods, with nearly 90 per cent of global trade transported safely and cleanly by shipping means (IMO).[34] This is an industry that is famed for its peaks and troughs, but a sudden increase/decrease in the movement of raw materials like iron ore is used as a proxy of the state of the global economy in the medium and long term. In June 2008 an index that tracks the average cost of hiring ships to shift raw materials such as iron ore, coal and grains across the globe, the Baltic Dry Index (BDI), collapsed falling by more than 90 per cent, in response to the financial crisis. This decline is an acknowledgement of the global economy slowing down, more details can be found in Alizadeh and Nomikos (2011). The effects on the shipping industry were profound and transparent in the increased numbers, of unemployed ships (laid-up), cancelled ship-building contracts and letter of credit refusals.

Furthermore, Oil seaborne trade represents 95 per cent of the global oil movement and consists of two main sub-trades; crude oil and oil products, these liquid cargos are transported on special vessels referred to as tankers. In general terms large tankers are associated with transporting crude oil and smaller vessels are associated with transporting oil products such as; kerosene and gasoline known as clean product trade, while dirty product trade refers to transporting lower distillates and residual oil. For example average daily earning's for a VLCC vessel in March 2000 was 29,778 dollars before rising to 86,139 dollars by December, for a 45 day voyage, earning a ship-owner an excess of 2.5 million dollars in December compared to March of the same year. In terms of our analysis, these earnings belong to distinct regime states, a VLCC employed in March would have been operating in a low earning state designated with low volatility levels, a daily earning average of 22,000 dollars and a fluctuation possibility

[34] International Maritime Organization. www.imo.org.

of around 6000 dollars. While a VLCC employed in December would have been operating in a high earning state designated with high volatility levels, a daily earning average of 63,000 dollars and a fluctuation possibility of around 31,000 dollars.

Moreover, a study of the impact of oil prices spikes on tanker freight rates by Poulakidas and Joutz (2009), find that the spot tanker market is influenced by the intertemporal relationship between current and future crude oil prices, thus, arguing that an increase in tanker freight price levels is consistent with an increase in oil price levels, excluding seasonal periods of low tanker demand due to refinery maintenance. This is in line with the empirical works of Mayr and Tamvakis (1999) where they find that the increase in demand for imported crude oil increases the demand for sea transportation leading to higher freight rate levels, and Alizadeh and Nomikos (2004) also conclude that a long-run relationship between freight rates and oil prices exist. This is consistent with an embraced fact in maritime economics literature that demands for tanker service is derived by the demand for crude oil and petroleum products. Therefore, it is reasonable to deduce that in the above studies a common ground is that part of the volatility within the tanker market is due to changes in oil prices, promoting the idea of a spillover effect and suggesting the existence of exogenous structural breaks within tanker freight rates along with endogenous structural breaks influenced by global and local adjustments in demand and supply, in the underline commodity and in freight services, respectively.

7.4.2. The data section

In this subsection we describe the data sample used in this chapter and briefly describe time charter equivalents rates relevant to voyage charter and time charter contracts.

7.4.2.1. Describing the data

The main source for the data used in this chapter is Clarkson intelligence network; this is weekly average earnings for different tanker segments, referred to as time charter equivalents (TCE) and measured in dollars per day. This is calculated by Clarkson to be easily comparable to time charter rates, in contrast to worldscale (daily) values used in the value-at-risk chapter of this thesis, they also provide better insight into freight earnings as bunker and voyage costs (not operation and fixed costs, such as wages and loans) is excluded from these measures. Therefore, in this chapter, freight price levels are referred to simultaneously as freight rate earnings, a study of freight price levels not returns.

Furthermore, Clarkson started reporting TCE rates from1990 by collecting freight quotes from different sources on the day and reporting the calculated average prevailing freight price. This represent level of earnings for a particular tanker route on the day in dollars terms excluding any voyage cost, in other words, it's the cost of hiring that particular tanker for a day, hence, the term TCE. With new enforced safety regulations, such as a requirement for all tankers to have double bottoms, and with countries such the US clearing only modern vessels to entre their ports, old tankers where phased out. Therefore, Clarkson started in 1997 reporting another series that represents modern tankers, and with numbers of old tankers decreasing in comparison to new built, the new series is better representative of current freights. Thus we roll over between the two series to obtain a longer comprehensive sample and a better time-line representative of freight earnings.

7.4.2.2. Time charter equivalents (TCE)

In the shipping industry the cost of transporting a specified amount of cargo between any two ports is known as the freight rate price and is expressed in either dollars per day or dollars per metric tonne (US dollars /mt). The former expression of freight rate refers to the daily cost of hiring a vessel, and is used to calculate trip-charter and time-charter rates, due to exclusion of voyage costs, while the latter expression of freight rate refers to the cost of transporting one tonne of cargo from A to B, and is used to calculate voyage-charter (spot) rates. In simple terms, the main difference between the two expressions is that a spot freight rate includes voyage costs, which is the shipowner's responsibility and is estimated in the freight quote. Thus, a time-charter quote represents net freight earnings for a shipowner. Therefore, shipping agents tend to calculate a time-charter-equivalents (TCE) for voyage charter contracts to easily compare different opportunities within the spot market and the time-charter markets. The TCE, for a spot fixture that is quoted in dollars per tonne, is calculated for a particular voyage by deducting total voyage costs[35] from the lamp sum of total freight payment (dollars/tonne

[35] Voyage costs include port charges, canal dues and bunker costs, more details can be found in Alizadeh and Nomikos (2009).

× amount of cargo transported) and then divided by the estimated number of days for a round trip for this particular route, in which the resulting value is a TCE of a spot freight rate expressed in dollars per day.

In contrast to the dry market, tanker voyage (spot) rates are negotiated and reported in Worldscale.[36] This is examined in more detail in the value-at-risk chapter, For more details of payments methods, duration and allocation of different costs and responsibilities to counterparties under different contracts see Alizadeh and Nomikos (2009). Moreover, the Clarkson intelligence network[37], known throughout the maritime world as a comprehensive and reliable information provider, calculates a TCE for weekly tanker spot freight rates that can be comparable to time charter rates and is considered to be accurate estimates of tankers net earnings in the spot market and has formed the bases of recent empirical work within maritime literature, for example Koekebakker *et al* (2006), Adland and Cullinane (2006) and Alizadeh and Nomikos (2011).

7.4.3. Basic analysis

The analysis of this chapter is based on a constructed data set that represent spot freight rates for four tanker segments and also a series representing the unconditional tanker freight market. These series' are average time-charter-equivalent (TCE)[38], a measure of freight earnings in dollars per day, representing the cost of the daily hire of a vessel excluding voyage costs such as bunker cost. This data set was provided by Clarkson intelligence network for four tanker segments; VLCC, Suezmax, Aframax and Panamax, in addition, to the weighted average tanker earning index representing the overall earnings for tanker vessels, in this chapter, the overall tanker market is referred to as the unconditional tanker sector. In addition, two sets that represent one-year and three-year time charter contracts are used to construct forward curves. These contracts are agreements to hire a vessel for a specific period normally six, twelve and thirty six months and similar to TCE they represent daily freight earnings excluding voyage costs.

[36] Worldwide Tanker Nominal Freight Scale: the worldscale association in London calculates the cost (break-even) of performing a round trip voyage between any two ports. Based on a standard vessel specification, calculations for transportation costs include assumption for bunker prices, port disbursements, canal dues and other fixed costs. Freight prices are measured in US dollars per metric ton, for each route, which is referred to as the flat rate.

[37] http://www.clarksons.net/sin2010/

[38] For details of calculation of TCE and the associated assumptions see Sources and Methods document at shipping intelligence network website, www.clarksons.net

In other wards, these contracts are quoted in dollars per day and designate pure freight earnings as ship-owners are responsible for only the fixed costs, such as maintenance, management and financial liabilities, excluding variable costs such as bunker costs, which are considered to be the main cost in shipping operations.

The data sample under investigation starts from May 5, 1990 through December 31, 2010. Clarkson network provide two time series' that represent average earnings for three tanker segments that reflect freight earnings, for vessels built in early nineties and another for modern vessels. Therefore, in this study the data sample starts with average 1990 tankers series and than is rolled over to modern tanker series to obtain a longer and more comprehensive time series'. This constructed data set for three segments better represents freight earnings during the last 20 years as most vessels that were built in the nineties are phased out and most employed vessels are of the modern type, these vessels are more efficient, reliable and comply with the International Maritime Organisation (IMO) safety and environment regulations. The different tanker segments investigated in this chapter and the data spam used is reported in Table 7.1.

Table 7.1: Rollover points for the constructed data set

	Average Earnings Built 1990/91	Average Earnings Modern
VLCC	05/01/1990 to 27/12/1996	03/01/1997 to 31/12/2010
Suezmax	05/01/1990 to 27/12/1996	03/01/1997 to 31/12/2010
Aframax	05/01/1990 to 27/12/1996	03/01/1997 to 31/12/2010
Panamax	Dirty Products 50K Average Earnings	
WATE	Weighted Average Earnings All Tankers	

Note Table 7.1: illustrates the rollover points between the two sets for three segments to provide the series used in this study. The four tanker sizes represent the different tanker segments. In addition, to a waited average tanker earning series that represents the overall tanker sector earnings.

Source: Author.

Basic statistics reported in Table 7.2 for TCE spot freight earnings clearly indicate a positive correlation between the size of tanker vessels and their four statistic moments, the larger the size of the tanker vessel the higher the daily mean earnings, and their volatility levels and excess returns. Excess freight volatility is evident in the wide spread between minimum, mean and maximum values for freight price-level earnings.

All routes show signs of positive skewness, high kurtosis and departure from normality represented by the Jarque-Bera. There is also clear evidence of ARCH effects in freight price-levels and returns, with different lag levels, Engle's ARCH (1982).

Table 7.2: Basic statistics for segments of tanker freight prices

Freight Price Level Earnings 05-01-1990 to 31-12-2010 (1096 observations)					
Segments	VLCC $/Day	Suezmax $/Day	Aframax $/Day	Product $/Day	WAT $/Day
Minimun	$8,785	$6,535	$8,625	$3,577	$6,861
Mean	$42,596	$32,178	$28,939	$20,823	$22,621
Maximum	$229,480	$155,120	$126,140	$76,703	$81,999
Std Dev	$31,410	$23,323	$18,599	$13,206	$12,987
Skewness	2.3074 (31.23)**	1.8697 (25.31)**	1.8264 (24.72)**	1.4759 (19.97)**	1.441 (19.50)**
Excess Kurtosis	7.471 (50.60)**	4.140 (28.04)**	4.078 (27.62)**	2.112 (14.30)**	2.016 (13.66)**
ARCH (1-2)	3177.3 [0.00]	2685.9 [0.00]	6027.9 [0.00]	9469.5 [0.00]	11112 [0.00]
ARCH (1-5)	1373.3 [0.00]	1070.3 [0.00]	2411.5 [0.00]	3788.2 [0.00]	4508.5 [0.00]
ARCH (1-10)	691.19 [0.00]	577.21 [0.00]	1240.2 [0.00]	1909.8 [0.00]	2310.8 [0.00]
ARCH (1-20)	346.04 [0.00]	291.04 [0.00]	629.08 [0.00]	986.45 [0.00]	1192.5 [0.00]
Normality Test	3521.4 [0.00]	1421.4 [0.00]	1368.7 [0.00]	601.5 [0.00]	564.90 [0.00]

Note Table 7.2: represents summary of basic statistics of price-level earnings for weekly shipping freight rates, for four tanker segments. Total observations are 1096 for freight price-levels. It is clear from minimum, maximum and standard deviation of freight prices the large spread and high volatility in freight prices. All routes show signs of positive skewness, high kurtosis and departure from normality represented by the Jarque-Bera test, the 5% critical value for this statistic is 5.99. Values ( ) are t-statistics, and ** represent significance level at 1%. Values in [ ] are p values, which are significance for all routes. Engle's ARCH (1982) test is used to examine the presence of ARCH effects in freight series, with 2,5,10 and 20 Lags.

Source: Author’s estimations.

7.4.4. Time charter rates and forward curves

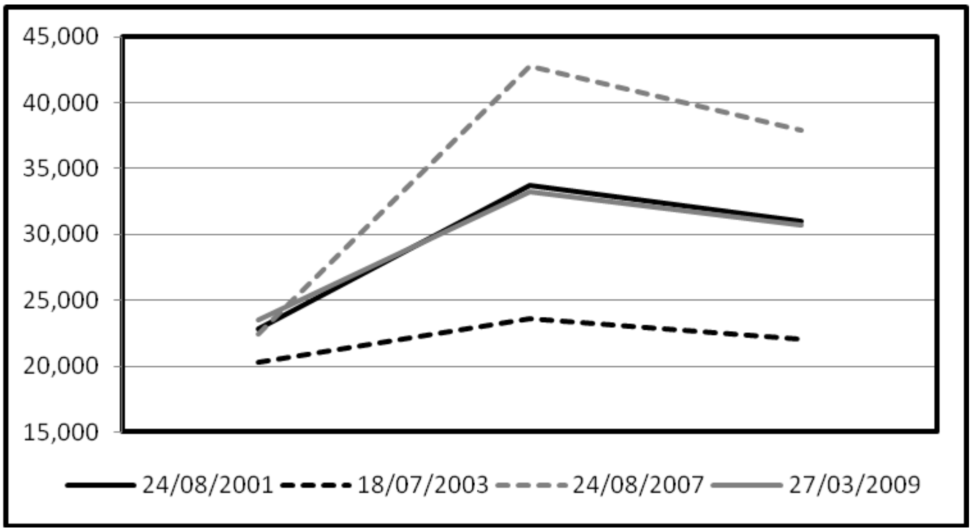
On the one hand, both voyage-charter and trip-charter freight rates are spot contracts, although they differ in their methods of payments and costs allocations, where the former is quoted in dollars per tonne and the latter is quoted in dollars per day. On the other hand, time-charter freight rates are period (forward) contracts and cover more than one voyage, with voyage costs excluded from freight costs and are quoted in dollars per day. Thus, a quoted time-charter rate represents a shipowner’s daily freight earnings for a specified period of time, and is perceived as the current market expectations of short and long term futures spot prices. For more details on different freight rate contracts and their specification see Alizadeh and Nomikos (2009). Moreover, a time-charter contract is an agreement between a ship-owner and a charter, where the latter agrees to hire a vessel from the former for a specified period of time and under certain conditions defined in a charter-party, agreeing a daily freight rate price in dollars. The period of a time-charter contract can be any thing from couple of weeks to several years, the most popular time-charter contracts are 6-months, 1-year and 3-years. These contracts are used by Alizadeh and Nomikos (2011) to construct freight forward curves, to identify contango and backwardation market conditions, where they conclude that when spot rates are above long term time-charter rates (backwardation), volatility is higher compared to periods when spot rates are lower than long term time-charter rates (contango). Therefore, the freight forward market can be used to asses' the changes in freight dynamics in relation to different market conditions. Additionally, the price of a financial forward contract and the underlying physical commodity is related through forces of demand and supply, where the former reflects the current market expectation of the future spot price of the latter, as argued by Edwards and Ma (1992). For extensive detail of price discovery within the freight market using forward curves see Alizadeh and Nomikos (2009).

Therefore, due to the importance of freight dynamics, a number of studies embarked on modelling the dynamic behaviour of shipping freight rate volatility and assessing their forecasting ability. Most of these studies failed to examine the dynamic changes in freight rates during different market conditions, for example; Kavussanos (1996); Glen and Rogers (1997); Kavussanos and Alizadeh (2002a); Alizadeh and Nomikos (2011); Alizadeh and Nomikos (2007); and Angelidis and Skiadopoulos (2008). This deficiency is identified in the work of Alizadeh and Nomikos (2011) where they investigate the asymmetric behaviour of freight-rate volatility in relation to market conditions, by including a cubic function of the slop of the forward curve in their conditional variance (EGARCH-X) framework, thus, capturing freight volatility dynamics in relation to the market being in contango or backwardation. They estimate the slop of the forward curve as the difference between the short (one-year) and long-term (three-year) time-charter rates. Thus, arguing that the slop of the forward curve is in fact an error correction mechanism that explains changes in freight rates through changes in its magnitude and sign.

In the current application we embrace this concept of using forward curves to assess freight dynamics during the super boom cycle in relation to markets being in contango and normal backwardation conditions and comparing this in relation to the estimated conditional freight earning limitations in this chapter. Therefore, forward curves are constructed based on estimated periods of contractions and expansions during the super boom cycle, to represent markets in contango and normal backwardation conditions, respectively.

For example Figures 7.1 and 7.2 illustrate market expectations of future freight rates based on forward covers constructed by connecting a spot rate with a one-year and a three-year time charterer rates, for contractions and expansions periods, respectively, within our estimated super boom cycle. For example, in the first graph the forward curve starting at 24 August 2001 illustrates market expectation of future prevailing rates at this date, indicating that spot rates are at discount to short term (one-year) and long term (three-year), a market condition that is known as contango. Following the same principle, in the second graph the forward curve starting at 13 December 2002 illustrate market expectation of future prevailing rates at this date, indicating that spot rates are at premium to short term (one-year) and long term (three-year), a market condition that is known as backwardation.

Figure 7.1: constructed forward curves in contraction periods during the super boom cycle

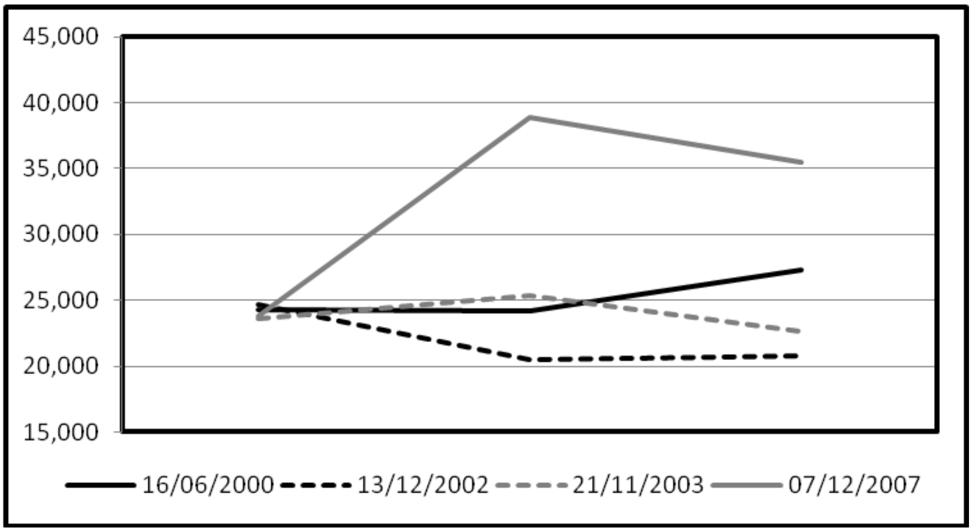


Note Figure 7.1: illustrates constructed freight forward curves in contraction periods, for the unconditional tanker market (WATE) highlighted in the final section of Table 7.7. This is constructed by joining spot, one-year and three-year freight rates to construct a freight forward curve. The date is the starting date of a specific period. The vertical axes represent freight rates in dollars per day and horizontal axes represent the starting date for each constructed forward curve.

Source: Author's estimations.

The above is an illustration of a plot of four constructed forward curves during our estimated contraction periods within the super boom period, for the unconditional tanker market described in Table 7.7 in the final section and denoted by even numbered phases. Each forward curve is constructed of three turning points; spot freight rates; one-year time charter rates and three-year time charter rates. The values of these freight rates and time charter rates are represented in the vertical access in dollars per day. Thus, a presentation of the market anticipation of expected future spot freight prices in the short and long term. Following the same token, the below Figure is an illustration of a plot of four constructed forward curves during our estimated expansion periods.

Figure 7.2: constructed forward curves in expansion periods during the super boom cycle



Note Figure 7.2: illustrate constructed freight forward curves in expansion periods. This is constructed by joining spot, one-year and three-year freight rates to construct a freight forward curve. The date is the starting date of a specific period. The vertical axes represent freight rates in dollars per day and horizontal axes represent the starting date for each constructed forward curve.

Source: Author's estimations.

7.4.5. Significance tests results

This subsection examines outputs of stationary and structural break tests. These tests investigate the issue of stationarity and the significance of a homogenous structural break within freight earning price levels for the tanker sector. The results are reported in Table 7.3 and based on multiple tests explained in the methodology section 7.3.1 and 7.3.3. The table reports five tests results subsequently, for the five data sets under investigation, which represents earnings for four different tanker segments and a waited average earning for the whole tanker sector.

The first part reports obtained results from a Chow test and an Equal variance test; the results are highly significant, identifying a homogenous structural break within tankers earnings. These tests require an input to split the sample to two periods; this time-break is estimated by a Markov switching regime model, for each time series and is in aligns with a homogenous structural break identified by a visual inspection of all time series plots. The second and third part reports ADF unit-root tests with only a constant and with both constant and trend, respectively. The appropriate numbers of lags were chosen based on minimizing the Schwartz information criterion and the estimated statistics are compared to critical values derived from the response surfaces in MacKinnon (1991). The forth and final part report results of two Perron (1997) unit-root tests with unknown endogenous time break. The first test is applied to the full sample, thus identifying the most significant time-break and, while the second test is applied to part of the sample, starting from the first identified time-break. The appropriate number of lags is chosen based on Perron's general to specific recursive procedure.

The objective of undertaking the Chow test for a single known structural break is to examine the hypotheses of a significant structural shift in tanker freight earnings during the second quarter of 2000. The results are consistent and significant across all tanker segments, in other words these structural shifts are significant breaks and are homogenous. The only exception is the waited average earning series, as this represents an average of all earnings in the tanker sector. This is aligned with the equal variance tests which indicate that pre and post boom periods are distinct periods. In our analysis we refer to the period post this distinct structural break as the super boom-cycle that coincided with the most recent world economical boom. As for examining stationarity, a Unit-Root test indicates that a unit root hypotheses are rejected at 5 per cent significant level for all tanker routes. These results are easily improved with the Perron (1997) unit root test that takes in account one unknown endogenous break. Implementing the test to two subsamples indicate that freight earnings are conditional stationary. In other words our findings strongly indicate that freight earning price-levels are unconditional stationary aligned with maritime economical theory and recent empirical work, in contrast with earlier empirical work. For more detailed discussion of stationarity of freight earnings see Koekebakker *et al* (2006).

Furthermore, Perron's test is another way to investigate the most significant structural break for the whole sample, as this is a one break test that does not rollout the possibility of more than one structural break. Results of the latter test point out that for all segments there are two distinct structural breaks around the 4th quarter of 2003 and the 4th quarter of 2007, coinciding with the shipping economical boom and the recent financial crisis, respectively.

Table 7.3: Unit-root and structural-breaks tests for tanker freight earnings

Test	VLCC	Suezmax	Aframax	Product 50k	WATE
A Chow Test for a Single known (Based on a MSR framework) Significant Structure Break					
Total Obss	1096	1096	1096	1096	1096
Chow T	F(2,1092)= 4.33 [0.0133]	F(2,1092)= 6.34 [0.0018]	F(2,1092)= 3.51 [0.030]	F(2,1092)= 3.91 [0.020]	F(2,1092)= 2.24 [0.106]
Equal Var T	F(555,537)= 20.88 [0.000]	F(548,544)= 21.75 [0.000]	F(553,539)= 25.25 [0.000]	F(551,541)= 9.48 [0.000]	F(549,543)= 12.02 [0.000]
Break Date	05/05/2000	23/06/2000	19/05/2000	02/06/2000	16/06/2000
Time Break	540	547	542	544	546
ADF Unit-Root Test with only a Constant					
ADF(Lags)	-5.161**(5)	-3.439*(16)	-3.250*(19)	-3.081*(17)	-3.220*(20)
AIC	18.237	17.781	16.617	15.689	15.344
BIC	18.27	17.865	16.715	15.777	15.446
HQ	18.25	17.813	16.654	15.722	15.383
Unit-Root Critical Values 5% =-2.86* 1% =-3.44** MacKinnon (1991)					
ADF Unit-Root Test with a Constant & Trend					
ADF(Lags)	-5.934**(5)	-4.276**(16)	-4.103**(20)	-3.792*(17)	-3.887*(20)
AIC	18.231	17.777	16.614	15.686	15.342
BIC	18.269	17.865	16.654	15.779	15.448
HQ	18.245	17.81	16.654	15.721	15.382
Unit-Root Critical Values 5% =-3.42* 1% =-3.97** MacKinnon (1991)					
A Unit-Root Test with an Unknown Endogenous Time Break Perron (1997) Examining the sample 5/01/1990-31/12/2010					
ADF-TB(Lags)	0.91106 (-6.654)** (5)	0.90243 (-6.5851)** (8)	0.93235 (-6.4371)** (10)	0.92188 (-8.3056)** (2)	0.95072 (-5.9258)** (11)
Break Date	10/10/2003	26/09/2003	26/09/2003	31/10/2003	17/10/2003
Time Break(1)	719	717	717	722	720
Unit-Root-TB Critical Values 5% =-5.08* 1% =-5.57**					
A Unit-Root Test with an Unknown Endogenous Time Break Perron (1997) Examining the sample From the Time-Break(1) to the End of the Sample					
ADF-TB(Lags)	0.85058 (-6.4549)** (3)	0.82062 (-5.3527)* (8)	0.87327 (-5.4493)* (8)	0.88627 (-6.1191)** (1)	0.91230 (-5.5429)* (3)
Break Date	07/12/2007	09/11/2007	02/11/2007	26/12/2008	23/11/2007
Time Break(2)	936	932	931	991	934
Unit-Root-TB Critical Values 5% =-5.08* 1% =-5.57**					

Note Table 7.3: represents in four parts a summary of structural-breaks and Unit-Root tests statistics for weekly price-level earnings for tanker shipping freight rates, this represents four tanker segments. The first part: illustrate chow and equal variance tests with known time-breaks, this time-break and date-break is based on the starting of the boom cycle for each segment, indicated by the output of the MSR model. The second and third parts: illustrates outputs of ADF tests with constant and constant & trend, respectively. The final part; illustrate Perron (1997) Unit-Root procedure with unknown time-break. * and ** represents significance level at 5% and 1%, respectively.
Source: Author's estimations.

7.4.6. Structural breaks and volatility levels in freight price-level earnings

Implementing a multi-state Markov-switching-regime framework on four different segments of the tanker market, clearly indicate that earnings within the tanker market generally switch between two distinct sates; a low earning state (cargo-owner market) and a high earning state (ship-owner market), these states exhibit low and high fluctuations in their earnings, respectively. Our empirical results and analysis of the conditional freight limitations pre-2000, reported in Table 8.4, for example, show that daily average freight earnings within the VLCC sector, during contractions (cargo-owners markets) and expansions (ship-owners market), are around 18,300 dollars per day and 33,200 dollars per day, respectively, and the level of departure from these earnings are 3,800 dollars per day and 5,500 dollars per day, respectively. Put into perspective daily earnings for a VLCC tanker can fluctuate between 14,500 dollars per day and 38,700 dollars per day, this is an excess/deficiency of 24,000 dollars per day depending on prevailing market conditions, referred to in this study as regime earning state. As for a product vessel, daily earnings for a Panamax fluctuate between just fewer than 8,000 dollars per day and 18,700 dollars per day with an excess/deficiency of 10,000 dollars per day. On average daily earning in the tanker segment increase/decrease by nearly 100 per cent when market freight conditions shift from a low/high regime state to a high/low regime state. Averages and volatilities of freight price-levels are consistent with basic statistics findings and maritime literature, in regards to their positively correlation with vessels size, with larger tanker vessels exhibiting higher freight earnings and volatilities in comparison to smaller tankers, which is consistent across all regime states. This finding is aligned with maritime economic theory, stating that while demand for shipping services is inelastic, the supply of shipping services is highly elastic when freight rates are at low levels and highly inelastic when freight rates are at high levels due to the restricted supply of shipping services in the short time. Thus, on the one hand, low freight earnings accompanied by low volatilities are explained by excess of shipping services in comparison to demand, hence, low freight rates due to efficient shipping markets, causing low steaming of vessels to save on fuel costs and an increase in the number of vessels exiting the markets by taking either the option of layup (that can not be maintained for a long time, especially for ships financed by expensive loans) or exiting through the scrapping market. On the other hand, high freight earnings accompanied by high volatilities are explained by deficient shipping services in comparison to demand, and market conditions are characterised by fast steaming, short ballast hauls and an increase in new built orders.

Moreover, there is a distinct and consistent shift in the structures and volatilities of freight earnings for all tanker freight level prices, which had occurred at the second quarter of the year 2000, this coincided with the boom period that had lasted on average for 550 weeks. This is a homogenous structural shift for the tanker markets and the results indicate that tanker freight average daily earnings and volatilities levels had shifted from 18000 dollars per day to 38000 dollars per day, from 2400 dollars per day to 11000 dollars per day, respectively. This is an increase in freight earnings and its volatilities for all tanker segments of more than 100 per cent and 350 per cent, respectively. Furthermore, the segment sector is an important influence on the magnitude of these shifts which is clearly positively correlated with the size of tanker vessels. In summery, tanker freight earnings pre the boom-cycle from 1990 to 2000, is better captured by a distinct two state regimes, while post-2000 homogenous structural shift, a more volatile distinct structural is appropriate. This is explored further by applying the same framework to the boom period to capture these different characteristic.

Estimated results from a multi-state Markov switching regime model applied to conditional and unconditional tanker freight earnings are statistically significant and reported in Table 7.3. Setting the scene to investigate the possibility of conditional freight earnings limitations under distinct market forces, these market conditions are assumed to be shipping agent controlled by, either solo cargo-owners or solo ship-owners. The columns in Table 7.3 from left to right correspond to conditional tanker segments (tanker sizes), from largest to smaller sector, subsequently, the last column (WATE) correspond to freight earnings for the unconditional (overall) tanker sector, this is a waited average tanker earning index, calculated by Clarkson intelligence network to mimic earnings within the tanker sector, in other words, WATE rates correspond to earnings for a shipping company that operates a portfolio of vessels that consists of all tanker segments. For all tanker segments exclusion of the Suezmax segment, regimes 1, 2 and 3 represent market states denoting cargo-owner market, ship-owner market and super boom cycle, respectively, and volatility regimes 1, 2, 3 define dispersion within each regime state (market condition), respectively. As for the Suezmax segments, empirical trails indicated that a four regime state is better suited to represent distinct freight earning states for these vessels.

The probability of switching from one market state to another is expressed in Table 7.3 by the transition probability π_{ij} where i,j={1,2,3 and 4}, a value of zero for a transitional probability indicates the disconnection between the two relevant states, this is evident to the importance of an intermediate state between the two, while a value of 1.0 (100 per cent) indicate the nonexistence of the probability of switching between the relevant two states, which is evident to a permanent structural shift in freight earning dynamics.

Furthermore, the final section of Table 7.3 reports, for each regime state, the average percentage weight relevant to the whole sample and the average duration in weeks (resilience) before shifting to another regime state, donated by avg weight regime 1, 2, 3 and 4 and avg duration regime 1, 2, 3 and 4, respectively. Thus, postulating a significant departure in freight dynamics post-2000 with 50 per cent of our data sample representing a super boom cycle characterised as an extreme volatile period in comparison to the pre-2000 period and that the resilience of freight earnings within cargo-owners markets are higher than within ship-owners markets.

In summary, based on the last twenty years (full data sample), tanker freight earning levels exhibit a strong tendency to remain in a high/low earning regime state relevant to switching back and forth between the two distinct states. Furthermore, there is obscurity of freight earning levels switching from the low earning state to the super boom cycle directly without an intermediary state. Most importantly, there is strong evidence of changes in freight earnings dynamics post-2000, expressed by a significant structural break, for all tanker segments and illustrated in Figures 7.3, 7.4, 7.5 and 7.6, and exemplified by an estimated 100 per cent transitional probability of freight earnings post-2000, a strong tendency to remain in the super boom period, this is reported in Table 7.3 and denoted by π_{33}, for VLCC, Aframax, Product and WATE tanker segments, and by π_{44} for the Suezmax tanker segment.

Table 7.4: Markov-switching conditional variance regime models estimations for weekly tanker freight earnings

	VLCC	Suezmax	Aframax	Product 50k	WATE
Regime 1 MWP	18347.4 (90.8)†	13091.2 (84.1)†	14183.3 (70.6)†	9812.17 (56.5)†	11769.8 (44.8)†
Regime 2 MWP	33226.4 (154.0)†	19440.4 (85.4)†	22576.6 (97.6)†	16325.5 (80.2)†	18147.0 (47.7)†
Regime 3 MWP	76121.2 (69.8)†	30669.8 (127.0)†	50000.6 (60.4)†	36307.7 (91.7)†	37922.2 (49.5)†
Regime 4 MWP		65508.8 (85.1)†			
Volatility Regime 1	3810.98 (21.8)†	2486.81 (21.0)†	2235.54 (13.4†)	1841.82 (12.7)†	1916.50 (20.5)†
Volatility Regime 2	5531.26 (31.7)†	1800.71 (19.6)†	3425.15 (19.6)†	2430.30 (24.0)†	2389.45 (11.3)†
Volatility Regime 3	33337.8 (297.0)†	5494.32 (46.0)†	17834.9 (69.8)†	11484.1	11132.0 (71.0)†
Volatility Regime 4		22280.3 (77.0)†			
Transition $\pi 11$	0.959711 (72.9)†	0.947027 (53.6)†	0.976462 (103.0)†	0.969859 (90.3)†	0.976579 (108.0)†
Transition $\pi 22$	0.959126 (73.8)†	0.907758 (42.0)†	0.969323 (78.2)†	0.960465 (76.4)†	0.967851 (83.4)†
Transition $\pi 33$	1.0	0.934066 (35.3)†	1.0	1.0	1.0
Transition $\pi 44$		1.0			
Transition $\pi 12$	0.040289	0.052973	0.023538	0.030141	0.023421
Transition $\pi 13$	0	0	0	0	0
Transition $\pi 14$		0			
Transition $\pi 21$	0.0373000 (2.99)†	0.0588513 (3.3)†	0.0267289 (2.3)*	0.0355206 (2.9)†	0.0281118 (2.59)†
Transition $\pi 23$	0.0035743	0.033391	0.0039484	0.004014	0.0040373
Transition $\pi 24$		0			
Transition $\pi 31$	0	0	0	0	0
Transition $\pi 32$	0	0.0565277 (2.3)*	0	0	0
Transition $\pi 34$		0.0094068			
Transition $\pi 41$		0			
Transition $\pi 42$		0			
Transition $\pi 43$		0			
Avg Weight Regime 1	23.72%	21.53%	26.46%	26.64%	27.28%
Avg Duration Regime 1	23.64 Weeks	21.45Weeks	48.33 Weeks	32.44 Weeks	42.71 Weeks
Avg Weight Regime 2	25.46%	18.80%	22.90%	22.90%	22.45%
Avg Duration Regime 2	23.25 Weeks	11.44 Weeks	35.86 Weeks	25.1Weeks	30.75 Weeks
Avg Weight Regime 3	50.82%	9.49%	50.64%	50.46%	50.27%
Avg Duration Regime 3	557 Weeks	14.86 Weeks	555 Weeks	553 Weeks	551.0 Weeks
Avg Weight Regime 4		50.18%			
Avg Duration Regime 4		550 Weeks			

Note Table 7.4: represents summary of Markov-Switching Regime models estimations, for different segments of tanker daily freight price-level earnings, illustrating statistics for each regime state, in the form of; average earning, fluctuating range (volatility), average weight, average duration transition probabilities between all states according to the following form; Transition probabilities π_{i|j} = P(Regime i at t | Regime j at t+1). A transition probability of 1.0 represents the probability of staying in the boom state. Estimation is based on the sample 05/01/1990 to 31/12/2010, number of Observations are 1096. † and * represents significance level at 1% and 5%, respectively.

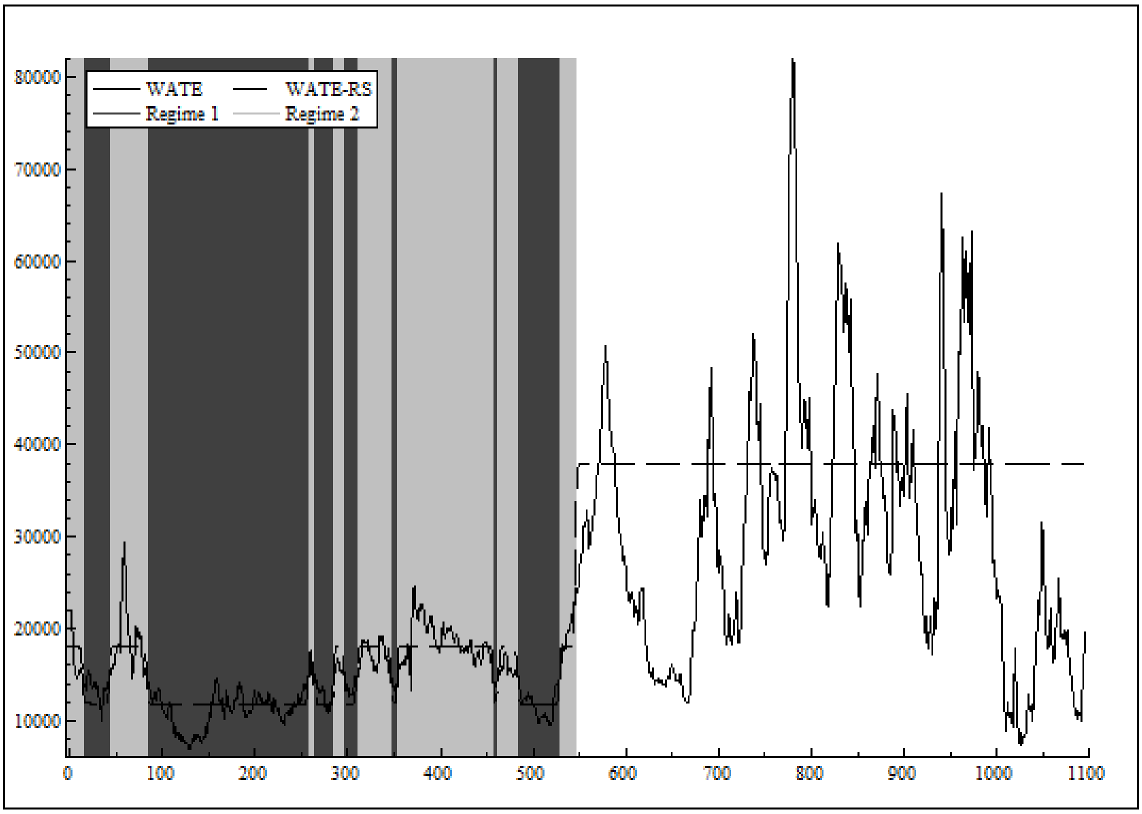
Source: Author's estimations.

7.4.7. Freight earnings expressed in regime states

Figures 7.3, 7.4, 7.5 and 7.6 present the estimated distinct regime states for different tanker segments imposed on their freight earning levels from 1990 to 2010, which are defined by the dashed line and the sold line, respectively, while the shaded areas distinguish between the high freight earning state (black) and the low freight earning state (gray). A visual inspection of Figures 7.3, 7.4, 7.5 and 7.6 that represent tanker earnings for the waited average tanker earnings, VLCC earnings, Aframax earning and Product average tanker earnings, respectively, clearly indicate that a significant homogenous structural change in freight earnings had accord post-2000 and that the dynamics of freight earnings differ from pre-2000 to post-2000.

Visual analysis of the post-2000 period identify two prolonged recessions, the first, post the dot-com crisis, third quarter of 2001, lasting for 15.5 months, the second, post the financial crisis, first quarter of 2009 and still going on, this is reported in Table 7.5 and more illustrated in Figure 7.7. Additionally, a prolonged and extreme volatile period of expansion can be seen between the last quarter of 2003 and third quarter of 2007. Furthermore, average earnings and freight volatilities pre-2000 had fluctuated between two regime-states, high and low, and that post- 2000 clear structural shifts occurred causing a significant change in the dynamics of freight earnings. On one hand, this shift in the structural of freights post the boom time break is most likely to be a permanent one simply because of the innovations that followed, for example; the growing use of freight derivatives and the new methods in financing new built. On the other hand, if this was a temporary shift representing a shipping business cycle and affected by random events and with freight rates reverting to the previous structural levels, this could have serious implications for shipping finance as low volatility levels coinciding with low demand will damage the derivatives markets. This examination of pre and post the structural-break is based on a three-state Markov-switching regime model.

Figure 7.3: A three-state regime for unconditional tanker earnings

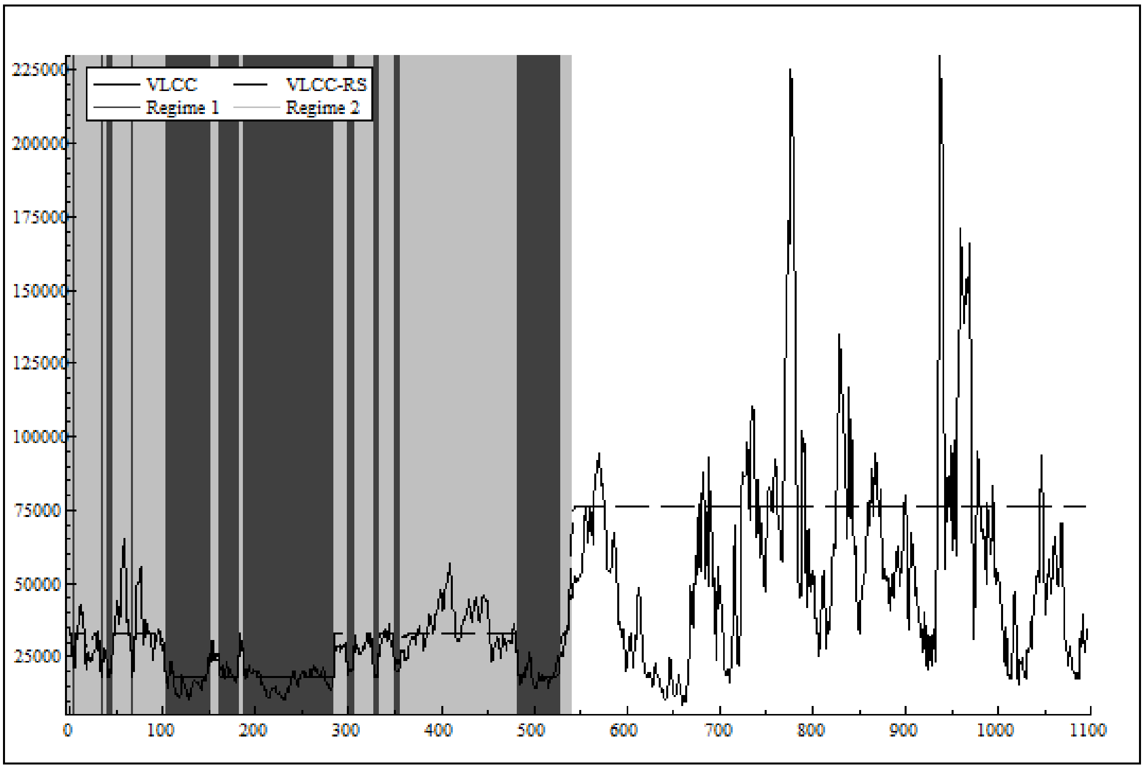


1991 1995 2000 2005 2010

Note Figure 7.3: illustrates market state dependency for unconditional tanker earnings, were the shifts between unconditional tanker earnings regimes states (WATE-RS) are denoted by a dashed line. A three-state regime; high earning state pre-2000 (regime 2), low earning state pre-2000 (regime 1) and the super boom cycle period after a structural shift in earning levels post-2000, from left to right. This is imposed on the weighted average of tanker earning data series (the solid dark line), a data set that represents unconditional freight earnings for different tanker vessels, for the period from 05/01/1990 to 31/12/2010. The shaded areas highlight the high and low earning states pre-2000 and the white area highlight the period after the structural shift post-2000; this is the super boom cycle. The vertical axes represent average daily unconditional tanker freight earnings in thousands and the horizontal axes represent the number of the weekly observation with the relevant year imposed at bottom of the graph. These estimates are based on outputs of markov-switching regime models applied to the WATE full data sample.

Source: Author’s estimations.

Figure 7.4: A three-state regime for VLCC tanker earnings

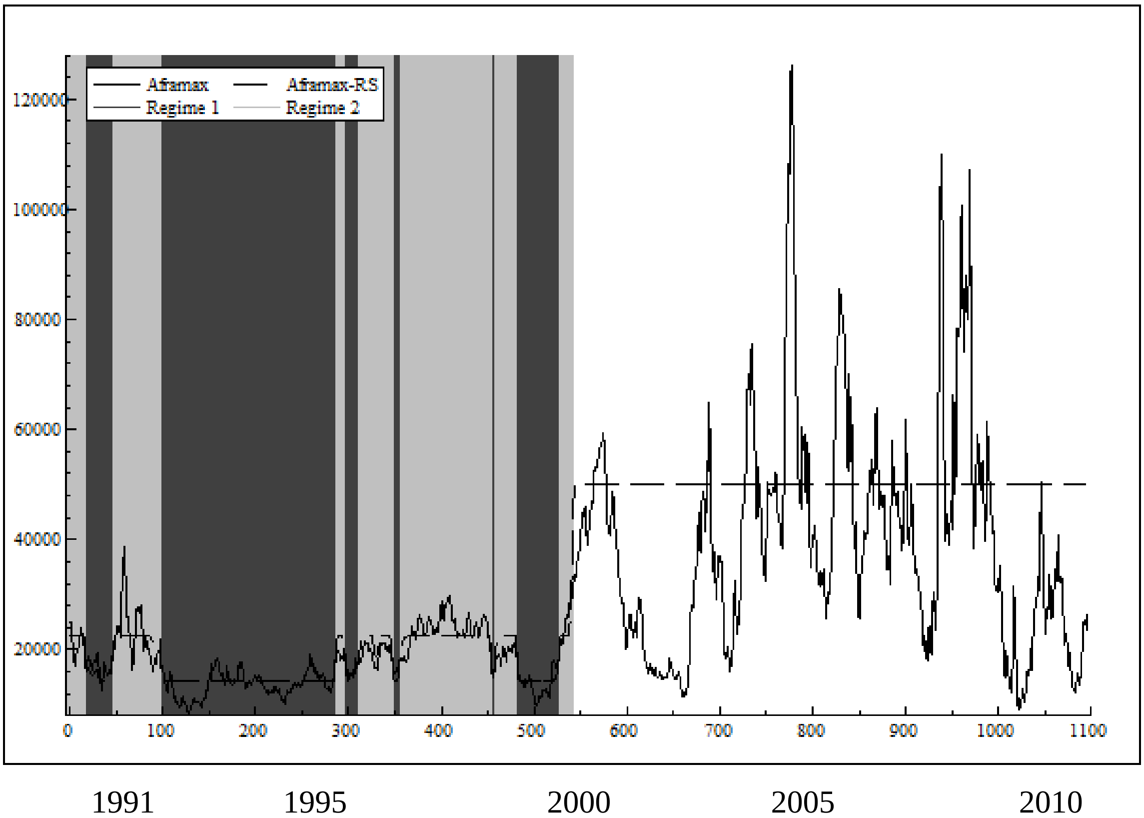


1991 1995 2000 2005 2010

Note Figure 7.4: illustrates market state dependency for VLCC tanker earnings, were the shifts between VLCC regimes states (VLCC-RS) are denoted by a dashed line. A three-state regime; high earning state pre-2000 (regime 2), low earning state pre-2000 (regime 1) and the super boom cycle period after a structural shift in earning levels post-2000, from left to right. This is imposed on the VLCC tanker earning series (the solid dark line), a data set that represents freight earnings for very large tanker crude carriers, for the period from 05/01/1990 to 31/12/2010. The shaded areas highlight the high and low earning states pre-2000 and the white area highlight the period after the structural shift post-2000; this is the super boom cycle. The vertical axes represent average daily VLCC tanker freight earnings in thousands and horizontal axes represent numbers of weekly observation with the relevant year imposed at bottom of the graph. These estimates are based on outputs of markov-switching regime models applied to the full VLCC data sample.

Source: Author's estimations.

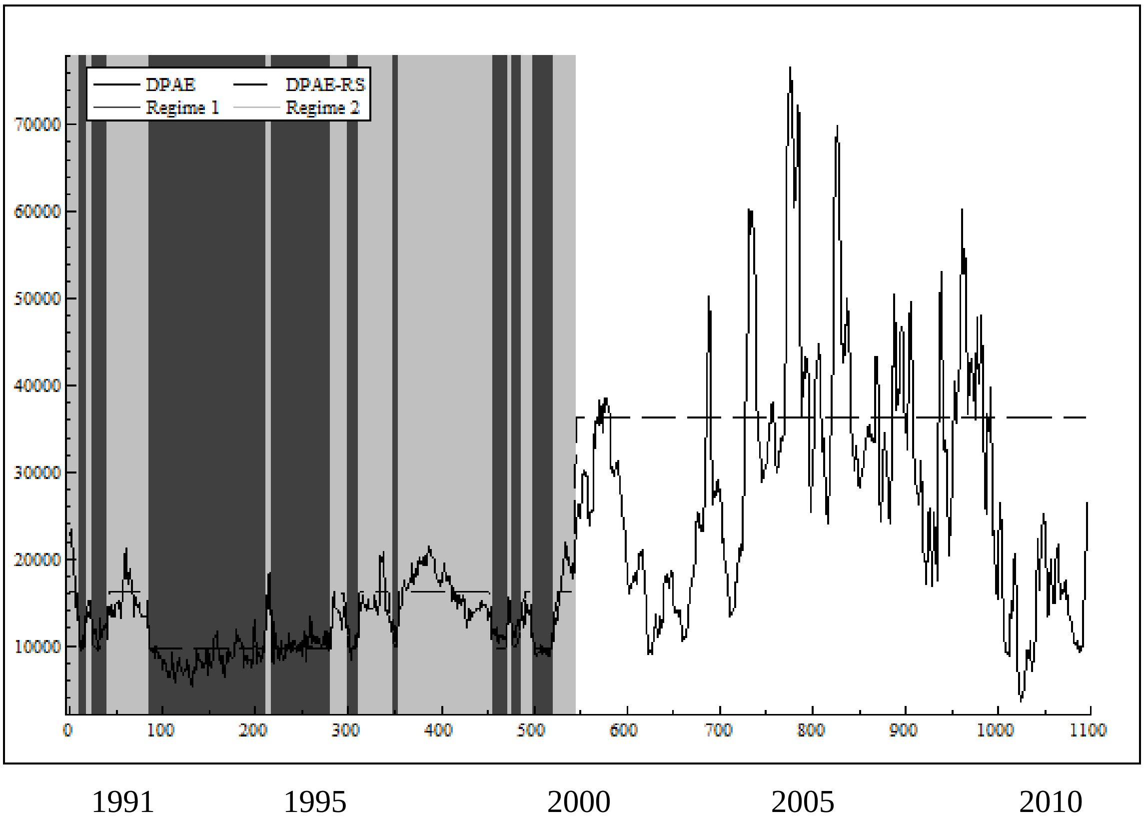
Figure 7.5: A three-state regime for Aframax tanker earnings



Note Figure 7.5: illustrates market state dependency for Aframax tanker earnings, were the shifts between Aframax regimes states (Aframax-RS) are denoted by a dashed line. A three-state regime; high earning state pre-2000 (regime 2), low earning state pre-2000 (regime 1) and the super boom cycle period after a structural shift in earning levels post-2000, from left to right. This is imposed on the Aframax tanker earning series (the solid dark line), a data set that represents freight earnings for the Aframax tanker sector, for the period from 05/01/1990 to 31/12/2010. The shaded areas highlight the high and low earning states pre-2000 and the white area highlight the period after the structural shift post-2000; this is the super boom cycle. The vertical axes represent average daily Aframax tanker freight earnings in thousands and horizontal axes represent numbers of weekly observation with the relevant year imposed at bottom of the graph. These estimates are based on outputs of markov-switching regime models applied to the full Aframax data sample.

Source: Author's estimations.

Figure 7.6: A Three-state regime for dirty product average tanker earnings



Note Figure 7.6: illustrates market state dependency for Product tanker earnings, were the shifts between Product regimes states (DPAE-RS) are denoted by a dashed line. A three-state regime; high earning state pre-2000 (regime 2), low earning state pre-2000 (regime 1) and the super boom cycle period after a structural shift in earning levels post-2000, from left to right. This is imposed on the DPAE tanker earning series (the solid dark line), a data set that represents freight earnings for the dirty product sector, for the period from 05/01/1990 to 31/12/2010. The shaded areas highlight the high and low earning states pre-2000 and the white area highlight the period after the structural shift post-2000; this is the super boom cycle. The vertical axes represent average daily Product tanker freight earnings in thousands and horizontal axes represent numbers of weekly observation with the relevant year imposed at bottom of the graph. These estimates are based on outputs of markov-switching regime models applied to the full Product data sample.

Source: Author's estimations.

7.4.8. Tanker earnings during the super boom cycle

Empirical findings indicate that tanker freight earnings, post-2000 structural break, exhibited periods of expansions and contractions structuring a 10 year super boom cycle, which consists of four booms (expansions) and four recessions (contractions), subsequently. Furthermore, the freight dynamics within these expansions and contractions are asymmetric and consistent with markets conditions of normal backwardation and contango, respectively.

In the commodity market, the terms normal backwardation and contango are used to describe the entire shape of the forward curve. The former refers to downwards sloping forward curves, where forward prices are below spot prices, and the latter refers to upwards sloping forward curve, where forward prices are above spot prices. In other wards, backwardation condition is associated with shortage of the commodity for immediate delivery, and contango is associated with oversupply of the commodity for immediate delivery. Alizadeh and Nomikos (2011) associate backwardation in the freight markets with periods of high demand of shipping services relevant to an inelastic supply curve and contango in the freight markets with periods of low demand for shipping services relevant to an elastic supply curve.

This chapter examines the above in relation to a definition of distinct market states, influenced by shipping agents, within an estimated super shipping boom cycle. Therefore, we model conditional freight limitations within freight earnings and postulate that freight earnings switch between two distinct market states influenced by either ship-owners or cargo-owners. Findings are of twofold. On the one hand, a ship-owner's market characterised by higher freights and volatilities levels influence lower long-term freight rates and volatilities, while a cargo-owner market characterised by lower freight rates and volatilities, influence higher long-term freight rates and volatilities, leading to backwardation and contango market conditions, respectively. On the other hand, the alignment of estimated periods of expansions and contractions with backwardation and contango market conditions, respectively, is a profound empirical finding, suggesting the relevance of a Markov switching regime framework in forecasting the turning points between the two conditions, because of its usefulness in measuring lengths of expansions and contractions during a business cycle.

The results of a multi-state Markov-switching regime framework applied post-2000 period (during the super boom cycle) are presented in Table 7.5. Empirical findings show that the dynamics of tanker freight earnings are asymmetric due to distinct market forces, which are controlled by shipping agents, either cargo-owners or ship-owners. The columns in the table represent different tanker segments, arranged from left to right based on largest to smaller sector, the last column (WATE) represent freight earnings for the unconditional tanker sector, a waited average tanker earning index, calculated by Clarkson intelligence network to mimic daily aggregated earnings within the tanker sector, in other words representing earnings for a company that operates a portfolio of numerous tanker vessels that substitutes all tanker segments.

Regimes 1, 2 and 3 represent market states denoting cargo-owner market state, transitional state and ship-owner market state, respectively, and volatility regimes 1, 2, 3 define dispersion within each regime state (market condition), respectively, the probability of switching from one market state to another is expressed in Table 7.5 by the transition probability π_{ij} where i,j={1,2 and 3}, a value of zero for a transitional probability indicates the disconnection between the relevant two states and providing grounds for a transitional state. In other words, results presented in Table 7.5 postulates for all tanker segments that once in a regime state there is a strong probability of remaining in the same state rather to switch back and forth. Most importantly, the non existence of a probability of freight earnings switching between a lower regime state and a higher regime state, indicate the significance of the identified transitional regime state in this study to distinguish between the two distinct regime states. Finally, Table 7.5 reports the average weight of each regime state relevant to the sample (post-2000 to end of sample) in percentages and the average duration in weeks of each regime state resilience before shifting to another regime state, donated by avg weight regime 1, 2, and 3 and avg duration regime 1, 2 and 3, respectively. This study empirical evidence indicates that on average the duration of a period of contraction is longer than the duration of a period of expansion, for smaller vessels and visa versa for larger vessels. Thus, periods of lower earnings and volatility levels within freight markets are longer than periods of higher earnings and volatility levels for Product and Aframax, contrary to VLCC and Suezmax vessels. Furthermore, the above results are illustrated in Figure 7.7, where the freight market state dependency for unconditional tanker earnings are denoted by the solid line, expressing shifts between low state to high state and visa versa through a transitional state, this is imposed on unconditional tanker earnings during the super boom period. For example, freight market state dependency for unconditional tanker earnings during the super boom period is represented by the solid line and imposed on average unconditional earnings denoted by the dashed line, while each numbered bracket indicate a specific phase of the super boom cycle, with odd and even numbers representing expansions and contractions, respectively. The dark, gray and white shaded areas indicate cargo-owners state, transitional state and ship-owner state, corresponding to low earning regime state, transitional regime state and high earning regime state, respectively, and represented by the switching solid line. Vertical axes represent average daily earnings in dollars, while horizontal axes represent relevant weekly observation number with the relevant year imposed at the bottom of the graph.

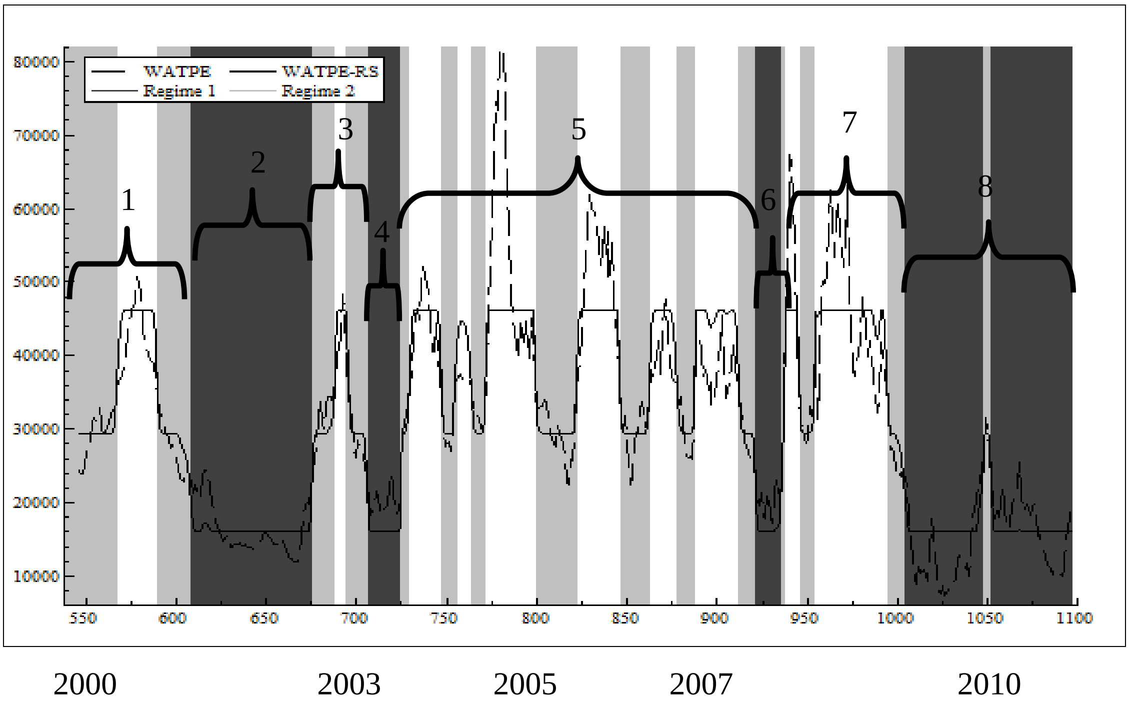
Table 7.5: Markov-switching conditional variance regime models estimations for weekly tanker freight earnings (boom-cycle)

Markov-Switching Conditional Variance Model Estimations for Tanker Price Earnings (Boom-Period)					
	VLCC	**Suezmax**	**Aframax**	**Product 50k**	**WATE**
Start of Boom-Period	**05/05/2000**	**23/06/2000**	**19/05/2000**	**02/06/2000**	**16/06/2000**
Regime 1 MWP	24821.2 (34.7)†	20763	19431.5 (7.99)†	14287.1 (48.5)†	16085.5 (49.4)†
Regime 2 MWP	52751.6 (48.6)†	41836.1 (18.6)†	37302.7 (8.02)†	27661.9 (78.4)†	29390.9 (47.4)†
Regime 3 MWP	97167.5	74560.5 (17.8)†	62111.6	44721.3 (65.0)†	46219.7 (33.7)†
Volatility Regime 1	7822.43	6278.17 (23.5)†	5236.1	4106.46 (25.2)†	4141.00 (11.5)†
Volatility Regime 2	6977.36	5854.95 (21.5)†	4776.44	3603.85 (18.4)†	3566.23 (17.5)†
Volatility Regime 3	35415.8	22019.6	17677.9	10391.4 (57.0)†	9822.79 (34.3)†
Transition $\pi 11$	0.938542 (51.7)†	0.943408 (46.5)†	0.970532 (72.0)†	0.964014 (68.3)†	0.977972 (89.3)†
Transition $\pi 22$	0.866625 (31.1)†	0.848180 (25.1)†	0.900141 (38.3)†	0.891186 (35.9)†	0.907244 (38.9)†
Transition $\pi 33$	0.93642	0.9108	0.93361	0.93397	0.94418
Transition $\pi 12$	0.0513827 (3.02)†	0.056592	0.029468	0.035986	0.022028
Transition $\pi 13$	0.010076	0	0	0	0
Transition $\pi 21$	0.0707885 (3.51)†	0.0573336 (2.77)†	0.0343439 (2.46)*	0.0386606 (2.51)*	0.0302588 (2.25)*
Transition $\pi 23$	0.062587	0.094487	0.065515	0.070154	0.062497
Transition $\pi 31$	0	0	0	0	0
Transition $\pi 32$	0.0635785 (3.19)†	0.0891973 (2.92)†	0.0663949 (2.45)*	0.0660337 (3.52)	0.0558200 (3.10)†
Avg Weight Regime 1	33.03%	31.82%	33.51%	34.36%	34.48%
Avg Duration Regime 1	15.33 Weeks	14.58 Weeks	31 Weeks	27.14 Weeks	38 Weeks
Avg Weight Regime 2	30.88%	32.73%	33.69%	32.37%	30.31%
Avg Duration Regime 2	8.19 Weeks	6.21 Weeks	11 Weeks	8.95 Weeks	11.13 Weeks
Avg Weight Regime 3	36.09%	35.45%	32.79%	33.27%	35.21%
Avg Duration Regime 3	18.27 Weeks	12.19 Weeks	16.55 Weeks	15.33 Weeks	19.4 Weeks

Note Table 7.5: represents summary of Markov-Switching Regime models estimations, for different segments of tanker daily freight price-level earnings, illustrating statistics for each regime state, in the form of; average earning, fluctuating range (volatility), average weight, average duration transition probabilities between all states according to the following form; Transition probabilities π_{i|j} = P(Regime i at t | Regime j at t+1). A transition probability of 1.0 represents the probability of staying in the boom state. Estimation is based on the sample 05/01/1990 to 31/12/2010, number of Observations are 1096. † and * represents significance level at 1% and 5%, respectively.

Source: Author's estimations.

Figure 7.7: A three-state regime for tanker earnings post-2000 and during the super boom cycle



Note Figure 7.7: illustrates market state dependency for unconditional tanker earnings post the significant structural change post-2000. Were the shifts between unconditional tanker earnings regimes states (WATE-RS) are represented by the solid line. A three-state regime; a transitional regime state post-2000 (regime 2, shaded gray), high earning state post-2000 (regime 3, shaded white) and the low earning state(regime 1, shaded dark) after a structural shift in earning levels post-2000, from left to right. This is imposed on the weighted average of tanker earnings series, a data set that represents unconditional freight earnings for different tanker vessels (the solid dark line), for the period from 16/06/2000 to 31/12/2010. Odd and even numbers denote expansion and contraction periods, respectively, the vertical axes represent average daily unconditional tanker freight earnings in thousands and horizontal axes represent numbers of weekly observation with the relevant year imposed at bottom of the graph. These estimates are based on outputs of markov-switching regime models applied to the WATE data series post-2000 structural shift sample.
Source: Author's estimations.

Moreover, Table 7.6 reports statistics of the subsequent periods of expansions and contractions during the super boom cycle, denoted by odd and even numbered phases, respectively. These are daily average freight earnings and daily average volatility levels during each phase, for four different tanker segments and a waited average earning index. These statistics are illustrated in Figures 7.8 and 7.9, respectively. In regards to the period of the highest average earnings and volatilities levels, the seventh expansion phase of the super boom cycle stands out, from late 2007 to early 2009, characterised as a period of high profits and extreme volatility, for tanker owners in the last 10 years, for the three largest tanker sectors. Interestingly, this unique phase arrives after a short contraction phase, for three months, triggered by the turmoil in financial markets. Thus, the financial crisis had a sort and long term affect on tanker freight markets; these are transparent in the 6th phase and the 8th phase of the super boom cycle, respectively. The immediate effect lasted for three months, while the long term effect started early 2009 and still ongoing.

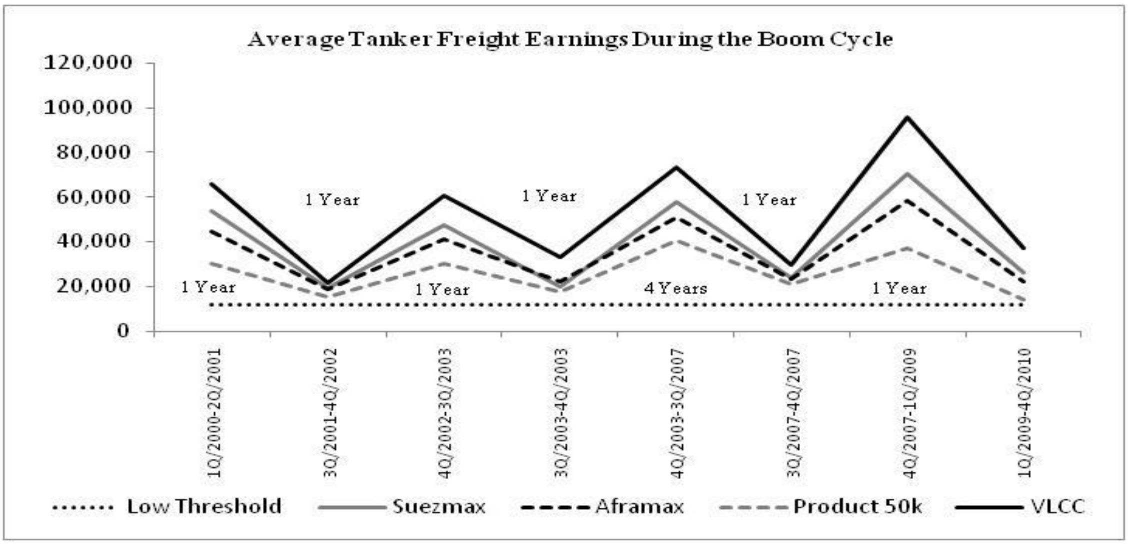
Table 7.6: Average freight earnings and volatilities for expansions and contractions during the super boom-cycle period

	VLCC		Suezmax		Aframax		Product 50k		WATE	
	Avg	SD	Avg	SD	Avg	SD	Avg	SD	Avg	SD
Phase 1	65,934	14,173	53,501	11,749	44,490	8,255	30,418	5,024	33,461	7,734
Phase 2	21,797	9,620	19,540	6,221	18,897	5,213	15,183	3,372	16,389	3,508
Phase 3	60,547	15,446	47,642	13,042	41,257	8,963	29,962	8,217	32,708	6,377
Phase 4	33,335	14,184	20,085	5,647	22,284	4,597	17,337	2,926	19,976	1,625
Phase 5	73,247	34,518	57,964	23,632	50,832	18,591	**40,449**	**12,498**	39,320	11,742
Phase 6	29,847	5,068	24,126	7,085	23,460	3,780	20,871	3,209	20,219	1,890
Phase 7	**95,840**	**45,757**	**70,267**	**28,490**	**58,635**	**21,593**	37,114	9,795	**41,529**	**11,965**
Phase 8	37,346	17,223	26,324	11,464	22,194	8,752	14,373	5,713	15,550	5,497

Note Table 7.6: reports the estimated eight phases of expansions and contractions subsequently, during the estimated super boom cycle. The table reports average earnings and volatility levels for all tanker segments.
Source: Author's estimations.

Because the starting date of each phase is similar across all tanker segments during the supper boom cycle, we plot averages of freight earnings and volatilities across all tanker segments, for comparisons. The objective of such plots is to examine the changes in the dynamics of freight earnings during the super boom cycle across all tanker segments. Examining these different illustrations, one can observe a consistent increase in the levels of freight earnings and volatility across all tanker segments, represented by high daily averages during phases of expansions and contractions during the super boom cycle, and strong evidence of seasonality with most phases lasting around one year. Furthermore, Figure 7.10 illustrate the changes in levels of freight volatility during the full data sample, by plotting estimated average earnings in Table 7.4 and Table 7.5 along their estimated relevant possible fluctuations. For example, daily averages freight earnings and volatilities for a VLCC during the last 20 years differ according to market condition and are asymmetric pre and post-2000. First, pre-2000, daily average freight earning levels switch between low and high earnings states, from 18,347 dollars per day to 33,226 dollars per day, with an estimated changeability (plus/minus) of 3,810 dollars per day and 5,531 dollars per day, respectively[39]. Second, post-2000, daily average freight earning levels had exhibited a significant change denoted by an average of 76,121 dollars per day with an estimated changeability of 33,338 dollars per day. These dispersions in freight volatilities are illustrated in Figure 7.10 denoted by different volatility bands across all tanker segments. This illustration indicates clearly the continence upward increase in freight volatility levels for all tanker segments.

Figure 7.8: Average tanker freight earnings during the super boom cycle

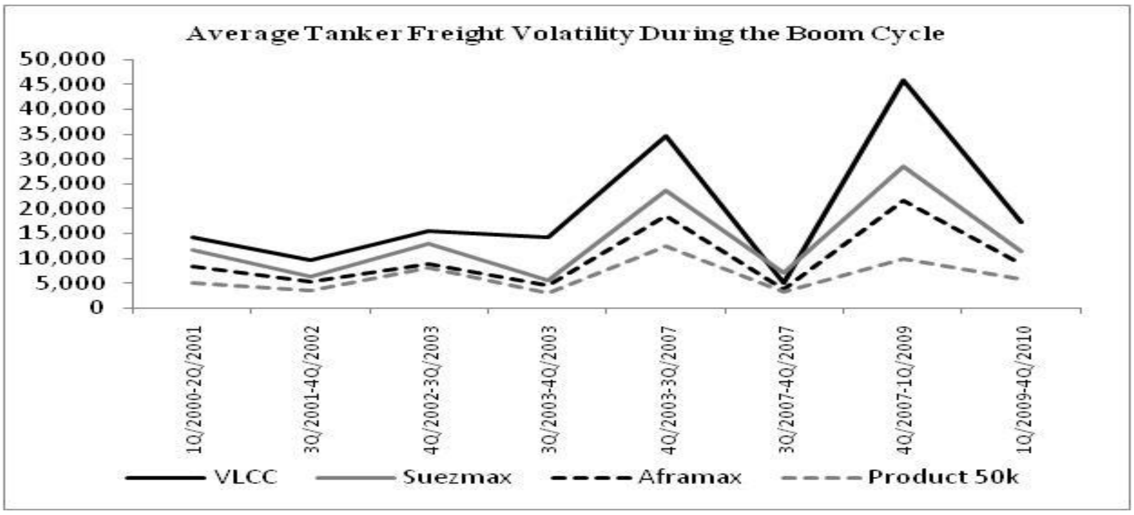


Note Figure 7.8: illustrated average freight earnings during the boom-period from 2000 to 2010 for the expansion and contraction 8 phases, subsequently analysed in Table 7.7. The dates denote the coordinated phases for all tanker segments. Values are in dollars per day and represented by the vertical axes. The daily threshold is 11,769 dollars per day (Table 7.3 Regime 1 for waited average tanker earnings) and is based on the lowest daily average unconditional tanker earnings.

Source: Author's estimations.

[39] Values obtained from table 8.4.

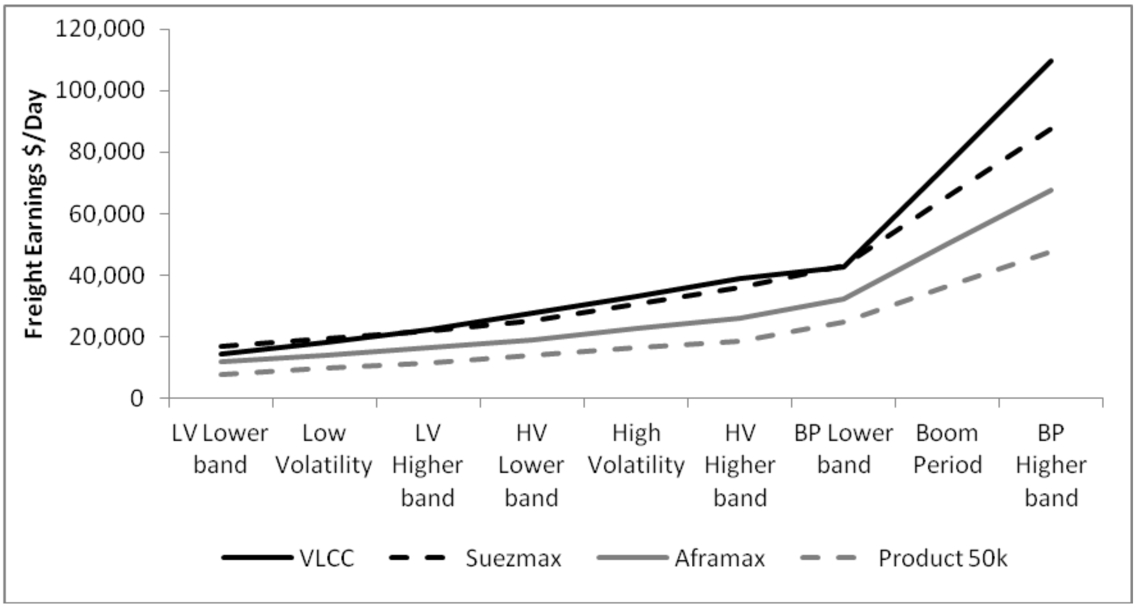
Figure 7.9: Average tanker freight volatility during the super boom cycle



Note Figure 7.9: illustrates daily average freight volatilities during the boom-period from 2000 to 2010 for the expansion and contraction 8 phases, subsequently analysed in Table 7.7. The dates denote the coordinated phases for all tanker segments. Freight values are in dollars per day and represented by the vertical axes.

Source: Author's estimations.

Figure 7.10: Freight earnings volatility structural change tanker markets



Note Figure 7.10: illustrates changes in daily average freight volatility levels across all tanker segments and for the whole sample pre and post-2000, during different market conditions. The two periods are pre-2000 and post-200, with the former volatility levels switching between low and high state, including volatility fluctuation bands, lower volatility and higher volatility bands, the latter is represented with one boom-period and accompanying bands. This highlights the changes in tanker earnings volatilities levels for the past 20 years.

Source: Author's estimations.

Table 7.7 presents a summary of characteristics and dynamics of the freight market in respect to the analysis of this chapter for the estimated super boom cycle post-2000. The table consists of five sections; the first four represents four tanker segments and the final section represent the unconditional tanker market. Each section consists of eight phases representing expansions and contractions periods with the relevant tanker segment during the super boom cycle. There are eight main columns with the last two divided to four sub columns each. From left to right these columns represent the relevant phase of each period (expansion/contraction), the relevant tanker segment, the estimated starting date of each phase, the estimated ending date of each phase and the estimated duration for each phase measured in months. As for the last two columns, they report, for a specific period (expansion/contraction) the freight values at the estimated starting and ending date of the relevant phase, along the average freight value and average volatility during the whole phase, for the spot market and the forward market, respectively. For example in regards to estimated results in this chapter, a VLCC tanker operating from the period of 23 November 2007 to 20 March 2009, a duration of 15.9 months, would had been operating in an expansion period driven by ship-owners market conditions, a period characterised by an average daily earnings of around 97,000 dollars with a possible fluctuation of 35,000 dollars, either way. This coincide with reported statistics of the seventh phase within the super boom cycle for the VLCC market, indicating that on the 23 of November 2007 prevailing freight earnings in the spot market were 74,157 dollars per day.

Table 7.7: The characteristics and dynamics of the freight market

Phase	Segments	Market Type	Start Phase	End Phase	Duration	Spot Tanker Freight Rate				Forward Freight			
					Months	Start	End	Avg Spot	Avg Vol	1-YTC	Avg FP	3-YTC	Avg FP
1	VLCC	Exp	05/05/2000	20/04/2001	11.5	46,079	47,924	65,934	14,173	34,500	65,934	35,000	42,772
2		Con	27/04/2001	11/10/2002	17.5	36,155	29,688	21,797	9,620	48,000	25,295	40,000	39,408
3		Exp	18/10/2002	25/04/2003	6.2	48,956	42,262	60,547	15,446	28,000	48,739	28,500	68,105
4		Con	02/05/2003	31/10/2003	6.0	23,804	38,462	33,335	14,184	30,000	56,820	29,000	72,427
5		Exp	07/11/2003	06/07/2007	44.0	82,407	41,112	73,247	34,518	36,500	83,292	31,000	78,327
6		Con	13/07/2007	16/11/2007	4.1	32,233	35,082	29,847	5,068	57,500	87,085	51,500	64,672
7		Exp	23/11/2007	20/03/2009	15.9	74,157	40,655	95,840	45,757	55,000	109,194	48,500	65,099
8		Con	27/03/2009	31/12/2010	21.1	36,444	32,405	37,346	17,223	49,000	37,013	43,000	37,346
1	Suezmax	Exp	23/06/2000	25/05/2001	11.1	49,375	31,887	53,501	11,749	28,000	52,576	28,000	35,714
2		Con	01/06/2001	25/10/2002	16.8	32,032	30,068	19,540	6,221	38,000	21,412	31,000	33,075
3		Exp	01/11/2002	20/06/2003	7.6	38,870	45,434	47,642	13,042	19,000	38,961	19,250	52,747
4		Con	27/06/2003	03/10/2003	3.2	30,907	26,195	20,085	5,647	27,000	37,148	24,000	50,651
5		Exp	10/10/2003	06/07/2007	44.9	33,268	34,985	57,964	23,632	26,000	54,691	24,000	60,476
6		Con	13/07/2007	16/11/2007	4.1	29,442	24,429	24,126	7,085	47,500	59,225	41,000	46,938
7		Exp	23/11/2007	20/03/2009	15.9	36,300	42,945	70,267	28,490	42,000	77,657	38,000	46,693
8		Con	27/03/2009	31/12/2010	21.1	30,402	30,488	26,324	11,464	35,000	25,436	32,500	26,324
1	Aframax	Exp	19/05/2000	18/05/2001	12.0	30,890	28,292	44,490	8,255	18,750	45,066	19,000	31,485
2		Con	25/05/2001	08/11/2002	17.4	28,515	27,613	18,897	5,213	27,000	20,025	22,000	29,651
3		Exp	15/11/2002	20/06/2003	7.2	30,056	32,254	41,257	8,963	18,000	18,714	18,500	46,551
4		Con	27/06/2003	24/10/2003	3.9	24,938	26,251	22,284	4,597	19,500	21,787	18,000	49,852
5		Exp	31/10/2003	13/07/2007	44.4	31,156	30,006	50,832	18,591	21,000	51,222	18,750	53,135
6		Con	20/07/2007	16/11/2007	3.9	27,671	24,246	23,460	3,780	35,000	52,637	31,000	39,688
7		Exp	23/11/2007	20/03/2009	15.9	33,329	29,153	58,635	21,593	31,000	65,266	29,000	39,234
8		Con	27/03/2009	31/12/2010	21.1	23,165	23,653	22,194	8,752	23,000	21,193	23,500	22,194
1	Product	Exp	02/06/2000	15/06/2001	12.4	21,655	22,544	30,418	5,024	15,500	30,914	N/A	23,009
2		Con	22/06/2001	22/11/2002	17.0	20,348	19,561	15,183	3,372	22,000	15,618	N/A	22,868
3		Exp	29/11/2002	27/06/2003	6.9	24,395	22,371	29,962	8,217	17,000	25,086	16,750	36,455
4		Con	04/07/2003	07/11/2003	4.1	21,240	20,294	17,337	2,926	18,000	31,083	17,000	38,990
5		Exp	14/11/2003	10/08/2007	44.9	21,169	21,228	40,449	12,498	18,000	39,587	16,750	41,142
6		Con	17/08/2007	19/10/2007	2.1	20,421	16,820	20,871	3,209	31,000	34,188	28,000	24,898
7		Exp	26/10/2007	23/01/2009	14.9	24,929	23,155	37,114	9,795	27,500	38,102	26,500	24,456
8		Con	30/01/2009	31/12/2010	23.0	21,399	26,389	14,373	5,713	26,000	12,877	24,000	14,373
1	WATPE	Exp	16/06/2000	17/08/2001	14.0	24,306	23,560	33,461	7,734	24,188	35,289	27,333	25,991
2		Con	24/08/2001	06/12/2002	15.4	22,817	21,561	16,389	3,508	33,750	14,957	31,000	25,785
3		Exp	13/12/2002	11/07/2003	6.9	24,702	23,487	32,708	6,377	20,500	27,979	20,750	36,134
4		Con	18/07/2003	14/11/2003	3.9	20,258	20,358	19,976	1,625	23,625	31,476	22,000	38,561
5		Exp	21/11/2003	17/08/2007	44.9	23,643	25,631	39,320	11,742	25,375	37,539	22,625	40,764
6		Con	24/08/2007	30/11/2007	3.2	22,433	19,984	20,219	1,890	42,750	38,202	37,875	27,875
7		Exp	07/12/2007	20/03/2009	15.4	23,841	22,819	41,529	11,965	38,875	45,069	35,500	27,392
8		Con	27/03/2009	31/12/2010	21.1	23,540	19,626	15,550	5,497	33,250	14,632	30,750	15,550

Note Table 7.7: reports the characteristics of 8 mini-cycles during the identified boom-period from 2000 to 2010. This consists of expansion and contraction periods subsequently. The columns are explained from left to right as following; number of cycles, tanker segment (tanker size), type of cycle (expansion/contraction), the estimated starting date of the cycle, the estimated ending date of the cycle, the duration of the cycle in months, daily freight price-levels at the start of the cycle, daily freight price-levels at the end of the cycle, average daily freight price-levels during the cycle period, average daily volatility (fluctuations in freight prices) levels during the cycle period, daily freight earnings for a one year time-charter contract at the start of the cycle and daily freight earnings for a three year time-charter contract at the start of the cycle. The time-charter contracts are used to construct forward curves.

Source: Author's estimations.

Furthermore, in perspective of gains and losses in shipping, it is interesting to examine different periods of earnings during the estimated super boom cycle. On the one hand, the 5th phase of the super boom cycle that lasted for nearly 45 months marking the longer expansion period in the last decade for tanker earnings, starting from the 4th quarter of 2003 through out the 3rd quarter of 2007, in respond to a 17.3 per cent boost in oil seaborne trade, which was partially due to a nearly 21.5 per cent increase in total seaborne trade between the years of 2003 and 2007. On the other hand, the 8th phase, which lasted for more than 21 months indicate the longer contraction period in the last decade[40], from the 1st quarter of 2009 until the 4th quarter of 2010, in response to the most recent financial turmoil. Strangely enough, during the midmost of the financial crisis, the tanker market had recorded the highest earnings for the last decade, this can be associated to insolvent banks disrupting the shipping finance market, with banks offloading their portfolios of shipping assets, this period is represented in our analysis by the seventh phase that lasted for one year and four months, from the last quarter of 2007 to the first quarter of 2009, with a daily earning average of nearly 41,529 dollars per day and possible fluctuations of nearly 11,965 dollars per day.

Moreover, Table 7.7 demonstrate changes in freight earning dynamics during the super boom cycle, by reporting freight levels at the start and end of each phase, in addition, to averages of freights and volatilities levels during the whole phase. We compare these characteristics with corresponding forward freight rates, in an attempt to examine the forecasting performance of forward freight curves in predicting future spot freight rates; these are illustrated in Figures 7.1 and 7.2, for contractions and expansions phase, respectively. We use a three-state MSR platform to identify expansions and contraction of freights, through a transitional state that distinguish between high (expansion) volatility state and low (contraction) volatility state.

By comparing forward freight contracts with prevailing spot freight rates at the time, its easy to see that three-year freight forecast perform better than a one-year one. For example in Table 7.7, section five, phase one, average daily earnings for the overall tanker sector at the start and end of the cycle that had lasted for just over a year was around 24,000 dollars, in affiliation with the value one-year time charter contract at the start of the cycle. In other words, a vessel fixed for one year by the second quarter of 2000 would have guaranteed an average daily earning of 24,000 dollars. On the other

[40] There are no clear evidence that this cycle had ended yet, as the end of the cycle represents the end of the data sample.

hand, if the same vessel was operating spot it would have earned a daily average of just over 33,000 dollars, provided that employment is available with limited ballast hauls. Therefore, in hindsight ship-owners will prefer a time-charter contract on voyage-charter for this scenario. Furthermore, a constructed forward curve indicate that market perception of prevailing freight rates at the time, indicate pessimistic sentiment in the short run and optimistic in the long run.

In summary, based on the last ten years (super boom cycle), tanker freight earning levels exhibit a strong tendency to remain in a high/low earning regime state relevant to switching back and forth between the two distinct states. Furthermore, there is obscurity of freight earning levels switching from the low earning state to the high earning state directly without a transitional state; this is reported in Tables 7.4 and 7.5, and denoted by π_{13} and π_{31} for all tanker segments.

Most importantly, conditional freight earning limitations under distinct market forces is asymmetric in the sense that when the market is under ship-owners control, denoted by a high earning state (expansions), daily tanker freight earning rates and volatility levels are much higher relevant to markets under cargo-owners control, denoted by low earning state (contractions). This is consistent with plots of constructed forward curves during expansions and contractions periods, representing markets in normal backwardation and contango, respectively, and constructed based on the estimated phases of the super boom cycle for expansion and contraction periods and illustrated in Figures 7.1 and 7.2 and explained in details in section 7.4.4 To put this in perspective, in a recent paper by Alizadeh and Nomikos (2011) they find evidence that the volatility of freight rates is related to the shape of the term structure and is asymmetric. Thus, they argue that when the market is in backwardation; spot earnings are above long term charter rates, volatility is higher compared to periods when the market is in contango; spot rates are lower than long term period rates, stressing the importance of the shape of the forward curve and the volatility dynamics of the freight market for risk management applications. Thus, in agreement with empirical statistics of this chapter, where estimated regime states; low earning state and high earning state, are characterizes by, low freight earning rates with low volatilities level and high freight earning rates with extreme volatilities levels, respectively.

7.4.9. Shipping business cycles and exogenous and endogenous factors

It is hard to see long-term cycles in shipping markets being determined endogenously, as suggested by Randers and Göluke (2007). Our view is that, freight dynamics are driven by the interaction of both endogenous and exogenous factors and that the magnitude of these affects depends entirely on prevailing market conditions at the time. This postulate is supported by our empirical findings, that exogenous structural-breaks within the freight markets are caused by macroeconomic events (the fact that demand for freight services are derived by demand for seaborne trade), these exogenous effects generate a change in shipping business cycles that are represented through endogenous breaks, due to equilibrium adjustments in freight services. In other words, a global economical event such as the most recent global boom or the financial crisis (exogenous effect), lead to significant changes in global trade effecting global shipping by increasing/decreasing demand for shipping services, with shipping being efficient markets, supply of shipping adjusts to changes in demand, the level of adjustment depends on the capacity and utilization of the current fleet (endogenous effect).

On one hand, low freight earning levels lead to slow steaming of vessels to reduce bunker costs, these low levels of earnings trigger an increase in laid-up vessels, coinciding with lower freight volatility levels. On the other hand, high freight earning levels lead to short ballast haul[41], this causes an increase in the number of employed vessels, which leads to a shift in the elasticity of the supply side, and this causes high volatility levels in freight earnings. For further research, this framework could provide empirical insight into the mechanisms of shipping cycles, Thus, the emphasis is clear on the importance of taken this in account when modelling and forecasting freight volatilities and in improving techniques of risk management.

An economical shock such as the most recent financial crisis caused a sudden reduction in demand for sea transport, triggering an end to a prolonged boom period. The question is how long it will take the shipping markets to react to such economical shock? Our view is that, here where endogenous factors come to play, as the capacity adjustment and utilization of the current fleet determine the time lag. In addition to the timing of the economical event in relation to market phase. For example the recent financial crisis had occurred in a time that shipping markets had enjoyed four years of expansions in, fleet capacity, shipping finance and freight derivatives markets, during

[41] A vessel that is in a ballast haul refers to a vessel that has no loaded cargo and is ballasted and not earning any income.

this time extreme high, freight levels and volatility prevailed attracting new players, such as hedge funds, traders and the like.

7.5. A summary of the chapter

The first part of this chapter deviates from the rest of the thesis and most empirical maritime literature in the sense that freight earning price levels are assumed to be conditional stationary based on our applied tests and in conformity with maritime economic theory. In summary our empirical findings agree with the maritime literature in the sense that, freight rates are driven by fundamentals, exhibit battens, non-normally distributed, extreme volatile, fat tailed and non-random. Our analysis shows that a multi-state Markov-switching regime framework has merits in identifying the asymmetry within expansions and contractions for shipping business cycles, providing a practical framework for measuring distinct phases within them. This should be explored further to include a forecasting framework that potentially would improve shipping risk management due to the linear components within the nonlinear model.

In this study we examined a sample of 20 years of tanker freight rates, motivated by a clearly observed visual structural change in level of freight earnings. Thus, the sample is divided into a pre- and post- significant homogenous structural break. This exogenous structural-break is estimated empirically through a Markov-switching regime framework and its significance is examined using the appropriate tests. In other ward, early findings indicate that freight earning levels and their volatilities fluctuate in general between high and low states. To investigate this postulate a multi-state Markov-switching regime framework was implemented to first examine the hypothesis of a significant homogenous structural shift within tanker earnings and second to estimate conditional freight limitations, distinguishing between a ship-owner and cargo-owner markets.

Furthermore, analyses of freight earnings statistics imply a positive correlation between the magnitude of earnings and tanker sizes regardless of the state of the market. This holds even in different market conditions, consistent with the literature. These empirical findings point out that the dynamics of freight earnings are best captured by multi-states and distinct regimes, due to their flexibilities' in allowing average earnings and their volatilities to switch between different states with distinct characteristics reflecting the condition of the market. On the one hand, low freight earning levels lead to slow steaming of vessels to reduce bunker costs, these low levels of earnings trigger an increase in laid-up vessels, which coincide with lower freight volatility levels. On the other hand, high freight earning levels lead to short ballasting hauls. This causes an increase in the number of employed vessels, which leads to a shift in the elasticity of the supply side, and this cause's high volatility levels in freight earnings. Moreover, the framework applied provides insight into the mechanisms of shipping cycles, by providing grounds to measure expansion and contraction phases. Thus, the importance of taking this in account when modelling and forecasting freight volatilities and in improving techniques of risk management is clear.

Furthermore, a Markov-switching framework applied to daily freight price earnings indicates that after the second quarter of 2000, the structure of the tanker freight markets had shifted to a much more volatile state with a higher mean across all tanker segments, this shift had lasted for more than 10 years. The question is; is this a permanent structural shift change or a super boom cycle that had possibly come to an end? This question remains unanswered. Even so, empirical findings announce that average freight earning for expansions and contractions during the last decade had not crossed our constructed threshold, which indicates that there is no empirical evidence supporting the idea that the boom shift has ended by shifting back to pre 2000 regime stats. However, there is a clear increase in freight earning volatility levels during contraction phases that can indicate an unstable market. Furthermore, analysis of the boom period reveals two significant breaks. These shifts mark the start of the longer and the most significant expansion phases during the boom period, respectively. The former responded to an increase in oil seaborne trade of 17.3 per cent between the years of 2003 and 2007. While the latter was in response to the turmoil in the banking sector caused by the financial crisis causing uncertainty and massive pressure on ship owners that had financed their purchase with expensive loans, causing numerous exits leading to a temporarily excess of demand. Furthermore, it seams that on average expansions and contractions cycles that represent the trough stage in Stopford's analyses exhibit clear seasonality effects lasting on average for one year.

7.6. Conclusion

In this chapter the short and long term effect of the financial crisis on tanker freight markets are examined through a multi-state Markov-regime switching model, the immediate effect lasted for three months, while the long term effect started early 2009 and is still ongoing.

Empirical results indicate that freight dynamics within tanker earnings had significantly changed post 2000 structural change relevant to the pre 2000 period, where average freight earning and volatility levels in the tanker sector had increased more than 150 per cent and 311 per cent from pre-2000, respectively. In comparing expansion phases controlled by ship-owners to contraction phases controlled by cargo-owners, we found that average earnings and volatilities levels had increased from more than 54 per cent and 24 per cent to more than 187 per cent and 137 per cent respectively, a significant increase that is consistent across all tanker sectors. This is based on the fact that high freight rates are dictated by ship-owners due to excess of cargo relevant to tonnage, creating an expansion period within freight earnings, while low freight rates are dictated by cargo-owners due to excess of tonnage relevant to cargo, creating a contraction period within freight earnings. Hence, influencing distinct market conditions within the freight market; the former as a pure shipowner market and the latter as a pure charterer (cargo-owner) market. Furthermore, the characteristics of these distinct markets are in coordination with the definition of freight dynamics during backwardation and contango market conditions.

On the one hand, a ship-owner's market characterised by higher freights and volatilities levels influence lower long-term freight rates and volatilities, while a cargo-owner market characterised by lower freight rates and volatilities, influence higher long-term freight rates and volatilities, leading to backwardation and contango market conditions, respectively. On the other hand, the alignment of estimated periods of expansions and contractions with backwardation and contango market conditions; is a profound empirical finding, postulating the applicability of a Markov switching regime framework in forecasting the turning points between the two conditions, because of its usefulness in measuring lengths of expansions and contractions during business cycles.

Another contribution of this chapter is the introduction of a transitional state that is used to indicate the switching time between expanding and contracting markets along with mean values and volatility ranges for freight rates during different market conditions. This is used in this thesis to measure expansion and contraction periods, and can be used to make important management and operation decisions, such as the time to lay-up a vessel and the appropriate adjustment to steaming speed. The outcome of MSM provides thresholds that indicate different freight bands during different market conditions. In other words, the importance of creating freight thresholds based on means of freight levels and their associated volatility levels, according to market conditions, is to provide a better assessment in making the choice between laying-up or trading a vessel, an important decision that is made by ship-owners.

Chapter Eight

8. The dynamics of tanker freight cycles: The financial crisis case II

8.1. Introduction

In maritime literature, contraction and expansion periods within freight markets are characterised as periods of lower and higher volatilities, respectively, thus, identifying the former as a period of low risk and the latter as a period of high risk. According to the literature this is due to high elasticity and low elasticity of freight supply at the time, respectively. Thus, the shape of the freight supply curve is due to high elasticity and low elasticity of freight supply during contractions and expansions phases of the freight shipping cycle, respectively. Empirical findings in the previous chapter justify the use of distinct regime states to better explain freight dynamics within a conditional freight limitation framework, providing a clear distinction between a period that is largely controlled by ship-owners and a period that is largely controlled by cargo-owners. As the main focus of this thesis is to estimate and manage freight risk, it is imperative that the variation in the freight risk-return relation is investigated on the basis that up and down market movements are defined as shipping agent controlled. Therefore, each freight return is classified to belong to a distinct earning state using indicator functions and constructing a conditional five-beta freight return model. In other words, motivated by the findings in chapter seven, the consistency of a freight-beta sensitivity measure across different market conditions is tested through a conditional five-beta freight-return model. Moreover, this framework is suitable to measure and compare total risk across tanker segments by computing their relevant specific and systematic risks.

Therefore, the contribution of this chapter to the literature is of threefold. First, using a Markov-switching regime framework, each daily freight return in our sample is classified as belonging to a distinct earning state that is influenced by either ship-owners or cargo-owners (charterers), pre- and post a significant homogenous structural break. Second, the hypothesis of a consistent freight-beta is tested under a new definition of market movements, thus, investigating whether freight risk-return relations vary, depending on market conditions and in particular during the last decade, a period of triumphs and misfortunes for the shipping industry. Finally, freight risk within the tanker market is decomposed into its components; specific and systematic risk.

In summary, the empirical work within this chapter complements previous work conducted in chapter seven by investigating whether the freight risk-return relationship varies depending on markets dynamics, particularly pre and during the most recent shipping economic boom that was ended by the financial crisis. The rest of the chapter is organised as follows. Section 8.2 examines relevant literature. Section 8.3 presents the employed methodological framework. Section 8.4 discusses empirical work and findings. Section 8.5 concludes the chapter.

8.2. Literature review

The main objective of this chapter is to investigate to what extend the beta risk-return relationship in freight markets depends on market movements, in which a definition is needed to classify market dynamics. As this chapter uses Markov-switching regimes to define market dynamics, it is paramount that we review the relevant literature on the topic. Therefore, the usefulness of Markov-switching regime models in improving estimations and classifications of market dynamics in distinct regimes is examined along with the usefulness of incorporating this in a capital asset structure to better asses the sensitivity of beta risk-return in different market conditions.

In this chapter we argue that dynamics within spot freight markets are better expressed through distinct states. Therefore, the robustness of a constant freight beta under different market conditions is investigated by allowing the first and second moments of freight returns to switch stochastically between different market conditions. While Nomikos and Alizadeh (2004) and Alizadeh *et al* (2008) classify up/down market movements based on volatility levels within returns, we classify our distinct regime states based on levels and volatilities within earning price levels. In our opinion this better captures the long-term dynamics within freight rates. This concept is more established in estimating the high degree of correlation between a derivative instrument and its underlying asset. Alizadeh and Nomikos (2012) apply this concept to shipping markets stating that the long-term/short-term correlation between a forward freight contract (FFA) and its underlying spot freight contract can be captured using level prices/returns, to better reflect the long-term/short-term co-movement. Thus, it is empirically acceptable that long-term correlation between a forward contract and its relevant underlying asset is higher than the short-term correlation, simply because of the two variables following a common trend in the long run, contrary to the short run due to frequent changes in market conditions.

However, Doornik and Hendry (2009c) suggest that a multi-regime switching means model could match the NBER[42] cycle determined by the NBER business-cycle committee, by examining a plot of real and growth quarters of US GNP arguing that this can be a motivation to use regime-switching models by allowing the mean growth rate to shift between recessions and normal growth periods. They restate that the objective of a regime-switching model is to allow for different behaviour distinguishing between the

[42] The National Bureau of economic Research: http://www.nber.org.

natures of different states and simultaneously estimating the transition from one state to another.

Additionally, a wide range of papers investigates the usefulness of Markov switching regime models in improving value-at-risk measures in comparison to other traditional parametric and non-parametric models. For example Guidolin and Timmermann (2003) combine the filtered historical simulation and the switching regime volatility as an alternative method to forecast VaR values. This is investigated further in the value-at-risk chapters.

In the literature many studies explore different ways to identify up and down market movements. For example Kim and Zumwalt (1979) use a simple three level threshold to classify market movements based on the average monthly market return, the average risk-free rate and value of zero. An inclusive investigation into the relationship of the risk-return in the tails of the market return distribution can be found in the work of Crombez and Vennet (2000), where they use a two thresholds framework to identify up and down markets, based on a zero and the risk-free rate, they extend their two regime structure to a three regime framework to account for neutral markets. Their classifications are based on average positive/negative market returns combined with variations of standard deviations of market returns. The condition of the market is identified by comparing the realized market return with the different thresholds levels, thus classifying the market as up/down markets. They conclude that classifications of up and down markets better explain their conditional beta risk-return relationship.

The work done in this chapter was mainly influenced by the work of Galagedera and Faff (2005) where they incorporate market movements into an asset pricing model by taking account of the conditional market volatility. They classify three regimes based on market conditional volatility models via a GARCH model. They define three indicators classifying daily volatilities belonging to one of the three markets volatility regimes: low volatility market (LVM), neutral volatility market (NVM) and high volatility (HVM) market. This is based on the xth and (1-x)th percentiles of the conditional variance series, for LVM and HVM, respectively. Their definition of a three regime structure is as follows:

$$I_{Lt} = \begin{cases} 1 & if\ \sigma_t^2 < \sigma_L^2 \\ 0 & otherwise \end{cases}$$

$$I_{Nt} = \begin{cases} 1 & if\ \sigma_L^2 \leq \sigma_t^2 \leq \sigma_H^2 \\ 0 & otherwise \end{cases}$$

$$I_{Ht} = \begin{cases} 1 & if\ \sigma_t^2 > \sigma_H^2 \\ 0 & otherwise \end{cases}$$

where $\sigma_L^2$and σ_H^2 are the xth and (1-x)th percentiles of the conditional variance series, thus, grouping the time series into three groups depending on the prevailing volatility. They first measure market beta through an unconditional single-beta security return generating process and than extend it to account for market volatility. Therefore, measuring systematic risks corresponding to their identified regimes, they refer to this model as a three-state regime-switching model with percentile as threshold parameters. Motivated by their work we undertake similar steps to investigate whether freight risk-return relation vary, depending on market movements and in particular during the last decade. Our classification of up and down market movements is based on five indicators corresponding to expansion (up) markets and contraction (down) markets pre-2000 significant structural break; and expansion (up) markets, transitional (neutral) markets and contraction (down) markets post-2000 structural break, these distinct regime states are identified through a multi-state Markov-switching regime framework and incorporated in a conditional five-beta freight return model.

Moreover, Huang *et al* (2011) investigate the contagion effect among the stock market, real estate market, credit default market and energy market, during the most recent financial crisis. They use a Markov switching regime VAR application to capture market regime shifts. Their results reveal that contagion within these markets is nonlinear with two distinct regimes; a risky regime and a stable regime, characterized by a large mean with high volatility and a smaller mean with small volatility, respectively. Additionally, they classify duration periods for the latter being twice longer than the former. They argue that this is consistent with empirical observations that the duration of economic prosperity tend to be longer than those of volatile periods.

Most importantly, the use of Markov-switching regime models in the maritime literature is scarce. For example one of the earliest researches to incorporate such models in their work was Kavussanos and Alizadeh (2002b) where they suggest a two-state Markov regime switching seasonal (MRSS) model to compare seasonal fluctuations in freight rates between periods of market expansion and contraction in the tanker market. Their model is an extension of a deterministic seasonal model to account for different market conditions. They state that their framework is a combination of two linear models, which captures the seasonal behaviour of freight rates when the market is in contraction and expansion, and that these market conditions are relevant to high elasticity and low elasticity of the freight supply, respectively. Thus, they stress that the shape of the freight supply curve is due to high elasticity and low elasticity of supply during troughs and peaks phases of the freight shipping cycle, respectively. Thus, as described by Stopford (1997, 2002, 2009) the shipping supply function is elastic when freight rate is low and inelastic when freight rate is high. Kavussanos and Alizadeh (2002b) started their argument by reviewing the work of Canova and Ghysels (1994) who argued the inconsistent of the magnitude of seasonality in macroeconomic variables over time and that the deterministic seasonality depends on the prevailing market conditions relevant to the phase of the business cycle. Another paper by Nomikos and Alizadeh (2004) uses a Markov-switching regime model to determine the time-varying minimum variance hedge ratio in stock index futures markets, based on an argument that evidence from the literature suggest that robust estimates of the conditional second moments can be obtained by allowing freight volatility to switch stochastically between different market conditions. A more recent study by Alizadeh *et al* (2008) examined the performance of hedge ratios generated from Markov regime switching models in oil future markets, based on the rational that dynamic relationship between spot and future prices are better characterised by regime shits.

Abouarghoub and Biefang-Frisancho Mariscal (2011) find empirical evidence that supports the case that shipping tanker freight returns shift between two regimes, a high volatility regime and a low volatility regime and that market shocks in general increase the volatility of freight returns and has a lasting effect. Their work is based on a two-state Markov-switching regime framework to different tanker markets segments. This approach provides a different method of indicating upwards and downwards market movements than other applications presented in the literature. For example a broad weak market evaluation in the financial literature is based on the value of the observed return in respect to zero, where markets are classified as bearish or bullish are conditional on returns being negative or positive, respectively. Another, better, method of market evaluation in the financial literature has been in respect of the observed return to a set of averages of negative and positive returns. On the one hand, if observed return is smaller than average estimated negative returns than market is classified as bearish. On the other hand, if observed return is larger than average positive estimated returns market is classified as bullish. Thus, producing a broad neutral interval in which the market is classified as neither bullish nor bearish. For measuring freight returns see the value-at-risk chapter (chapter four).

8.3. Methodological framework

Empirical findings in chapter seven suggest the suitability of a five distinct market state framework to better capture the dynamics within tanker freight earnings. In other words, changes in price levels and volatilities of tanker freight earnings are influenced by distinct market movements. This dynamic behaviour has been empirically identified in chapter seven as being asymmetric pre- and post-2000 and shipping agents controlled. This has motivated us to examine the risk-return relationship in freight earnings within this concept, which is a different perspective for market movements than previous work in the literature. Therefore, conditional shipping freight rate is represented by a two-state and a three-state pre and post the 2000 exogenous structural-break, respectively. From a risk perspective and in few wards, the empirical objective of this chapter is of twofold. First, to examine the consistency of a freight-beta sensitivity measure during different market conditions, this is tested through a conditional five-beta freight return model, influenced by previous findings[43]. Second, to measure and compare total risk across tanker segments by computing their relevant specific and systematic risks.

Based on the above and assuming that shipping freight rates are unstable and volatile over time, we suggest that a sensitivity measure such as a freight beta will be inconsistent across various earning regime states. To test this postulate, we define five market conditions with different regime states based on a Markov-switching regime framework and develop a conditional five-beta freight return model. Each estimated beta will correspond to different market movements, such as when freight rates are at low levels and when they are at high levels, pre- and post-2000, in addition to a transitional state for the period post-2000. This multifactor model is used to investigate the dynamic structure of freight returns in different market conditions and is constructed in the following steps.

The first step is to use an appropriate shipping earning index as a proxy of earnings within the shipping industry. We derive the various earning state regimes using a MSR framework, obtaining five distinct freight earning regimes. These definitions are based on indicator functions. In other words, the daily return in each tanker segment is classified as belonging to a distinct earning state according to the corresponding regime state creating a five dummy return framework. This generated process is estimated

[43] The methodology of chapter seven is applied to a proxy of unconditional shipping markets (not just tankers) to better represent returns' sensitivity to market movements.

using the method of ordinary least squares, for a large sample of freight returns for different tanker segments.

In the second step, we investigate the sensitivity of unconditional freight rates in each tanker segment to the overall shipping sector. This is carried out through an unconditional single-beta freight return model. This model is extended in the third step to estimate betas in the pre-low, pre-high, post-low, post-transitional and post-high earning state structures. This interpretation of the freight factor beta model should improve our understanding of freight returns fundamentals by decomposing freight risk into its systematic and specific risks components. This framework, along with the method of estimation and the tests used are explained in more details in the following sections.

8.3.1. Market freight earning state regimes

Empirical work in chapter seven suggests that earning dynamics within the tanker freight markets are better defined using a multi-state Markov-switching regime framework, postulating that freight rates switch between different levels of earnings and volatilities dependent on the prevailing market conditions at the time. In the initial part of this chapter we adopt the same methodology as chapter seven, section 7.3.2, this time applied to the *ClarkSea Index* (CSI), which is a time series that reflects daily earnings within the whole shipping industry instead of just the tanker sector. This time series is described and illustrated in section 8.4.1 and Figure 8.1, respectively. Our Markov-switching regime estimation identifies five different regime states, in which we classify each daily earning as belonging to a distinct earning state. Thus, our definition of five regime states using indicator functions is as follows:

$$I_t^{PLV} = \begin{cases} 1 & if\ returns\ are\ in\ the\ pre-2000\ low\ earning\ state\ (regime\ 1) \\ 0 & otherwise \end{cases}$$

$$I_t^{PHV} = \begin{cases} 1 & if\ returns\ are\ in\ the\ pre-2000\ high\ earning\ state\ (regime\ 2) \\ 0 & otherwise \end{cases}$$

$$I_t^{BLV} = \begin{cases} 1 & if\ returns\ are\ in\ the\ post-2000\ low\ earning\ state\ (regime\ 3) \\ 0 & otherwise \end{cases}$$

$$I_t^{BTV} = \begin{cases} 1 & if\ returns\ are\ in\ the\ post-transitional\ earning\ state\ (regime\ 4) \\ 0 & otherwise \end{cases}$$

$$I_t^{BHV} = \begin{cases} 1 \ \ if \ returns \ are \ in \ the \ post-2000 \ High \ earning \ state \ (regime \ 5) \\ 0 \ \ otherwise \end{cases}$$

The above abbreviations PLV, PHV, BLV, BTV and BHV indicate pre-2000 low volatility, pre-2000 high volatility, boom-period low volatility, boom-period transitional volatility and boom-period high volatility. Based on our indicator framework our data sample follows five market regimes that are classified as; low earning state pre-2000 structural break; high earning state pre-2000 structural break; low earning state post-2000 structural break; transitional earning state post-2000 structural break; high earning state post-2000 structural break. The empirical work for this part is presented in section 8.4.2 and reported in Table 8.1. Additionally, multi-state regime shifts during the pre- and post-2000 periods for the CSI are illustrated in Figures 8.2 and 8.3, respectively. Similar to chapter eight we investigate and test the significance of these structural breaks that are the basis of our dummy structure. The empirical tests are based on the methodology in section 7.3.3 and can be found in section 8.4.2 and are presented in Table 8.3.

8.3.2. The unconditional single-beta freight return model and the decomposing of the total risk to specific and systematic risks

A measure of market freight beta is expressed through a single-factor framework. Thus, the unconditional single-beta freight return is estimated using a market model in the following form:

$$r_{i,t} = \alpha_i + \beta_i r_t^m + \varepsilon_{i,t} \tag{8.1}$$

where $r_{i,t}$ is the freight earning return for a specific tanker segment *i* in period *t* and r_t^m is return on the shipping market portfolio *m* in period *t*. The latter is represented by the *ClarkSea Index*, which is a proxy of daily earning in the shipping sector. This is used here as a benchmark for shipping market returns. Thus, we can rewrite equation 8.1 as:

$$r_{Seg,t} = \alpha_{Seg} + \beta_{Seg} r_t^{CSI} + \varepsilon_{Seg,t} \quad \text{where} \quad \varepsilon_{Seg,t} \sim N(0, \sigma^2) \tag{8.2}$$

where $r_{Seg,t}$ is the freight earning return for a specific tanker segment *seg* in period *t* and r_t^{CSI} is the return on shipping market portfolio *CSI* in period *t*. α_{Seg} and β_{Seg} represents over/under performance and positive/negative sensitivity of the tanker segment *seg* relative to the shipping market benchmark, respectively. While $\varepsilon_{Seg,t}$ represent the estimated residuals within the regression and are assumed to be normally distributed and homoscedastistic. The results are discussed in section 8.4.4 and represented in Table 8.6 along with the results for the whole system of equations.

In respect of analysis, a positive/negative value of α_{Seg} is used as an indication of outperformance/underperformance of freight returns for a specific tanker segment relative to the shipping market benchmark. Most importantly, β_{Seg} is used as a risk factor to measure returns' sensitivity for a specific tanker segment relative to the shipping market benchmark. Furthermore, total freight risk is estimated by computing its components. First, systematic risk by $\beta_{Seg} \times \sigma_{CSI}$, where β_{Seg} is the estimated coefficient from the above regression and σ_{CSI} is the unconditional standard deviation for CSI returns. Second, specific risk $\sigma_{\varepsilon_{Seg}}$, which is the estimated standard deviation for the residuals within each tanker segment regression. Both are annualized for each tanker segment and the total risk is expressed in the form:

$$\text{Total Risk} = \sqrt{\text{Systematic Risk}^2 + \text{Specific Risk}^2} \tag{8.3}$$

Thus, the total risk components are measured as:

$$\text{Systematic Risk } = \beta_{Seg} \times \sigma_{CSI}\sqrt{52} \tag{8.4}$$

and

$$\text{Specific Risk} = \sigma_{\varepsilon_{Seg}} \times \sqrt{52} \tag{8.5}$$

Where $\sigma_{\varepsilon_{Seg}}$ is the standard deviation for the regression (for a specific tanker segment) residuals. The results can be found in section 8.4.6 and represented in Table 8.7.

8.3.3. The Conditional five-beta freight return multivariate model expressed in a dynamic system of equations and the decomposing of the total risk to specific and systematic risk

The unconditional single-beta freight return equation (8.2) is extended to accommodate different market conditions, in particular pre- and post- the estimated exogenous structural-break, where a general form can be expressed as:

$$R_{i,t} = \alpha_i + \sum_{j=1}^{k} B_i^j I_t^j r_{i,t} + v_{i,t} \quad \text{where } i, \text{ and } j = 1,2,3,4,5,\ k=5 \quad v_{i,t} \sim [0, \sigma_i^2] \qquad (8.6)$$

Thus, a conditional five-beta freight return model is established to investigate freight beta state dependency within the tanker market and can be expressed as:

$$r_{Seg,t} = \alpha_{Seg} + \beta_{Seg}^{PLV}(I_t^{PLV} r_t^{CSI}) + \beta_{Seg}^{PHV}(I_t^{PHV} r_t^{CSI}) + \beta_{Seg}^{BLV}(I_t^{BLV} r_t^{CSI}) + \beta_{Seg}^{BTV}(I_t^{BTV} r_t^{CSI}) + \beta_{Seg}^{BHV}(I_t^{BHV} r_t^{CSI}) + \varepsilon_{Seg,t} \qquad (8.7)$$

where β_{Seg}^{PLV}, β_{Seg}^{PHV}, β_{Seg}^{BLV}, β_{Seg}^{BTV} and β_{Seg}^{BHV} are sensitivities measures for tanker segments to changing market conditions and I_t^{PLV}, I_t^{PHV}, I_t^{BLV}, I_t^{BTV} and I_t^{BHV} are dummy variables corresponding to distinct market conditions, these are; pre-boom low earning state, pre-boom high earning state, post-boom low earning state, post-boom transitional volatility state and post-boom high earning state, respectively. While specific risk is represented by residuals of the tanker segment regression, $\varepsilon_{Seg,t}$ through its unconditional volatility (standard deviation), systematic risk is represented by a conditional volatility expression that corresponds to changing market conditions, during which freight volatility is switching between distinct states. Thus, calculating total freight risk for equation 8.6 is an extension of equation 8.3 and can be expressed as a general form of total freight risk and written as:

$$\text{Total Risk} = \sqrt{\left(\sum_{rs=1}^{5} \beta_{Seg}^{rs} \times \sigma_{CSI,rs}\sqrt{52}\right)^2 + \left(\sum_{rs=1}^{5} w_{Seg}^{rs} \times \sigma_{\varepsilon_{Seg}}\sqrt{52}\right)^2} \qquad (8.8)$$

where *rs* refers to regime state and w_{Seg}^{rs} is the weight of the specific regime state relevant to the whole sample, for each tanker segment *seg*, where the numbers from 1 to 5 correspond to five tanker sectors VLCC, Suezmax, Aframax, Product and WATE, and the five estimated market conditions, respectively. The systematic risk for each tanker segment is computed by multiplying the estimated conditional betas from regressions 8.7 by the annualised conditional standard deviation of market returns during distinct regime states.

$$\text{Systematic Risk} = \left(\beta_{Seg}^{PLV} \times \sigma_{CSI,PLV}\sqrt{52}\right) + \left(\beta_{Seg}^{PHV} \times \sigma_{CSI,PHV}\sqrt{52}\right) + \left(\beta_{Seg}^{BLV} \times \sigma_{CSI,BLV}\sqrt{52}\right) + \left(\beta_{Seg}^{BTV} \times \sigma_{CSI,BTV}\sqrt{52}\right) + \left(\beta_{Seg}^{BHV} \times \sigma_{CSI,BHV}\sqrt{52}\right)$$

(8.9)

Unconditional freight specific risk for each tanker segment is simply estimated by computing the square-root of the variance of freight returns $\sqrt{\sigma^2_{\varepsilon_{Seg,t}}}$. Therefore, this is extended to estimate conditional freight specific risk, capturing market dynamics.

$$\text{Specific Risk} = \left(w_{Seg}^{PLV} \times \sigma_{\varepsilon_{Seg}} \times \sqrt{52}\right) + \left(w_{Seg}^{PHV} \times \sigma_{\varepsilon_{Seg}} \times \sqrt{52}\right) + \left(w_{Seg}^{BLV} \times \sigma_{\varepsilon_{Seg}} \times \sqrt{52}\right) + \left(w_{Seg}^{BTV} \times \sigma_{\varepsilon_{Seg}} \times \sqrt{52}\right) + \left(w_{Seg}^{BHV} \times \sigma_{\varepsilon_{Seg}} \times \sqrt{52}\right) \tag{8.10}$$

As for the overall shipping market systematic risk this is estimated using the variance of CSI returns, $\sqrt{Variance(R_{CSI,t})}$ or $\sqrt{\sigma^2_{R_{CSI,t}}}$, where the *ClarkSea Index* CSI is a proxy of earnings for the whole shipping markets. In summary, for a series of tanker freight returns, systematic risk arises from the volatility of freight returns of the series and specific risk arises from the volatility of residuals of the risk factor related model.

8.3.4. System formulation

It is suggested in the literature that different tanker segments are interrelated. Hence, we estimate our model using simultaneous equations. Therefore, equation 8.2 applied to five data sets under investigation and rewritten as one system of equations is expressed as:

$$\begin{pmatrix} r_{VLCC,t} \\ r_{Suezmax,t} \\ r_{Aframax,t} \\ r_{Product,t} \\ r_{WATE,t} \end{pmatrix} = \begin{pmatrix} \alpha_{VLCC} & \beta_{VLCC} \\ \alpha_{Suezmax} & \beta_{Suezmax} \\ \alpha_{Aframax} & \beta_{Aframax} \\ \alpha_{Product} & \beta_{Product} \\ \alpha_{WATE} & \beta_{WATE} \end{pmatrix} \begin{pmatrix} 1 \\ r_t^{CSI} \end{pmatrix} + \begin{pmatrix} \varepsilon_{VLCC,t} \\ \varepsilon_{Suezmax,t} \\ \varepsilon_{Aframax,t} \\ \varepsilon_{Product,t} \\ \varepsilon_{WATE,t} \end{pmatrix} \tag{8.11}$$

Following the same token equation 8.7 can be expressed as:

$$\begin{pmatrix} r_{VLCC,t} \\ r_{Suezmax,t} \\ r_{Aframax,t} \\ r_{Product,t} \\ r_{WATE,t} \end{pmatrix} =$$

$$\begin{pmatrix} \alpha_{VLCC} & \beta^{PLV}_{VLCC} & \beta^{PHV}_{VLCC} & \beta^{BLV}_{VLCC} & \beta^{BTV}_{VLCC} & \beta^{BHV}_{VLCC} \\ \alpha_{Suezmax} & \beta^{PLV}_{Suezmax} & \beta^{PHV}_{Suezmax} & \beta^{BLV}_{Suezmax} & \beta^{BTV}_{Suezmax} & \beta^{BHV}_{Suezmax} \\ \alpha_{Aframax} & \beta^{PLV}_{Aframax} & \beta^{PHV}_{Aframax} & \beta^{BLV}_{Aframax} & \beta^{BTV}_{Aframax} & \beta^{BHV}_{Aframax} \\ \alpha_{Product} & \beta^{PLV}_{Product} & \beta^{PHV}_{Product} & \beta^{BLV}_{Product} & \beta^{BTV}_{Product} & \beta^{BHV}_{Product} \\ \alpha_{WATE} & \beta^{PLV}_{WATE} & \beta^{PHV}_{WATE} & \beta^{BLV}_{WATE} & \beta^{BTV}_{WATE} & \beta^{BHV}_{WATE} \end{pmatrix} \begin{pmatrix} 1 \\ r^{PLV}_{CSI,t} \\ r^{PHV}_{CSI,t} \\ r^{BLV}_{CSI,t} \\ r^{BTV}_{CSI,t} \\ r^{BHV}_{CSI,t} \end{pmatrix} +$$

$$\begin{pmatrix} \varepsilon_{VLCC,t} \\ \varepsilon_{Suezmax,t} \\ \varepsilon_{Aframax,t} \\ \varepsilon_{Product,t} \\ \varepsilon_{WATE,t} \end{pmatrix}$$

(8.12)

This is a five-beta regime-switching freight-return model with market conditions as threshold parameters. Where $r^{PLV}_{CSI,t} = I^{PLV}_t \times r^{CSI}_t, r^{PHV}_{CSI,t} = I^{PHV}_t \times r^{CSI}_t, r^{BLV}_{CSI,t} = I^{BLV}_t \times r^{CSI}_t, r^{BTV}_{CSI,t} = I^{BTV}_t \times r^{CSI}_t \, and \, r^{BHV}_{CSI,t} = I^{BHV}_t \times r^{CSI}_t$, and B^{PLV}, $B^{PHV}, B^{BLV}, B^{BTV}$ and B^{BHV} are measures of tanker segments sensitivities to different market conditions, these are; sensitivities to pre-boom low earning state, pre-boom high earning state, post-boom low earning state, post-boom transitional earning state and post-boom high earning state, respectively. The system 8.12 is an unrestricted reduced form (URF) and can be expressed in a more compact way as:

$$\boldsymbol{r}_{seg,t} = \boldsymbol{B}\boldsymbol{r}_{CSI,t} + \boldsymbol{v}_t \qquad (8.13)$$

In which the matrices are expressed in bold face upper case and the vectors in bold face lower case. Where $\boldsymbol{r}$ is a (5×1) vector of endogenous variables, these are freight return observations at time *t* relevant to a defined data set r_t, which is a proxy of earning returns within the shipping industry, this is a non-modelled variable and classified as restricted, while *A* and *Beta's* are (5×1) vectors of unrestricted variables. Hence, each equation in the system has the same variables on the right-hand side. Since *A* and *Beta's* are unrestricted variables, the system can be estimated using multivariate least squares method. This requires that $V_t \sim ID_n(0,\Omega)$, where Ω is constant over time and is singular owing to identities linking elements of r_t, these are managed by estimating only the subset of equations corresponding to stochastic endogenous variables. Thus, if $V_t \sim ID_n(0,\Omega)$ is valid OLS coincides with maximum likelihood estimation (MLE).

8.3.5. System estimation

The system can be expressed in the following compact way

$$\boldsymbol{r}_{seg,t} = \boldsymbol{B}\boldsymbol{r}_{CSI,t} + \boldsymbol{v}_t \qquad t = 1, \dots, T \text{ and } \boldsymbol{v}_t \sim [0,\Omega] \tag{8.14}$$

where $\mathrm{E}[v_t]$=0 and $\Omega = \mathrm{E}[v_t v_t']$, $\boldsymbol{r}_{seg,t}$ is a (5×1) vector matrix that represents freight earning returns for four tanker segments and the overall tanker sector under investigation, while $\boldsymbol{r}_{CSI,t}$ is a (6×1) vector matrix that represents freight earning returns for the overall shipping sector and $\boldsymbol{B}$ is a (5×6) matrix representing market parameters. v_t is a (5×1) vector matrix that represents the corresponding residuals for each equation in the system. Thus, the system can be expressed more compactly by using

$\boldsymbol{R}'_{seg} = (\boldsymbol{r}_{seg,1}, \boldsymbol{r}_{seg,2} \dots \dots, \boldsymbol{r}_{seg,T})$, $\boldsymbol{R}'_{CSI} = (\boldsymbol{R}_{CSI,1}, \boldsymbol{R}_{CSI,2} \dots \dots, \boldsymbol{R}_{CSI,T})$ and $\boldsymbol{V}'_{seg} = (\boldsymbol{v}_{seg,1}, \boldsymbol{v}_{seg,2} \dots \dots, \boldsymbol{v}_{seg,T})$.

Therefore, equation 8.14 can be expressed as $\boldsymbol{R}_{seg} = \boldsymbol{B}\boldsymbol{R}_{CSI} + \boldsymbol{V}$ and as $\boldsymbol{R}'_{seg} = \boldsymbol{B}\boldsymbol{R}'_{CSI} + \boldsymbol{V}'$. Where $\boldsymbol{R}'_{seg}$ is $(n \times T)$, $\boldsymbol{R}_{CSI}$ is $(k \times T)$ and $\boldsymbol{B}$ is $(n \times k)$, with $k = nm$. Thus, $\widehat{\boldsymbol{B}'} = (\boldsymbol{R}'_{CSI}\boldsymbol{R}_{CSI})^{-1}\boldsymbol{R}'_{CSI}\boldsymbol{R}_{seg}$ and $\widehat{\boldsymbol{\Omega}} = \widehat{\boldsymbol{V}}'\widehat{\boldsymbol{V}}/(T-k)$. The residuals are defined by $\widehat{\boldsymbol{V}} = \boldsymbol{R}_{seg} - \boldsymbol{R}_{CSI}\widehat{\boldsymbol{B}'}$ and the variance of the estimated coefficients is defined as $V\left[vec\widehat{\boldsymbol{B}}'\right] = E\left[vec\left(\widehat{\boldsymbol{B}}' - \boldsymbol{B}'\right)\left(vec\left(\widehat{\boldsymbol{B}}' - \boldsymbol{B}'\right)\right)'\right]$. In which $vec\boldsymbol{B}'$ is an $(nk \times 1)$ column vector of coefficients.

Furthermore, assuming that $\boldsymbol{V} \sim [\boldsymbol{0}, \boldsymbol{\Omega}]$ holds and that all the coefficient matrices are constant. Thus, the log-likelihood function $\ell(\boldsymbol{B}, \boldsymbol{\Omega} | \boldsymbol{R}_{seg}, \boldsymbol{R}_{CSI})$ depends on the following multivariate normal distribution.

$$\ell(\boldsymbol{B}, \boldsymbol{\Omega} | \boldsymbol{R}_{seg}, \boldsymbol{R}_{CSI}) = -\frac{Tn}{2}\log 2\pi - \frac{T}{2}\log|\boldsymbol{\Omega}| - \frac{1}{2}\sum_{t=1}^{T} v'_t \boldsymbol{\Omega}^{-1} v_t \tag{8.15}$$

By differentiating the above equation with respect to $\boldsymbol{\Omega}^{-1}$ and equating that to zero, we find the following

$$= K_c - \frac{T}{2} log|\mathbf{\Omega}| - \frac{1}{2} tr\ (\mathbf{\Omega}^{-1}\boldsymbol{V}'\boldsymbol{V})$$

$$= K_c + \frac{T}{2} log|\mathbf{\Omega}^{-1}| - \frac{1}{2} tr\ (\mathbf{\Omega}^{-1}\boldsymbol{V}'\boldsymbol{V})$$

$$2\boldsymbol{V}'\boldsymbol{V} - dg\,(\boldsymbol{V}'\boldsymbol{V}) = 2T\mathbf{\Omega} - Tdg(\mathbf{\Omega})$$

where *tr* and *dg* stands for trace and diagonal of the matrix, respectively. $K_c = \frac{-Tn}{2}(1 + log2\pi)$ and is a constant. Given that $\mathbf{\Omega} = \mathrm{E}(\mathbf{T}^{-1}\mathbf{V}'\mathbf{V})$ we drive the concentrated log-likelihood function (CLF)

$$\ell_c(\boldsymbol{B}, \mathbf{\Omega}|\boldsymbol{R}_{seg}, \boldsymbol{R}_{CSI}) = K_c - \frac{T}{2}\log|\boldsymbol{V}'\boldsymbol{V}| + \frac{Tn\log T}{2} - \frac{Tn}{2}$$

$$= K_c - \frac{T}{2}\log|(\boldsymbol{R}'_{seg} - \boldsymbol{B}\boldsymbol{R}'_{CSI})(\boldsymbol{R}_{seg} - \boldsymbol{R}_{CSI}\boldsymbol{B}')| \qquad (8.16)$$

Based on least squares theory we minimize $(\boldsymbol{R}'_{seg} - \boldsymbol{B}\boldsymbol{R}'_{CSI})(\boldsymbol{R}_{seg} - \boldsymbol{R}_{CSI}\boldsymbol{B}')$ to find the maximum likelihood estimates $\widehat{\boldsymbol{B}'} = (\boldsymbol{R}'_{CSI}\boldsymbol{R}_{CSI})^{-1}\ \boldsymbol{R}'_{CSI}\boldsymbol{R}_{seg}$ and $\widehat{\mathbf{\Omega}} = T^{-1}\widehat{\boldsymbol{V}}'\widehat{\boldsymbol{V}}$. Thus, maximizing $\hat{\ell} = K_c - \frac{T}{2}\log|\widehat{\mathbf{\Omega}}|$ with $\widehat{\mathbf{\Omega}}$ scaled by *T*. More details of the adopted methods in this chapter can be found in Doornik and Hendry (2009a, p 145-150).

8.3.6. Multivariate testing

In the empirical section 8.4.4 specification-test information is presented along with the system regression outputs in Table 8.7.

The statistics for the unrestricted reduced form (URF) coefficients $\hat{\beta}_i^j$ and their standard errors are calculated to determine whether individual coefficients are significantly different from zero.

$$t - value = \frac{\hat{\beta}_i^j}{SE[\hat{\beta}_i^j]} \qquad (8.17)$$

Where the null hypothesis H_0 is $\hat{\beta}_i^j = 0$. The null hypothesis is rejected if the probability of getting a value different than zero is less than the chosen significance level. This probability is computed by $t - prob = 1 - Prob(|\tau| \leq |t - value|)$, in which τ has a Student *t*-distribution with *T*-*k* degrees of freedom. The standard error for each equation in the system is calculated by taking the square root of their residual variance, $\sqrt{\widetilde{\Omega}_i}$ for *i*=1,2,..,5. The *residual sum of squares* for each equation is calculated as $RSS = (T - k)\widetilde{\Omega}_i$. These are the diagonal elements of $\hat{V}'\hat{V}$. The highest attainable likelihood value for the system is calculated as $\hat{l} = -\frac{1}{2}\log|\widehat{\boldsymbol{\Omega}}| - \frac{Tn}{2}(1 + log2\pi)$ and is reported in Table 8.6, pp. 282, along with $-\frac{1}{2}\log|\widehat{\boldsymbol{\Omega}}|$, $|\widehat{\boldsymbol{\Omega}}|$ and $log|\widehat{\boldsymbol{\Omega}}_{\boldsymbol{0}}|$ values, also the total number of observations *T* and total number of parameters *Tn* in all equations.

In addition, in the empirical section 8.4.4 (the top part of Table 8.7) we report two different measures of *goodness of fit* for our system based on the likelihood-ratio principle R^2_{LR} and the lagrange multiplier principle R^2_{LM} for a single equation system and for the significance of each column of $\widehat{\boldsymbol{B}}$, respectively. Furthermore F-tests are conducted and results are reported for both methods, for the employed system of equations, in two parts. First, F-tests against unrestricted regressors, this uses Rao (1952) F-approximation (details provide below) to test the null hypothesis that all coefficients are zero (except the unrestricted variables, in our case is the constant in each equation), this is the reported F-statistic to test the significance of the *r* squared for a single equation system R^2_{LR} based on the likelihood-ratio principle, where $R^2_{LR} = 1 - |\widehat{\Omega}||\widehat{\Omega}_0|$ and $R^2_{LM} = 1 - \frac{1}{n}tr(\widehat{\Omega}\widehat{\Omega}_0)$. Second, F-tests on retained regressors are conducted and reported for the significance of each column of $\widehat{\boldsymbol{B}}$ together with their probability values under the null hypothesis that the corresponding column of coefficients is zero, thus, testing whether each variable is significant in the system, with the statistics $F(n, T - k + 1 - n)$.

Furthermore, testing for general restrictions is conducted for each single equation in the system and the overall system. Thus, we test the significance of deferent estimated betas for each regime state. Thus, writing $\widehat{\boldsymbol{\theta}} = vec\,\widehat{\boldsymbol{B}}'$ and corresponding variance-covariance matrix $V[\widehat{\boldsymbol{\theta}}]$, we test for non-linear restriction of the form $f(\theta) = 0$. Where the null hypothesis $H_0: f(\theta) = 0$ and the alternative hypothesis $H_1: f(\theta) \neq 0$ using a Wald test in the form:

$$w = \boldsymbol{f}(\widehat{\boldsymbol{\theta}})'\left(\widehat{\boldsymbol{J}}\,V[\widehat{\boldsymbol{\theta}}]\widehat{\boldsymbol{J}}'\right)^{-1}\boldsymbol{f}(\widehat{\boldsymbol{\theta}}) \tag{8.18}$$

where $\boldsymbol{J}$ is the Jacobian matrix and is the transformation of $\partial \boldsymbol{f}(\boldsymbol{\theta})/\partial \boldsymbol{\theta}'$. The Wald statistic follows a $x^2(s)$distribution, where s is the number of restriction that corresponds to number of equations in the system. The null is rejected if the test statistic is significant. We report the results for Wald test for general restrictions along with their corresponding p-values for each equation in the system and a joint test for the whole system in Table 8.7. Finally, correlation of actual and fitted data is reported in Table 8.7. Thus, we estimate the correlation between $r_{seg,t}$ and $\hat{r}_{seg,t}$ for all five tanker segments under investigation.

An important objective of using the previous framework is to quantify both systematic risk and specific risk within the freight market by relating the distribution of returns to the distribution of risk factors. Systematic risk is undiversifiable, while specific risk is not associated with the risk factor returns and can be reduced in theory by a well diversified portfolio. In our linear regression model specific risk is measured as the standard deviation of the residuals for each state and systematic risk is computed by multiplying the obtained freight beta by the square root of the variance of returns.

8.4. Empirical work and findings

In this section we present empirical analysis and findings. First, a proxy for overall shipping freight earning level-prices is analysed to identify dynamic changes for freight earnings within the shipping market and to better assess tanker earnings sensitivities to market forces. The *ClarkSea Index*[44] is the only published weekly indicator of earnings for all the main commercial vessel types. It is weighted according to the number of vessels in each fleet sector. Clarksons Research collects rates direct from the Clarksons brokers on a daily and weekly basis and these are used to calculate the earnings that go to make up the *ClarkSea Index*. The sectors in the *ClarkSea Index* are oil tankers (VLCC, Suezmax, Aframax and clean product carriers), dry bulk carriers (Capesize, Panamax, Handymax and Handysize), gas carriers (VLGC) and fully cellular containerships. This is motivated by findings in chapter seven, where a multi-state Markov-switching regime framework is used to examine the existence of a significant

[44] The ClarkSea Index is published in graphical/numerical form on the front page of the Clarksons Shipping Intelligence Weekly (SIW) and is downloadable as a time series and graph on SIN ñ Shipping Intelligence Network (www.clarksons.net).

structural shift within tanker freight earnings[45], similarly, the existence of a homogenous structural break within overall shipping freight earnings is examined. Furthermore, the same framework is implemented post the identified structural break to examine asymmetry within different earning states and to identify shifts between different states, thus, classifying each day within our sample to belong to a distinct earning state in respect to a proxy of shipping market earnings. This classification is presented in the second section and is paramount for the specification of our five-beta freight return model, where five regime states are identified through dummy variables and based on the MSR model output. Third, statistics for tanker freight returns is examined relevant to a two-state Markov switching regime framework. Fourthly, our constructed five-beta freight return model that tests the hypothesis of freight beta state dependency is presented. Finally, systematic and specific risks within freight earnings are compared and examined.

8.4.1. A proxy for shipping freight earnings

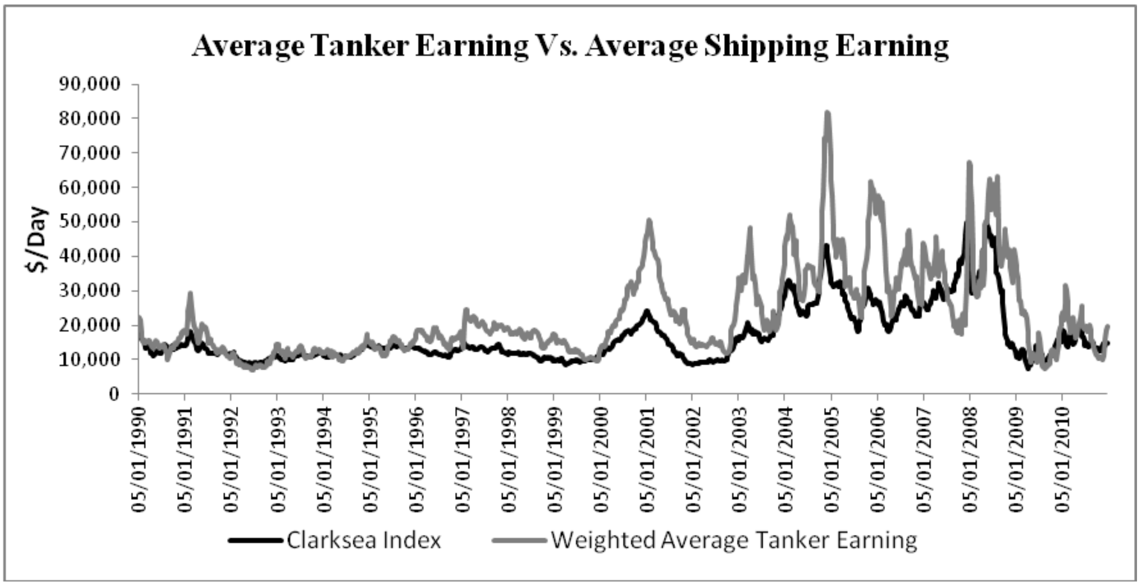
More than 90 per cent of international trade is transported by ships. This fact is confirmed by the International Maritime Origination, the United Nations, the International Chamber of Shipping, the US Federal Government and the European Union. For more details see Mandryk (2009). Within this tanker trade is the largest. For example in the year 2006 total seaborne trade broken down to the main shipping sectors and measured in percentages of transported tonnes; general cargo, containers, dry bulk and tankers were 9 per cent, 10 per cent, 38 per cent and 43 per cent, respectively[46]. Thus, it is reasonable to accept that there is a strong positive correlation between an index that tracks average tanker earnings and another that tracks earnings within the whole shipping market, simply because the former measure accounts for a large part of the latter. This is demonstrated in graph 8.1 by plotting the waited average tanker earning series against the *ClarkSea Index* (CSI) series, respectively. For both freight representations there is a significant structural change post the year 2000. As the main objective of this chapter is to examine the change in freight dynamics of tanker freight returns during the super boom period relevant to pre-2000 period in regards to market

[45] Freight earning level prices data series used in this chapter represents the whole shipping industry contrast to the data set used in chapter eight, where it represented different segments within the tanker sector and an overall representation of the tanker sector.

[46] http://www.imsf.info/papers/NewOrleans2009/Wally Mandryk_LMIU_IMSF09.pdf

movements by using a single factor model, the return on market portfolio is substituted by returns on the CSI.

Figure 8.1: Average tanker earnings vs. average shipping earnings



Note Figure 8.1: illustration of average daily earnings within the tanker industry in comparison to average earnings within the whole shipping industry. Vertical axis refers to daily earnings in dollars.

Source: Author's estimations.

8.4.2. The dynamics of freight earnings index expressed in multi regime states

To investigate sensitivities of freight betas to shipping market movements, we use the *ClarkSea Index* as a proxy for overall shipping freight earning returns, where each observed tanker return is classified as belonging to a distinct earning regime state and is defined through a MSR framework. Furthermore, empirical findings coincide with previous analysis of tanker freight earnings in chapter seven, in respect of earnings fluctuating between two-regime states pre 2000 and between three-regime states post 2000 and is evident in graphs 8.2 and 8.3.

Freight earnings for the overall shipping market after 2000 experience a structural change similar to tanker sector freight markets, where the dynamics of the shipping freight market increase by 10 per cent and 135 per cent in average earnings, and by 137 per cent and 462 per cent in average volatilities levels, for the low volatility state and the high volatility state, respectively. Over the long run it seems that the duration of each state evens out, with average duration for each regime state around 30 per cent, bearing in mind that a 30 per cent of the time earnings are classified as belonging to the transitional period, relevant to the literature freight rates are said to be through the trough stage of shipping freight cycle.

Estimated results from a multi-state Markov switching regime model applied to unconditional shipping freight earnings are statistically significant and reported in Table 8.1. The two columns in the table from left to right represent statistics for the CSI pre- and post-2000, respectively. This is a weighted average shipping earning index, calculated by Clarkson intelligence network to mimic earnings within the whole shipping sector. In other words, CSI rates correspond to earnings for a shipping company that operates a portfolio of vessels that consists of all shipping sectors. For both periods, in which the latter is a subsequent of the former, these two examined periods span from January 1990 to May 2000 and from May 2000 to December 2010, respectively, and are represented in two different columns. Regimes 1, 2 and 3 and their corresponding volatility regimes 1, 2 and 3 represent average daily earnings and their dispersions within for an operated ship within the shipping industry, respectively, for distinct market states, these states are; low earning state, high earning state and super boom period state for the pre-2000 period; and low earning state, transitional state and high earning state for the post-2000 period. Thus, the super boom period state in the pre-2000 period is decomposed into three distinct states that are represented in the second period. Overall the first two earning states in the pre-2000 period and the three earning states in the post-2000 period constitute our conditional five-state indicator framework, in which the five-beta freight return model is classified upon. Our empirical trials indicated that a three regime state is better suited to represent distinct freight earning states for a vessel daily average earning post-2000 in comparison to a two regime state framework pre-2000.

The probability of switching from one market state to another is expressed in Table 8.1 by the transition probability π_{ij} where i,j={1,2 and 3}, a value of zero for a transitional probability indicates the disconnection between the two relevant states, this is evident to the importance of an intermediate state between the two, while a value of 1.0 (100 per cent) indicate the nonexistence of the probability of switching between the relevant two states, which is evident to a permanent structural shift in freight earning dynamics.

Furthermore, the final section of Table 8.1 reports, for each regime state, the average percentage weight relevant to the whole sample and the average duration in weeks (resilience) before shifting to another regime state, denoted by ‘avg weight regime 1, 2 and 3’ and ‘avg duration regime 1, 2 and 3’, respectively. Thus, postulating a significant departure in freight dynamics post-2000 with 50 per cent of our data sample representing a super boom cycle characterised as an extreme volatile period in comparison to the pre-2000 period and that the resilience of freight earnings within cargo-owners markets are higher than within ship-owners markets.

Table 8.1: Markov-switching conditional variance regime models estimations for weekly shipping freight earning

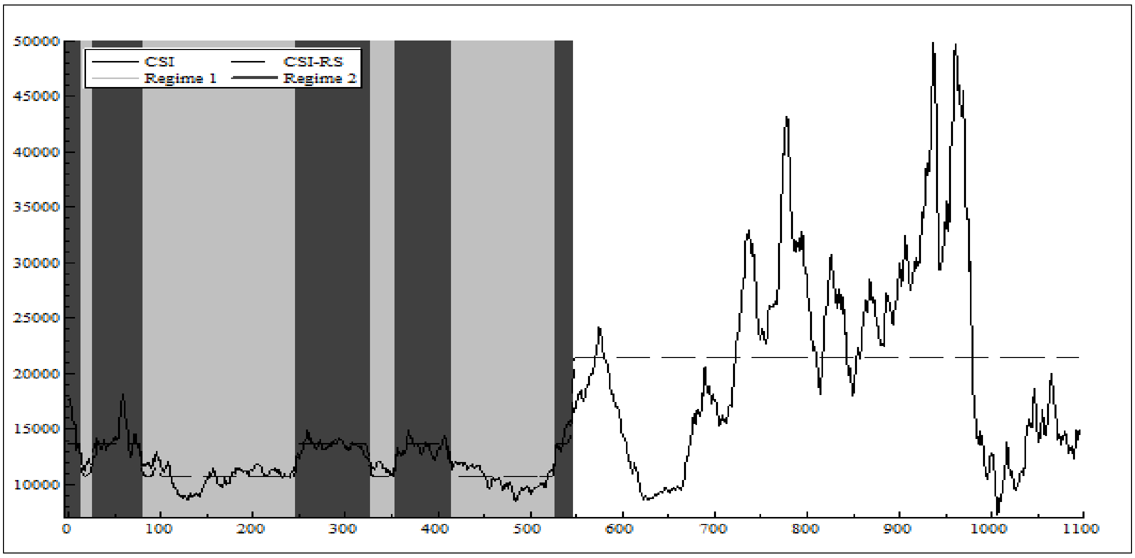
MSCV Model Estimations for Clarkson Sea Index		
	CSI	**CSI Post-Boom**
Start of Period	**05/01/1990**	**16/06/2000**
Regime 1 MWP	10791.9 (165.0)†	11916.6 (33.2)†
Regime 2 MWP	13729.4 (150.0)†	20141.8 (49.5)†
Regime 3 MWP	21428.2	32222.2 (62.9)†
Volatility Regime 1	991.3 (23.4)†	2348.0 (16.4)†
Volatility Regime 2	1108.27 (18.9)	2828.16 (13.3)†
Volatility Regime 3	9333.1	6225.42 (18.3)†
Transition $\pi 11$	0.986460 (146.0)†	0.982805 (98.2)†
Transition $\pi 22$	0.976366 (94.3)†	0.949363 (56.6)†
Transition $\pi 33$	1.0	0.97388
Transition $\pi 12$	0.01354	0.017195
Transition $\pi 13$	0	0
Transition $\pi 21$	0.0191973 (2.04)*	0.0224412 (1.99)*
Transition $\pi 23$	0.004437	0.028195
Transition $\pi 31$	0	0
Transition $\pi 32$	0	0.0261222 (2.25)*
Avg Weight Regime 1	29.38%	32.67%
Avg Duration Regime 1	80.5Weeks	45 Weeks
Avg Weight Regime 2	20.35%	32.12%
Avg Duration Regime 2	44.6 Weeks	19.67 Weeks
Avg Weight Regime 3	50.27%	35.21%
Avg Duration Regime 3	551 Weeks	38.8 Weeks

Note Table 8.1: represents summary of Markov-Switching Regime models estimations, for different segments of shipping daily freight price-level earnings, illustrating statistics for each regime state, in the form of; average earning, fluctuating range (volatility), average weight, average duration transition probabilities between all states according to the following form; Transition probabilities $\pi\_\{i|j\}$ = P(Regime i at t | Regime j at t+1). A transition probability of 1.0 represents the probability of staying in the boom state. Estimation is based on the sample 05/01/1990 to 31/12/2010, number of Observations are 1096. † and * represents significance level at 1% and 5%, respectively.

Source: Author's estimations.

In respect to the shipping industry earnings this application procedure indicates a 30 per cent in which markets can be classified as bearish markets and 20 per cent as being bullish. In the boom period even though it seams that high and low duration are equals, it is interesting to see that the transitional period has the same weight, this period is classified as the trough stage. A three-state Markov-switching regime model is illustrated in the below graph, where the switching between states are clearly demonstrated by the dashed line and the shaded background highlights the high volatility state and the low volatility state pre the boom-period, from left to right.

Figure 8.2: A three-state regime for shipping earnings

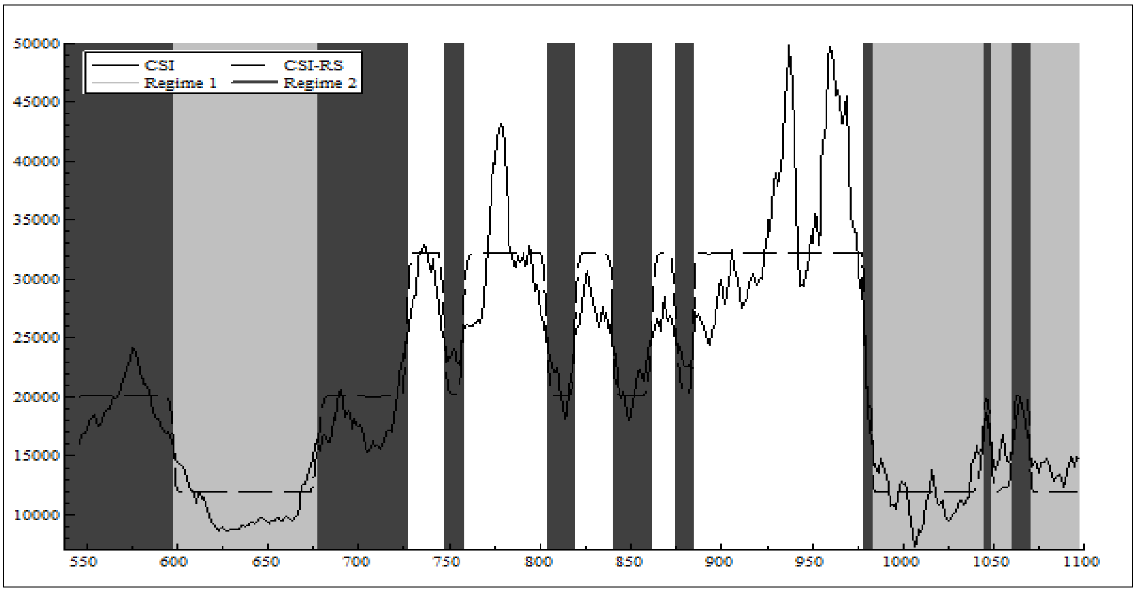


Note Figure 8.2: illustrates tanker market state dependency for average earnings in shipping markets. This is the *ClarkSea Index* that is calculated by Clarkson intelligent network as a proxy for shipping earnings, measured in dollars per day. The structural change is represented by a three-state regime (the dashed line) high state pre-2000 (regime 2), low state pre-200 (regime 1) and structural shift post-2000, from left to right. The solid line represents average earnings in shipping, for the period from 05/01/1990 to 31/12/2010. The shaded areas represent high and low volatility states pre-2000 and the white area represents structural shift post-2000. This is based on output of a markov-switching regime model.

Source: Author's estimations.

In the graph below, a three-state Markov-switching regime model illustrates the dynamic changes in freight earnings post the boom-period, with the dashed line representing switching states between low, transitional and high volatility regimes. It is entreating once examined the graph to observe cycle patens in earnings with a strong period of expansion between 27/12/2002 and 24/10/2009 representing a flourish in shipping markets that was triggered by world trade in addition to the development of the freight derivatives markets and introduction of FFA contracts in 2002. This flourish seems to have been ended by the financial crisis that had massively decreased world wide trade. These findings are aligned with early tanker analyses.

Figure 8.3: A three-state regime for shipping freight earnings for the boom-cycle period



Note Figure 8.3: illustrates regime states for the overall shipping sector imposed on the equivalent average shipping earnings price levels for the super boom-cycle period from 16/06/2000 to 31/12/2010. CSI represent average shipping earnings, by the dashed line, the solid line represent regime states, switching between a high volatility regime 3 state (white shade) to a lower volatility regime 1 state (dark shade) through a transitional regime 2 state (light shade).
Source: Author's estimations.

Similar to our work in chapter seven we carry out stationarity and structural break tests on CSI time series, to investigate the issue of stationarity and the significance of a homogenous structural break within freight earning price levels for the overall shipping market. The results are reported in Table 8.2 and based on multiple tests explained in the methodology section 7.3.1 and 7.3.3. The table reports five tests results subsequently. The first part reports obtained results from a Chow test and an Equal Variance test; the results are highly significant, identifying a homogenous structural break within shipping earnings. These tests require an input to split the sample to two periods; this time-break is estimated by a Markov switching regime model, for the time series and is in aligns with a homogenous structural break identified by a visual inspection of Figure 8.2. The second and third part reports ADF unit-root tests with only a constant and with both constant and trend, respectively. The appropriate numbers of lags were chosen based on minimizing the Schwartz information criterion and the estimated statistics are compared to critical values derived from the response surfaces in MacKinnon (1991). The forth and final part report results of two Perron (1997) unit-root tests with unknown endogenous time break. The first test is applied to the full sample, thus identifying the most significant time-break and, while the second test is applied to part of the sample, starting from the first identified time-break. The appropriate number of lags is chosen based on Perron's general to specific recursive procedure.

The objective of undertaking the Chow test for a single known structural break is to examine the hypotheses of a significant structural shift in shipping freight earnings during the second quarter of 2000. The results are significant and consistent with previous findings of the tanker sector, in other words these structural shifts are significant breaks and are homogenous. In our analysis we refer to the period post this distinct structural break as the super boom-cycle that coincided with the most recent world economical boom. As for examining stationarity, a Unit-Root test indicates that a unit root hypotheses are rejected at 5 per cent significant. These results are easily improved with the Perron (1997) unit root test that takes in account one unknown endogenous break. Implementing the test to two subsamples indicate that freight earnings are conditional stationary. In other words our findings strongly indicate that freight earning price-levels are unconditional stationary aligned with maritime economical theory and recent empirical work, in contrast with earlier empirical work. For more detailed discussion of stationarity of freight earnings see Koekebakker *et al* (2006).

Table 8.2: Unit-root and structural-breaks tests for freight earning returns for the shipping industry

Test	The Clarkson Sea Index	
A Chow Test for a Single known Significant Structure Break		
Total Obss		1096
Chow T		F(2,1092)= 2.59 [0.075]
Equal Var T		F(552,540)= 15.22 [0.000]
Break Date		26/05/2000
Time Break		543
ADF Unit-Root Test with only a Constant		
	Earning Level-Price	Earning Returns
ADF(Lags)	-3.325*(20)	-8.450**(18)
AIC	15.215	-5.308
BIC	15.317	-5.215
HQ	15.254	-3.273
Unit-Root Critical Values 5% =-2.86* 1% =-3.44** MacKinnon (1991)		
ADF Unit-Root Test with a Constant & Trend		
	Earning Level-Price	Earning Returns
ADF(Lags)	-4.136**(20)	-8.438**(18)
AIC	15.211	-5.306
BIC	15.318	-5.209
HQ	15.252	-3.269
Unit-Root Critical Values 5% =-3.42* 1% =-3.97** MacKinnon (1991)		
A Unit-Root Test with an Unknown Endogenous Time Break Perron (1997)		
ADF-TB(Lags)		0.95149 (-5.9255)** (11)
Break Date		26/09/2003
Time Break		717
Unit-Root-TB Critical Values 5% =-5.08* 1% =-5.57**		
A Unit-Root Test with an Unknown Endogenous Time Break Perron (1997)		
ADF-TB(Lags)		0.90899 (-5.5209)** (11)
Break Date		11/12/2008
Time Break		989
Unit-Root-TB Critical Values 5% =-5.08* 1% =-5.57**		

Note Table 8.2: represents in four parts a summary of structural-breaks and Unit-Root tests statistics for returns for one data set that represents freight earnings for the whole shipping sector. The first part: illustrate chow and equal variance tests with known time-breaks, this time-break and date-break is based on the starting of the boom cycle, indicated by the output of the MSR model. The second and third parts: illustrates outputs of ADF tests with constant and constant & trend, respectively, for freight earning level prices and freight returns. The final part; illustrate Perron (1997) Unit-Root procedure with unknown time-break. * and ** represents significance level at 5% and 1%, respectively.

Source: Author's estimations.

8.4.3. Tanker freight earning returns expressed in two distinct regime states

In contrast to the analysis in chapter seven and the above initial empirical work, the main application within this chapter examines freight earning returns not freight earning level-prices. Therefore, it is of interest to examine the existence of distinct market volatility conditions within freight returns. Thus, assuming that freight returns switch in general between two distinct earning states with asymmetric volatilities, we examine the data from a perspective of two states. Abouarghoub and Biefang-Frisancho Mariscal (2011) find empirical evidence that support the postulate of shipping tanker freight returns shifting between two regimes, a high volatility regime and a low volatility regime and that market shocks in general increase the volatility of freight returns and has a lasting effect. Their work is based on a two-state Markov-switching regime framework to different tanker markets segments. The output of their work is reproduced in this section. A two state Markov-switching conditional variance framework applied to tanker earning returns suggest that on average for our observed sample 60 per cent exhibit downwards movements and 40 per cent upwards movements with average durations of 38 weeks and 24 weeks before sifting subsequently, respectively.

Basic statistics reported in Table 8.3 for freight earning returns clearly indicate a positive correlation between the size of tanker vessels and their four statistic moments, the larger the size of the tanker vessel the higher the daily mean return, and their volatility level and excess return. Excess freight volatility is evident in the wide spread between minimum, mean and maximum values for freight price-level earnings. All routes show signs of positive skewness, high kurtosis and departure from normality represented by the Jarque-Bera. There is also clear evidence of ARCH effects in freight price-levels and returns, with different lag levels, Engle's ARCH (1982). While the positive skewness, high kurtosis and the Jarque-Bera normality test clearly illustrate the non-normality of the distribution, the mean daily returns are quite close to zero, which support the zero mean assumption. There is clear evidence of volatility clustering in daily freight returns, where there are high freight volatility periods mixed with low freight volatility periods, which suggests the presence of heteroscedasticity, see Figure 8.4. As a high ARCH order is vital to catch the dynamic of conditional variance, we apply Engle’s LM ARCH test on daily freight returns for different lags. This confirms the presence of ARCH effects which is what the literature suggests (Engle, 1982). The high positive value of skewness and the high kurtosis for daily tanker freight returns are tested; their t-tests and p-values are reported in Table 8.3.

Table 8.3: A summary of basic statistics for shipping freight earnings returns

Freight Earning Returns 12-01-1990 to 31-12-2010 (1095 observations)					
Segments	VLCC-Returns	Suezmax-Returns	Aframax-Returns	Product-Returns	WAT-Returns
Minimun	-68.26%	-77.38%	-46.68%	-70.63%	-31.10%
Mean	0.00%	0.03%	-0.01%	0.01%	-0.01%
Maximum	79.82%	88.06%	65.77%	61.37%	46.37%
Std Dev	0.15768	0.16551	0.10052	0.11507	0.078508
Skewness	0.4312 (5.83)**	0.4796 (6.48)**	0.5989 (8.10)**	0.0852 (1.15)	0.7441 (10.06)**
Excess Kurtosis	3.333 (22.56)**	3.196 (21.64)**	4.679 (31.68)**	4.431 (30.00)**	4.451 (30.13)**
ARCH (1-2)	38.08 [0.00]	23.90 [0.00]	42.07 [0.00]	19.70 [0.00]	67.47 [0.00]
ARCH (1-5)	26.91 [0.00]	13.97 [0.00]	20.14 [0.00]	11.19 [0.00]	27.58 [0.00]
ARCH (1-10)	14.56 [0.00]	10.48 [0.00]	14.84 [0.00]	8.58 [0.00]	15.97 [0.00]
ARCH (1-20)	8.58[0.00]	5.89 [0.00]	9.44 [0.00]	7.52 [0.00]	8.70 [0.00]
Normality Test	540.65 [0.00]	507.95 [0.00]	1064.5 [0.00]	897.26 [0.00]	1005.0 [0.00]

Note Table 8.3: represents summary of basic statistics of earning returns for weekly shipping freight rates, for four tanker segments. Total observations are 1095 for freight returns, respectively. It is clear from minimum, maximum and standard deviation of freight returns the large spread and high volatility in freight returns. All routes show signs of positive skewness, high kurtosis and departure from normality represented by the Jarque-Bera test, the 5% critical value for this statistic is 5.99. Values ( ) are t-statistics, and ** represent significance level at 1%. Values in [ ] are p values, which are significance for all routes. Engle's ARCH (1982) test is used to examine the presence of ARCH effects in freight series, with 2,5,10 and 20 Lags.

Source: Author's estimations.

Table 8.4: Markov-switching conditional variance regime models estimations for weekly tanker freight earning returns

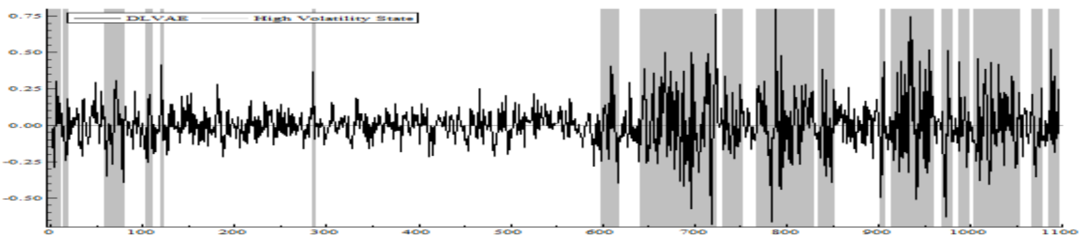
Markov-Switching Conditional Variance Model Estimations for Tanker Earning Returns					
	VLCC	**Suezmax**	**Aframax**	**Product 50k**	**WATE**
MWR-Low State	-0.002446 (-0.61)	-0.003694 (-0.89)	-0.001496 (-0.64)	-0.004769 (-1.78)**	-0.004169 (-2.15)*
MWR-High State	0.004054 (0.33)	0.004887 (0.48)	0.001879 (0.28)	0.0068837 (0.84)	0.005991 (1.04)
Low Volatility State	0.087507 (24.2)†	0.087707 (21.0)†	0.052636 (25.3)†	0.051946 (18.3)†	0.0415680 (27.3)†
High Volatility State	0.232596 (20.1)†	0.223094 (25.8)†	0.140976 (26.6)†	0.166380 (21.9)†	0.112940 (23.5)†
Transition $\pi 11$	0.967159 (76.6)†	0.958120 (52.8)†	0.985223 (133.0)†	0.864982 (33.6)†	0.967957 (91.2)†
Transition $\pi 22$	0.94406	0.95328	0.98043	0.81486	0.95237
Transition $\pi 12$	0.032841	0.04188	0.014777	0.13502	0.032043
Transition $\pi 21$	0.055939 (2.24)*	0.046722 (2.09)*	0.019575 (1.88)**	0.185141 (4.36)†	0.0476307 (2.59)*
Avg Weight LV State	64.02%	53.15%	56.16%	61.19%	60.09%
Avg Duration LV State	41.24 Weeks	32.33 Weeks	102.5 Weeks	10.31 Weeks	38.71 Weeks
Avg Weight HV State	35.98%	46.85%	43.84%	38.81%	39.91%
Avg Duration HV State	21.89 Weeks	28.5 Weeks	68.57 Weeks	6.54 Weeks	24.28 Weeks

Note Table 8.4: represents summary of Markov-Switching Conditional Variance Regime models estimations, for different tanker segments, this is weekly freight earning returns. Illustrating statistics for two regime states, low and high, in the form of; average earning, fluctuating range (volatility), average weight, average duration transition probabilities between states according to the following form; Transition probabilities π_{i|j} = P(Regime i at t | Regime j at t+1). Estimation is based on the sample 05/01/1990 to 31/12/2010, number of Observations are 1096. † and * represents significance level at 1% and 5%, respectively.

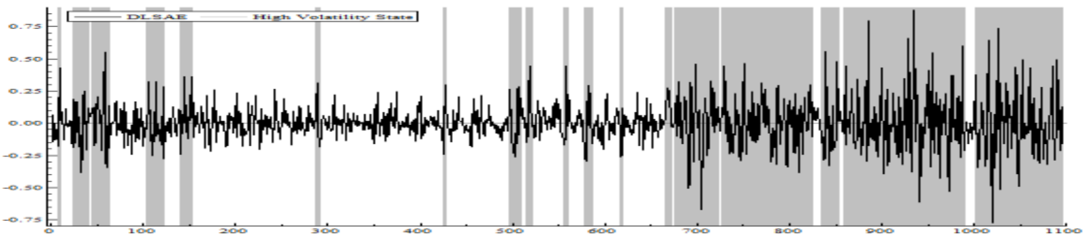
Source: Author's estimations.

Figure 8.4: Freight earning returns versus lower and higher volatility states for five distinctive tanker segments.

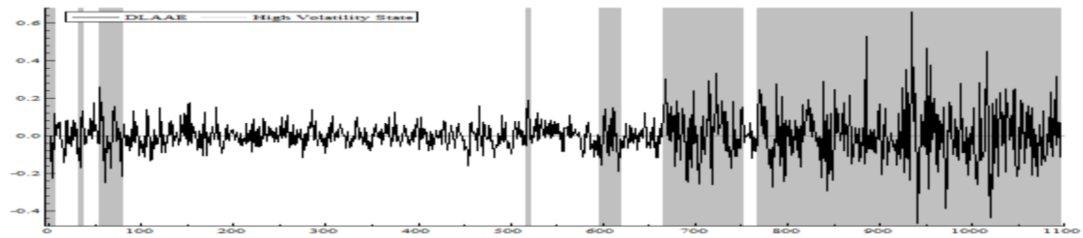
VLCC Freight Earning Returns Vs Low Volatility and High Volatility States



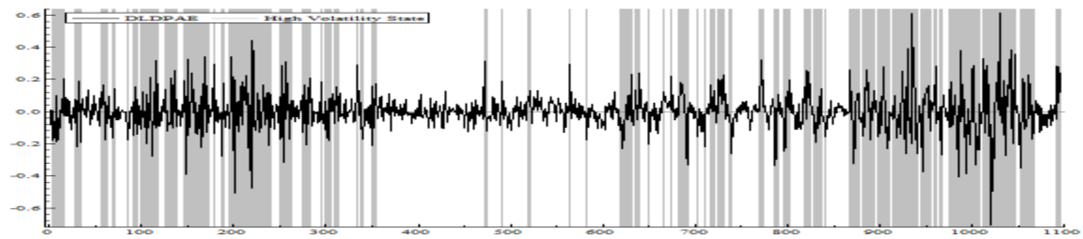
Suezmax Freight Earning Returns Vs Low Volatility and High Volatility States



Aframax Freight Earning Returns Vs Low Volatility and High Volatility States



Panamax Freight Earning Returns Vs Low Volatility and High Volatility States



Weighted Average Tanker Freight Earning Returns Vs Low Volatility and H-V States

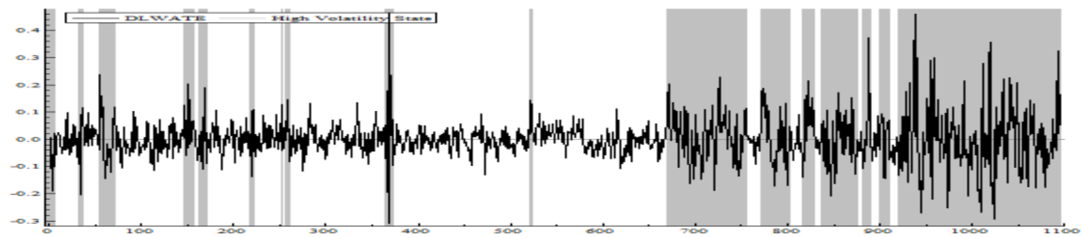


Figure 8.4: represents group graphs of a two state markov switching framework imposed on tanker earning returns for different segments. The shaded area represents the high volatility state and the white area represents the low volatility state. **Source:** Author's estimations using PcGive13 package.

8.4.4. Tanker freight returns sensitivities to market movements

Our empirical work on two decades of tanker freight earning price-levels data clearly indicate that a multi-state market classification is appropriate to explain freight dynamics and that these distinct regime states are better classified as; low earning freight state influenced by bearish conditions; high earning freight state influenced by bullish conditions; and transitional earning freight state were market is neither bearish nor bullish. Most importantly, a significant structural break around the second quarter of 2000 postulate a significant structural shift in freight earning levels and volatilities, pointing to asymmetries between pre- and post-2000 periods, promoting the merit of a five distinct regime states influenced by market dynamics. Thus, working from the postulate that freight earnings switch between five-state regimes for the sample under investigation we map a dummy structural based on the different regime states and implement in a five-state multifactor model to structural a conditional five-beta freight return model. The objective is to test the hypothesis of a stable freight beta against an unstable one across the various distinct regimes. In other words, our model takes in account five different freight market conditions these are tanker earnings sensitivities to downward and upwards market conditions, these market movements are identified by a MSR frame work, were these five conditions are established; downmarket movements pre-2000 (low-volatility state pre-2000), upmarket movement pre-2000 (high-volatility state pre-2000), downmarket movements post-2000 (low-volatility state post-2000), transitional condition post-2000 (transitional- volatility state post-2000) and upmarket movement post-2000(high-volatility state post-2000).

Thus, this study incorporates tanker freight market movements into a multi-factor framework by accounting for multi-regimes of conditional market conditions based on freight earnings switching between verity of distinct states, dependent on market state, a five state-regime is appropriate, were a two state- regime, low volatility and high volatility states, represent pre boom period, and a three state-regime, low volatility, transitional volatility and high volatility states, represent post boom period. The main objective of such a framework is to investigate whether freight returns for different tanker segments respond to market movements depends on the volatility state of the market. Furthermore, we investigate whether tanker market risk measured by betas estimated across multi-volatility regimes is a good measure of freight earning returns risk. This is a risk factor model that aims to quantify systematic freight risk with five-state regimes as threshold parameters.

8.4.4.1. The unconditional single-beta freight return framework

A single-factor framework is the basis for our unconditional single-beta freight return model, that is expressed through regression 8.2 and the results are reported in Table 8.5, where the first column represents conditional tanker segments (different tanker sizes) and the second and third columns report the constant and coefficient beta of regression 8.2 output, respectively. The forth and final columns correspond to the regression residuals standard deviation and the regression sum of squares, respectively. The results indicate a positive correlation between tanker size, beta value and volatility levels, an indication of higher risk associated with larger vessels relative to smaller once, a concept that is established in the current literate. In general the sensitivity of daily earnings for a VLCC to market movements is 4.6 per cent higher than for a Suezmax and is 14.5 per cent higher than for an Aframax and is 183 per cent higher than a product carrier. This is based on analysing unconditional freight beta without considering market movements. Thus, the contribution of this chapter to the literature is to further examine the previous concept under changing market conditions using a new definition of market dynamics, in an attempt to provide a better freight risk insight into the influences of shipping agents on freight dynamics. Additionally, decomposing estimated freight risk to systematic and specific components. In our opinion this provides a different perspective for shipping practitioners in viewing freight risk, thus, improving their risk management techniques.

Table 8.5: The unconditional single-beta freight return model

The unconditional single-beta freight return model CAPM				
	Constant	CSI Returns	Residuals SD	RSS
VLCC	0.00028 (0.06)	2.00060 (18.1)†	0.138489	20.963
Suezmax	0.00063 (0.14)	1.91278 (16.1)†	0.149018	24.271
Aframax	0.00023 (0.10)	1.74775 (28.8)†	0.075828	6.285
Product 50k	0.00024 (0.07)	0.70576 (7.88)†	0.112033	13.718
WATE	-0.00005 (-0.02)	0.28642 (4.60)†	0.0778286	6.6207

Note Table 8.5: reports freight returns sensitivities within different tanker segments in respond to market changes in the shipping sector. The overall return within the shipping sector is represented through CSI data series, which is considered as a measure of freight earnings in the shipping sector, this is known as the Clarkson Sea Index. The sensitivity of each tanker sector to market returns (unconditional Beta) is reported in the third column and referred to as CSI returns. These coefficients are reported along their t-values in brackets, where †, * and ** refers to significance at any level, significance at 5% and significance at 10%, respectively.

Source: Author's estimations.

8.4.4.2. The conditional five-beta freight return framework

Our multivariate five state-regime multi-factor framework investigates the sensitivity of tanker freight returns during changing markets, most importantly pre and post a significant structural shift (an early finding), this is examined for different tanker segments and in various market volatility conditions.

The output of the conditional five-beta freight return system is represented in two parts in Table 8.6. First, the top part, reports summary statistics of the unrestricted system of equation, this includes T (1095) the number of observations used in estimating the system and the number of parameters in all equations nk (5×6) where n represents the five equations in the system and k represents the six parameters (including the constant) in regression 8.7 and is followed by the log-likelihood value. As explained in section 8.3.3.2 the highest attainable likelihood value for the system of equations is estimated by maximizing $\hat{\ell} = K_c - \frac{T}{2}\log|\hat{\Omega}|$ with $\hat{\Omega}$ scaled by T, where K_c is a constant and is represented by $\frac{-Tn}{2}(1 + ln2\pi)$ which equals the value of -7768.688469. Thus, $\hat{\ell} = -7768.688469 - \frac{1095}{2}\ln|2.8196362 \times 10^{-11}| = 5531.087445$ and therefore, we report the log-likelihood, the omega and the $\frac{-Tn}{2}(1 + ln2\pi)$ values, along with $ln|R'R/T|$ which is paramount for calculating measures of the goodness of fit of the system and is explained in the multivariate testing section 8.3.4. Furthermore, we report two measures of goodness of fit for our system based on the Likelihood-ratio and Lagrange multiplier principles see section 8.3.4. Additionally, two F-tests are reported to test the null hypothesis that all estimated coefficients are zero and the significance of each column of the beta matrix in which results are highly significance for both tests, indicating the significance of beta's values in the system. In Table 8.6 top right side report the significance of each column of the beta matrix through an F-test on retained regressors, with abbreviations PLV, PHV, BLV, BTV and BHV read pre-2000 low volatility, pre-2000 high volatility, boom-period low volatility, boom-period transitional volatility and boom-period high volatility, this classification is based on a five market regime indicator framework and are defined as low earning state pre-2000 structural break; high earning state pre-2000 structural break; low earning state post-2000 structural break; transitional earning state post-2000 structural break; high earning state post-2000 structural break.

Second, the bottom part of the table reports outputs of each equation in the system. This part consists of ten columns from left to right presenting tanker segments, unconditional beta (sensitivity of earnings in each tanker segments to market changes, an output from Table 8.5), beta values pre-2000 for low earning and high earning states, general restriction test for the pre-2000 period, beta values post-2000 for low earning, transitional and high earning states, followed by a general restriction test for the post-2000 period and correlations between actual and fitted values. Additionally, in the bottom of the table we report general restriction tests for the whole system of equations for pre- and post-2000 periods. All estimated coefficients of the unrestricted reduced form (URF) are reported along their t-values and significance levels output, while general restriction tests are reported along their probabilities levels in brackets.

Table 8.6: A conditional five-beta freight return model

Conditional Multivariate-beta Freight return Model (OLS)

No. of observations 1095
No. of parameters 30
log-likelihood 5531.08745 -T/2log|Omega| 13299.7759
|Omega| 2.8196362e-011 log|R'R/T| -23.6233335
R^2(LR) 0.487521 R^2(LM) 0.102173
F-test on regressors except unrestricted: F(25,4032) = 31.7989 [0.0000]†

F-tests on retained regressors, F(5,1085) =
PLV 16.4130 [0.000]† PHV 15.4774 [0.000]†
BLV 51.1210 [0.000]† BTV 34.6016 [0.000]†
BHV 79.0226 [0.000]† Constant U 0.00291426 [1.000]

	CSI Returns	Pre Boom-Period		General Resteriction	Post Boom-Period			General	Correlation
	Un Beta	Low Earning	High Earning	Test Chi^2(1)	Low Earning	Transitional	High Earning	Resteriction Test	Actual & Fitted
VLCC	2.00060 (18.1)†	1.70513 (5.03)†	1.53204 (4.87)†	0.14008 [0.7082]	1.76249 (8.70)†	2.00084 (8.16)†	2.58623 (12.2)†	54.689 [0.0000]†	48.83%
Suezmax	1.91278 (16.1)†	1.67396 (4.62)†	1.11768 (3.33)†	1.26750 [0.2602]	1.33191 (6.15)†	2.31494 (8.84)†	2.69810 (11.9)†	81.365 [0.0000]†	45.92%
Aframax	1.74775 (28.8)†	1.44566 (7.86)†	1.25453 (7.35)†	0.58035 [0.4462]	1.59984 (14.6)†	1.73955 (13.1)†	2.25524 (19.7)†	133.57 [0.0000]†	66.96%
Product 50k	0.70576 (7.88)†	0.19585 (0.71)	0.47155 (1.85)**	0.54071 [0.4621]	0.88710 (5.40)†	0.58541 (2.95)†	0.90208 (5.26)†	3.7590 [0.0525]**	24.49%
WATE	0.28642 (4.60)†	0.81096 (4.28)†	0.83409 (4.75)†	0.00801 [0.9287]	0.07437 (0.66)	0.04094 (0.29)	0.24816 (2.10)*	1.0117 [0.3145]	20.09%
Joint Test		GenRes Chi^2(5) = 2.0477 [0.8425]				GenRes Chi^2(5) = 137.79 [0.0000]**			

Note Table 8.6: represents tanker freight segments sensitivity to different states of the shipping markets. Were CSI returns is a measure of freight earnings in the shipping sector, this is known as the *ClarkSea Index* and the Beta represents B's sensitivity of each sector to market returns, this is divided to two sets pre-boom period and post the boom period. General restriction test examines the hypothesis of constant beta's across different state regimes and the joint test is testing the hypothesis of joint constant beta's across all segments. †, * and ** refers to significance at any level , significance at 5% and significance at 10%, respectively.

Source: Author's estimations.

The overall results reported in Table 8.6 indicate the validity of the implemented system through highly significance parameters and satisfying general restriction tests. Furthermore, these empirical findings postulate the inconsistency of tanker freight beta's values across distinct regime states, in which dynamic freight beta is mainly influenced by the size of the tanker and the changing market conditions.

Furthermore, a hypothesis of a constant beta's across different market states (pre boom period) cannot be rejected in unconditional conditions, the same test post boom period clearly indicates the validity of a dynamic beta for crude tanker segments. Analysis of the results overwhelmingly suggests that all betas are positive and significant. This is an indication that the post-2000 period is a significant period for tanker earnings, in which freight levels and volatilities in price and return levels has changed dramatically requiring shipping participants to re-examine and improve their risk management strategies.

There is a clear positive correlation between the size of a vessel and corresponding volatilities of earnings, in line with the maritime literature that recognises that larger vessel are more exposed to freight volatility in comparison to smaller vessels due to the latter ability to switch to different routes and cargos. Some tanker segments are more susceptible to market movements than others. For example, an owner of a VLCC or a Suezmax is exposed more to risk earnings than an owner of an Aframax or a Panamax, due to the large loss in earnings levels during high volatility in comparison to low volatility periods, simply because a vessel with a smaller parcel size is more flexible in adapting to demand and supply in freight services than a larger one.

Thus, in Table 8.6 we express the changes in freight dynamics for variety of tanker segments, by estimating and comparing unconditional and conditional tanker freight betas, where the latter provides a better freight risk insight, simply because the sensitivities of tanker freight earnings are measured across distinct market conditions that are defined as shipping agent controlled.

8.4.5. Freight risk insight into market dynamics

Empirical findings in this chapter show that the dynamics of freight returns are better expressed through distinct regime states, in which the influences of the main shipping agents activities on freight levels and volatilities are accounted for. Furthermore, for the pre-2000 period, the higher beta's values during the lower earning state, a state that is defined as cargo-owner (charterer) controlled, relevant to the lower beta's values during the higher earning state, a state that is defined as ship-owner controlled, reflect the higher sensitivities of the former to market movements in comparison to the latter. However, this dynamic relationship is reversed in the last decade post-2000, where the lower earning state dominated by charterers are much less sensitive to market movements than the higher earning state dominated by ship-owners, reflected in higher beta values for the latter. In our opinion this is attributed to the wide increase use of freight derivatives by shipping agents to manage their freight risk exposure.

Following the same argument in section 8.4.4.1 and considering market dynamics through conditional betas, we have a better understanding of risk dynamics. First, pre-2000, in lower earning state (charterer market) daily earnings sensitivity for a VLCC to market movements is 1.9 per cent higher than a Suezmax and is 17.9 per cent higher than an Aframax and is 774 per cent higher than a product carrier. Second, post-2000, in higher earning state (ship-owner market) daily earnings sensitivity for a VLCC to market movements is 37 per cent higher than a Suezmax and is 22 per cent higher than an Aframax and is 225 per cent higher than a product carrier. There is convincing evidence that tanker freight dynamics have significantly changed from pre- to post-2000 reflected in estimated betas values, a sensitive market risk measure.

8.4.6. Systematic risk and specific risk for freight earnings

Another objective of implementing our multi-factor risk decomposition model for tanker freight earnings, based on five distinct states, is to monitor changes in systematic and specific risks during different market conditions. While specific risk does not change much in different market conditions in comparison to systematic risk, the latter is the main contributor to overall freight risk, as freight beta changes due to prevailing market conditions. Freight risk is clearly positively correlated to tanker segments as demonstrate in Tables 8.5 and 8.6.

In Table 8.7 we report the results for decomposed total freight risk to specific and systematic components, for each tanker segment under investigation and during different market state regimes. The columns in Table 8.7 from left to right correspond to unconditional/conditional beta, number of observations during each regime state, weight of the regime state relevant to the whole sample, tanker segment volatility during a particular regime state, the overall volatility of the shipping sector during the regime state period, the overall annual volatility of the shipping sector during the regime state period, estimated systematic risk during the regime state period, estimated specific risk during the regime state period and total risk during the regime state period. Additionally for each tanker segment conditional totals are calculated for volatility, systematic, specific and total risk. These totals are reported at the end of each segment section and are measured according to dynamic changes within each regime state and differ from unconditional measures that are reported in the first row each of the four sections of the table, and calculated as explained in the methodology section as the following example.

In the VLCC part, total segment volatility, total systematic risk, specific risk and total freight risk is computed subsequently as following.

$$Total\ Segment\ volatility = (0.0875^2 + 0.2326^2 + 0.0875^2 + 0.1674^2 + 0.2215^2)$$

$$Total\ Systematic\ Risk = (0.273^2 + 0.318^2 + 0.658^2 + 0.606^2 + 0.877^2)$$

$$Specific\ Risk = 0.318 \times \sqrt{52}$$

$$Total\ Risk = \sqrt{Systematic\ Risk + Specific\ Risk^2}$$

Table 8.7: Total freight risk decomposed to specific and systematic components

			Unc/Con Beta	No of Obs	Weight	Segment Volatility	Obs CSI Vol	Annual CSI Vol	Sys. Risk	Spes. Risk	Total Risk
VLCC		**Uncond Beta**	2.0	1096	100%	15.8%	3.8%	**27.40%**	**54.8%**	**99.9%**	**113.9%**
	Pre-B	Low-Vol	1.7	322	29.4%	8.75%	2.2%	**16.08%**	27.3%	29.24%	40.0%
		High-Vol	1.5	223	20.3%	23.26%	2.9%	**21.20%**	31.8%	20.25%	37.7%
	Post-B	Low-Vol	1.8	180.0	16.4%	8.75%	5.1%	**36.56%**	65.8%	16.34%	67.8%
		Tran-Vol	2.0	177.0	16.1%	16.74%	4.2%	**30.29%**	60.6%	16.07%	62.7%
		High-Vol	2.6	194.0	17.7%	22.15%	4.7%	**33.75%**	87.7%	17.61%	89.5%
						105.6%			**174.6%**	**99.5%**	**165.4%**
Suezmax		**Uncond Beta**	1.9	1096	100.0%	16.55%	3.8%	**27.40%**	**52.1%**	**107.4%**	**119.4%**
	Pre-B	Low-Vol	1.7	322	29.4%	8.77%	2.2%	**16.08%**	27.3%	31.14%	41.4%
		High-Vol	1.1	223	20.3%	22.31%	2.9%	**21.20%**	23.3%	21.57%	31.8%
	Post-B	Low-Vol	1.3	180.0	16.4%	5.24%	5.1%	**36.56%**	47.5%	17.41%	50.6%
		Tran-Vol	2.3	177.0	16.1%	17.41%	4.2%	**30.29%**	69.7%	17.12%	71.7%
		High-Vol	2.7	194.0	17.7%	32.48%	4.7%	**33.75%**	91.1%	18.76%	93.0%
						141.3%			**167.1%**	**106.0%**	**167.2%**
Aframax		**Uncond Beta**	1.7	1096	100.0%	10.06%	3.8%	**27.40%**	**46.6%**	**54.8%**	**71.9%**
	Pre-B	Low-Vol	1.4	322	29.4%	5.26%	2.2%	**16.08%**	22.5%	15.89%	27.6%
		High-Vol	1.3	223	20.3%	14.09%	2.9%	**21.20%**	27.6%	11.00%	29.7%
	Post-B	Low-Vol	1.6	180.0	16.4%	0.74%	5.1%	**36.56%**	58.5%	8.88%	59.2%
		Tran-Vol	1.7	177.0	16.1%	4.38%	4.2%	**30.29%**	51.5%	8.73%	52.2%
		High-Vol	2.3	194.0	17.7%	15.46%	4.7%	**33.75%**	77.6%	9.57%	78.2%
						35.0%			**133.6%**	**54.1%**	**127.6%**
Panamax		**Uncond Beta**	0.7	1096	100.0%	11.51%	3.8%	**27.40%**	**19.2%**	**80.8%**	**83.0%**
	Pre-B	Low-Vol	0.2	322	29.4%	5.19%	2.2%	**16.08%**	3.2%	23.69%	23.9%
		High-Vol	0.5	223	20.3%	16.60%	2.9%	**21.20%**	10.6%	16.40%	19.5%
	Post-B	Low-Vol	0.9	180.0	16.4%	3.80%	5.1%	**36.56%**	32.9%	13.24%	35.5%
		Tran-Vol	0.6	177.0	16.1%	6.50%	4.2%	**30.29%**	18.2%	13.02%	22.4%
		High-Vol	0.9	194.0	17.7%	17.50%	4.7%	**33.75%**	30.4%	14.27%	33.6%
						48.0%			**24.6%**	**80.6%**	**94.6%**

Note Table 8.7: represents systematic and specific risks for different tanker market segment during different market conditions. Bold values are annualized volatilities. Each section represents a different tanker size segment in a decanting order from largest to smallest, and decomposed in relation market conditions, low volatility state pre-2000, high volatility state pre-2000, low volatility post-2000, transitional state post-2000 and high volatility post-2000, in a decanting order, this is based on our conditional Five-Beta freight return model. The columns from left to right represent the following; unconditional and conditional beta, number of observations, weight of observed state in respect to overall sample, volatility of tanker segment and corresponding state volatility, volatility of overall shipping market and corresponding states, observed market volatility annualized (multiplied by $\sqrt{52}$), systematic risk, specific risk and total risk.

Source: Author's estimations.

8.5. Conclusion

As discussed in the literature section it is widely accepted among maritime economists that the shape of the freight supply curve is due to the high elasticity and the low elasticity of freight supply during contractions and expansions phases of the freight shipping cycle, respectively. Our empirical work in chapter seven contributes to the literature by defining contractions and expansions (market dynamic movements) as shipping agent controlled, distinguishing between a cargo-owner market and a ship-owner market, arguing that freight dynamics are triggered by activities of shipping agents, in the sense that a higher earning state with high volatility and a lower earning state with low volatility is mainly influenced by the activities of ship-owners and cargo-owners within freight markets, respectively. This postulate is explored further in this chapter by investigating the variation in the freight risk-return relation on the basis that up and down market movements are defined as shipping agent controlled.

Therefore, in this chapter, first, tanker freight beta across different segments is estimated for the last two decades to assess sensitivities of tankers' earnings to market movements. Second, the consistency of tankers' freight betas across distinct regime states is tested through a multi-beta freight return structure, where these distinct regimes are defined as shipping agent controlled. On the one hand, a measure of unconditional freight beta provides a general measure of earnings sensitivities within each tanker segment to market movements, which is comparable across tanker segments. On the other hand, a measure of conditional freight beta that accounts for freight dynamics provides a better freight risk insight into the influences of shipping agents on freight dynamics. Finally, total freight risk is assessed across different tanker segments and during changing markets by computing its systematic and specific risk components, which are known as undiversifiable and residuals risks, respectively. The evidence indicates that undiversifiable risk is quite high in comparison to residual risk, suggesting the importance of the need to use freight derivatives to manage such risks, especially that there is clear indications of an increase in risk exposure for shipping participants in the last decade, which is positively correlated to tanker segment. This is attributed to the recently increased freight demand, development in shipping finance and the developed freight derivative markets post-2000.

Chapter Nine

9. Summary of conclusions

9.1. Summary

Maritime literature suggests that freight supply is elastic and inelastic for lower and higher freight rates, respectively. This suggests that volatility dynamics within freight rates shift between two different freight structures. Hitherto, empirical work within the literature has not suggested any framework to capture the characteristics of these different structures.

Furthermore, the accuracy of any freight risk measure is conditional on the methodology used to estimate the volatility of the underlying asset. Thus, factors such as volatility clustering, non-normality, fat-tails and skewness that are associated with freight markets affect the accuracy of freight risk assessments. Therefore, in our work we incorporated asymmetries and distinctive time varying volatilities by adopting a multi-state Markov regime-switching distinctive conditional variance framework. This thesis explores variety of methods to measure short-term freight risk for different tanker segments and a portfolio of freight returns. In particular the state dependency of the underlying conditional variance process is investigated during different market conditions. Findings and suggestions for future research are presented in the following subsections.

9.2. Freight risk for single tanker segments

The suitability of parametric, non-parametric and semi-parametric models in measuring value-at-risk for tanker freight returns is revisited and our findings are in agreement with some recent studies, where semi-parametric based value-at-risk measures are superior in measuring short-term freight risk. The differences within the existing empirical maritime literature over how to measure freight risk are found to be down to the disagreement on the most suitable underlying conditional volatility measure. Empirical work within this thesis provides enough evidence of the distinctive nature of freight conditional volatility and that volatility dynamics within freight returns are better captured by a two-state Markov regime-switching conditional variance. Thus, the hypothesis of shipping freight returns shifting between two regimes, a higher freight volatility regime and a lower freight volatility regime is a postulate that is supported with enough evidence. This framework is able to capture the dynamics of freight returns of a lower and a higher distinct regime states that provide better insight into the elastic and inelastic part of the freight supply curve. These distinctive regimes within the supply curve are empirically classified as lower and higher volatility periods and are better captured by a fractional integrated conditional variance and a normal symmetric conditional variance models, respectively. The suitability of conditional volatility models to capture distinctive volatility dynamics within freight returns is conditional on the vessel size and shipping route and on the fact that long-memory is more pronounced in lower volatility levels than higher volatility levels. Consequently, these proposed representations are found to improve value-at-risk measures for short-term freight risk in comparison to other single-state conditional variance models.

Furthermore, analyses of the sample of returns for single- and multi-routes suggest that the occurrences of volatility clusters within freight returns are much higher during lower volatility levels than for higher volatility levels, and that the occurrences of the former is twice the latter. Most importantly, the duration period for the latter is on average four days and is consistent across all tanker routes, while it ranges from seven to thirteen and half days for the former depending on tanker segment. However, the same analysis applied to the BDTI, a series that is a proxy for earnings within the whole tanker market, suggests that durations are on average seven and sixteen and half for lower and higher volatility states, respectively. In other words, freight volatility clusters tend to have a low tendency to shift from lower volatility state to higher volatility state compared with a tendency of shifting from higher to lower volatility states. This is reflected in twice the value of the transitional probability and in shorter time durations for higher volatility states in comparison to lower volatility states. Furthermore, freight volatilities for larger tanker vessels are more sensitive to the magnitude and sign of market shocks in comparison to smaller tankers.

Therefore, this study investigates this postulate and consequently, accommodates these distinct dynamics in a value-at-risk measure for freight returns. As suggested earlier value-at-risk has become an essential tool to quantify risk in oil markets. Thus, maritime researchers apply value-at-risk methodology to tanker freight markets in recognition of interlinks between tanker freight markets and the underlying transported commodity. Thus, this risk measure can be used to quantify the maximum change in freight price in association with a likelihood level. This thesis improves freight risk measures by accounting for distinctive market conditions. In other words, proposing a framework to quantify the maximum change in freight price in association with a likelihood level, in particular during distinctive market conditions. Furthermore, the estimation of freight risk in this thesis is limited. As discussed earlier VaR should be complemented by expected shortfall to produce a more comprehensive risk monitoring. On the one hand, we are in agreement that VaR measure provides limited information for shipping practitioners and should be complemented with another risk tool to measure medium-term risk that largely benefits small and medium shipping enterprises. On the other hand, we believe that an accurate VaR measure along with a strong understanding of fundamentals and market structure is sufficient to measure short-term risk and meets the needs of large shipping enterprises.

In summary, the dissimilarities in findings within maritime literature regarding a preferred freight risk measure is found to be attributed to the possibility of freight rate returns switching between different volatility structures that are dynamically distinctive. Therefore, this study accommodates these distinct dynamics in a value-at-risk measure for freight returns. On the one hand, proposed value-at-risk measures in the literature can be used to quantify the maximum change in freight price with a likelihood level. On the other hand, the proposed value-at-risk measure in this thesis quantifies the maximum change in freight price in association with a likelihood level, in particular during distinctive market conditions. The findings support the postulate that tanker freight dynamics are state dependent and are better captured by distinctive conditional volatility models, and subsequently provide better risk measures, which are conditional on the size of tanker vessel and the type of trade.

9.3. Freight risk for a portfolio of freight returns

A comparison between single- and multi-state conditional variance based value-at-risk methods, to measure short-term freight risk, found that risk measures are improved by accounting for distinctive volatilities within different regime-states of freight dynamics. Furthermore, the postulate of distinctive conditional freight volatility is confirmed by uncorrelated risk factors extracted from a portfolio of freight returns and a conditional freight-beta framework. Our investigation of value-at-risk clearly suggests the superiority of filtered historical simulation based methods in comparison to normal and non-normal methods, in estimating short-term freight risk. Most importantly, value-at-risk measures that account for distinctive conditional volatility states within freight return dynamics outperform all other models.

Furthermore, empirical results from an orthogonal conditional variance model indicate that tanker markets are associated with distinct risk factors that influence and shape the volatility dynamics of the freight markets. The most pronounced characteristic that seems to influence other risk factors is the size of tanker segment, which is conditional on the volatility state at the time. In our view this is related to a 'changes in vessel size' effect in response to distinct volatility regime states. In simple terms, there is a positive correlation between the size of a vessel and corresponding volatilities of returns, consistent with existing maritime literature that recognises that larger vessels are more exposed to freight volatility in comparison to smaller vessels due to the latter's ability to switch between different routes and cargo consignments.

9.4. The dynamics of tanker freight earnings

The most recent prolonged strength in prices of the underlying transported commodity for tanker vessels is attributed in the literature to a structural change in price levels. This thesis assumes that freight rates are conditional stationary aligned with classic maritime economic theory. Therefore, by implementing a Markov regime-switching framework, the hypothesis of an upward exogenous structural shift in freight earnings post-2000 is found true and to be homogenous across different tanker segments. This is found to have triggered a prolonged period of shipping expansion and that the dynamics of freight earnings pre and post the structural break are asymmetric.

Analysis of the defined super-boom period in this thesis reveals two significant breaks. These upward and downward structural breaks mark the start of the longer and most significant expansions phases during the supper-boom period, respectively. The former is a response to an increase in oil seaborne trade of 17.3 per cent between the years of 2003 and 2007. The latter coincided with the most recent turmoil in the banking sector caused by the financial crisis. Interestingly the impact of the 2007 crisis on tanker markets is twofold. A short lived impact of three months and a long-term impact started early 2009 and is still continuing. However, the increase in uncertainty during the period from 2007 to 2009 is clearly reflected in much higher volatility levels for this contraction period compared with all other estimated contractions.

Furthermore, an investigation into the asymmetries of tanker freight earnings pre- and post-2000 clearly indicates a structural change in volatility dynamics. This is evident in increases in average freight earnings and volatilities levels of more than 150 per cent and 300 per cent, respectively, post-2000 relevant to pre-2000 period. This thesis defines higher freight earning levels and lower freight earning levels as ship-owners and cargo-owners controlled, respectively. Based on the fact that during the former phase there is an excess of cargo relevant to tonnage and vice versa for the latter. These phases are the expansion and contraction phases of a shipping cycle, respectively. Thus, in comparing expansion and contraction phases pre- and post-2000, findings indicate that average freight earnings and volatility levels had increased from 54 per cent and 24 per cent to more than 187 per cent and 137 per cent, respectively. This is another clear indication of a significant structural change in freight dynamics.

On the one hand, a ship-owner's market characterised by higher freights and volatilities levels influences lower long-term freight rates and volatilities, while a cargo-owner's market characterised by lower freight rates and volatilities, influences higher long-term freight rates and volatilities, leading to backwardation and contango market conditions, respectively. On the other hand, the alignment of estimated periods of expansions and contractions with backwardation and contango market conditions is an important empirical finding, suggesting the applicability of a Markov switching regime framework in forecasting the turning points between the two conditions, because of its usefulness in measuring lengths of expansions and contractions during business cycles.

9.5. The dynamics of tanker freight returns

The maritime literature suggests that the shape of the freight supply curve is due to the high elasticity and the low elasticity of freight supply during contractions and expansions phases of the freight shipping cycle, respectively. Therefore, in this thesis these phases are associated with periods that are largely controlled by either cargo-owners or ship-owners, respectively. This postulates that freight dynamics are distinct and triggered by activities of shipping agents, and that a lower earning state with lower volatility levels and higher earning state with higher volatility levels, are mainly influenced by the activities of cargo-owners and ship-owners, respectively. This finding is explored further through an investigation of the variation in the freight risk-return relation on the basis that up and down markets movements are defined as shipping agents controlled.

Therefore, this thesis studied the changes to tanker's earnings sensitivities to market movements through an unconditional and conditional freight-beta framework. On the one hand, a measure of unconditional freight beta provides a general measure of earnings sensitivities within each tanker segment to market movements, which is comparable across tanker segments. On the other hand, a measure of conditional freight beta that accounts for freight dynamics provides a better freight risk insight into the influences of shipping agents on freight dynamics. Finally, total freight risk is assessed across different tanker segments and during changing markets by computing its systematic and specific risk components, which are known as undiversifiable and residual risks, respectively. The evidence indicates that undiversifiable risk is quite high in comparison to residual risk, suggesting the importance of the need to use freight derivatives to manage such risks, especially given that there are clear indications of an increase in risk exposure for shipping participants in the last decade, which is positively correlated to tanker segment. This is attributed to the recently increased freight demand, development in shipping finance and the developed freight derivative markets post-2000.

In summary, the implications of these findings are important to shipping practitioners such as ship-owners, cargo-owners and portfolio managers. The ability to distinguish between the magnitude and duration of volatilities clusters within lower and higher regime states for tanker freight returns, should improve vessel operations, hedging and trading strategies.

9.6. Recommendation for future research

Market conditions such as active operating areas, shorter voyages, lower bunker consumptions and cargo consignment are important factors that affect and shape volatilities clusters within freight returns. Therefore, these externalities need to be investigated more across other shipping markets.

Furthermore, analysis within this thesis shows that a multi-state Markov regime-switching framework has merits in identifying the asymmetry within expansions and contractions for shipping business cycles. This is an empirical framework for measuring distinct phases within shipping freight cycles that should be explored further to include a framework for forecasting that potentially would improve shipping risk management due to the linear components within the nonlinear process.

Finally, analysis within this thesis for freight price-levels and returns are applied to two distinctive measures of spot tanker freight rates. One that is quoted in WorldScale points and is a representation of the cost of transporting a particular consignment of cargo on a particular round voyage in dollars per tonne. The other one is the TCE and is a representation of the cost of hiring a vessel in dollars per day for the same round voyage. The main difference is that the former measure includes all voyage costs while the latter excludes voyage costs. The main voyage cost is bunker cost that accounts for more than fifty per cent of total voyage costs. Thus, comparing the two measures for the same shipping segment can proved analysts with a better insight in to the affect of voyage costs on freight dynamics.

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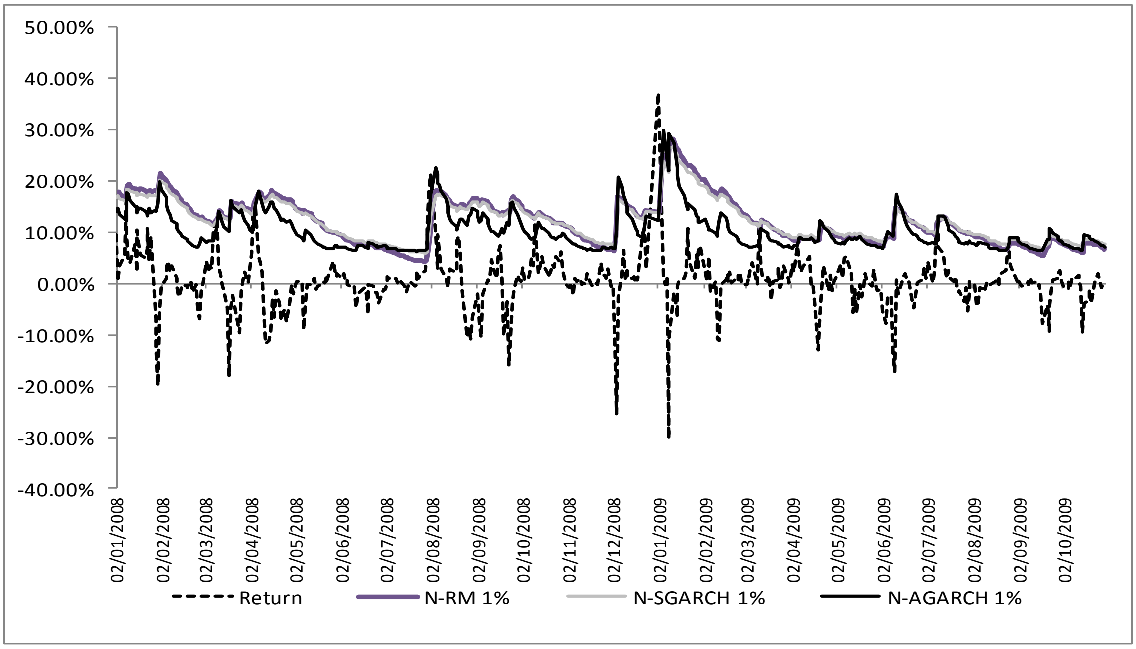
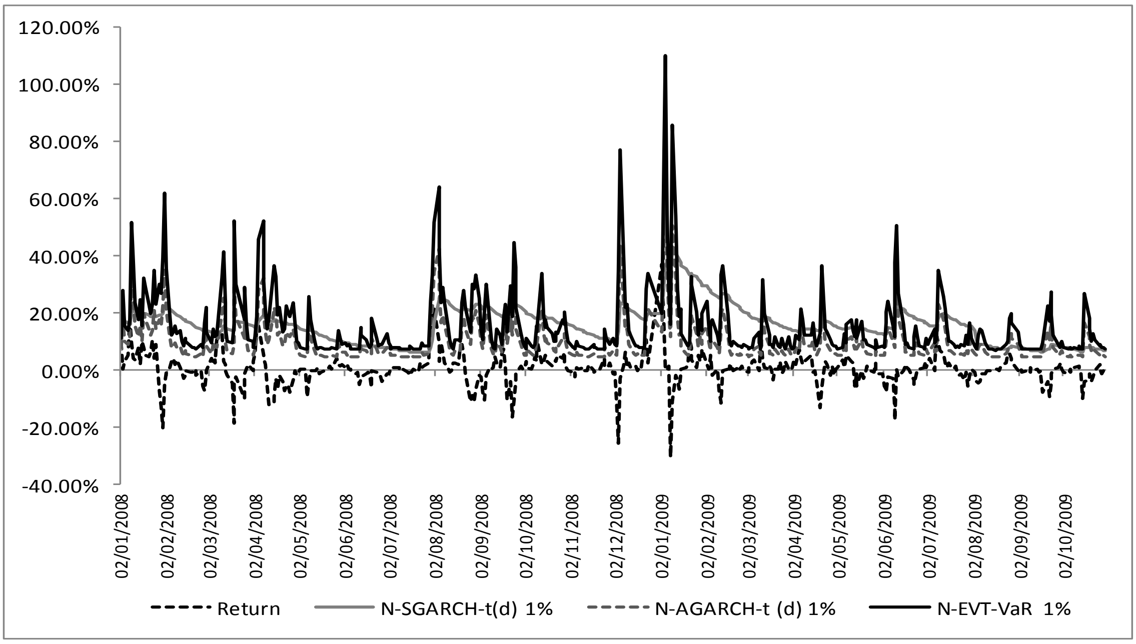
Appendix I

Normal one-day 1% value-at-risk for the tanker route TD3



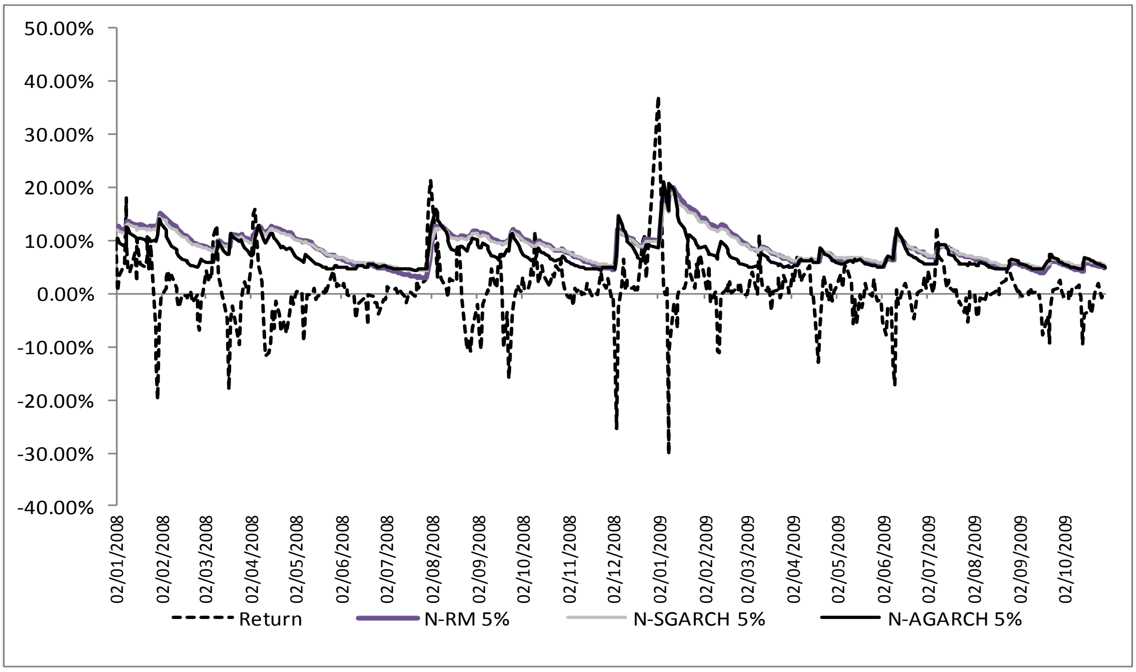
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 1% value-at-risk for the tanker route TD3



Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d), AGARCH-t(d) and EVT. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 5% value-at-risk for the tanker route TD3



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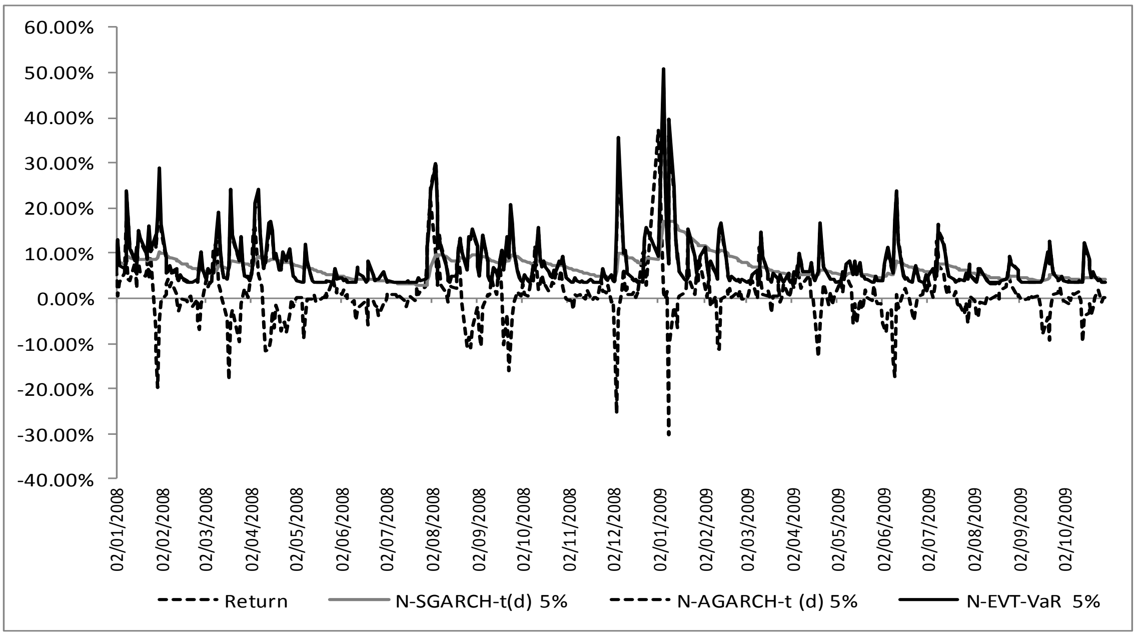
Normal one-day 5% value-at-risk for the tanker route TD3



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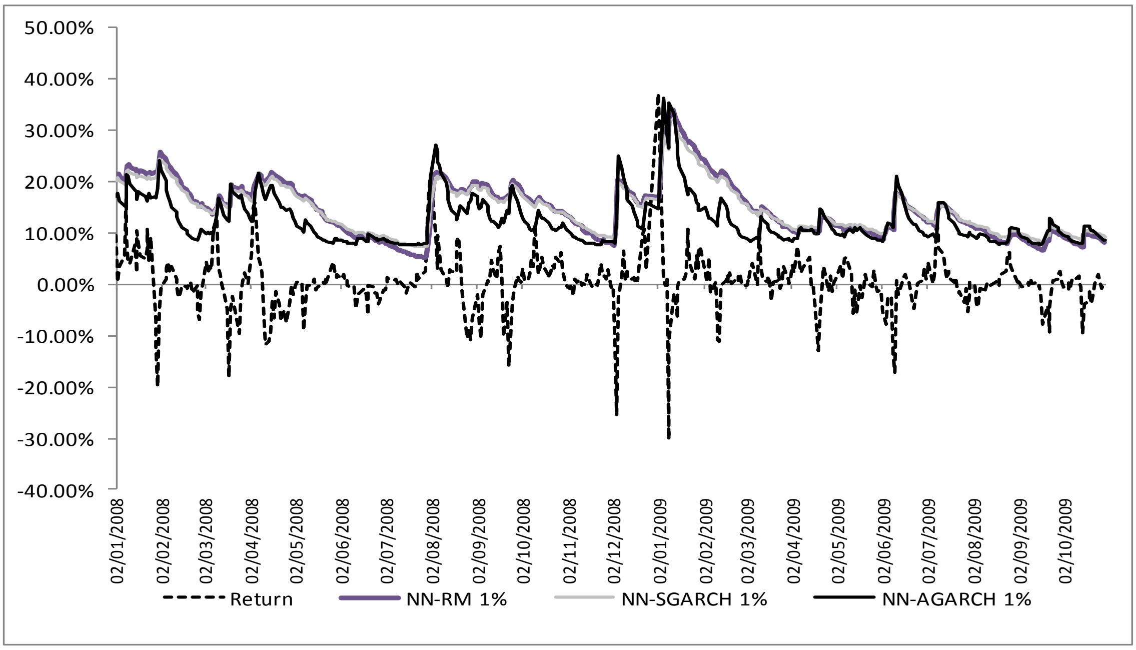
Non-Normal one-day 1% value-at-risk for the tanker route TD3



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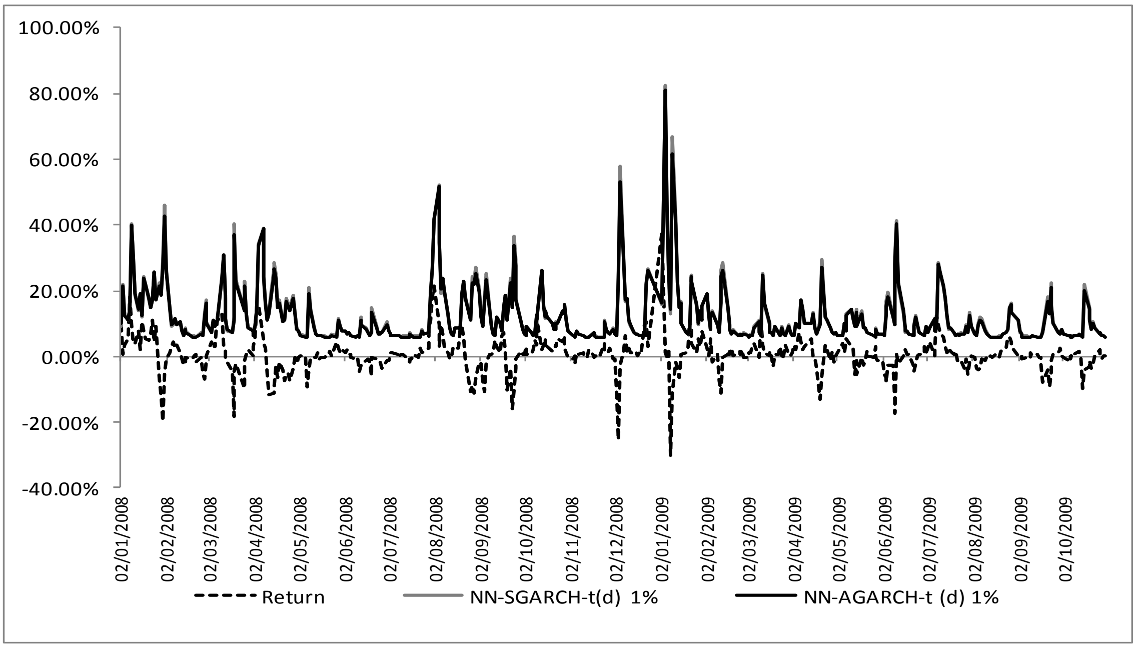
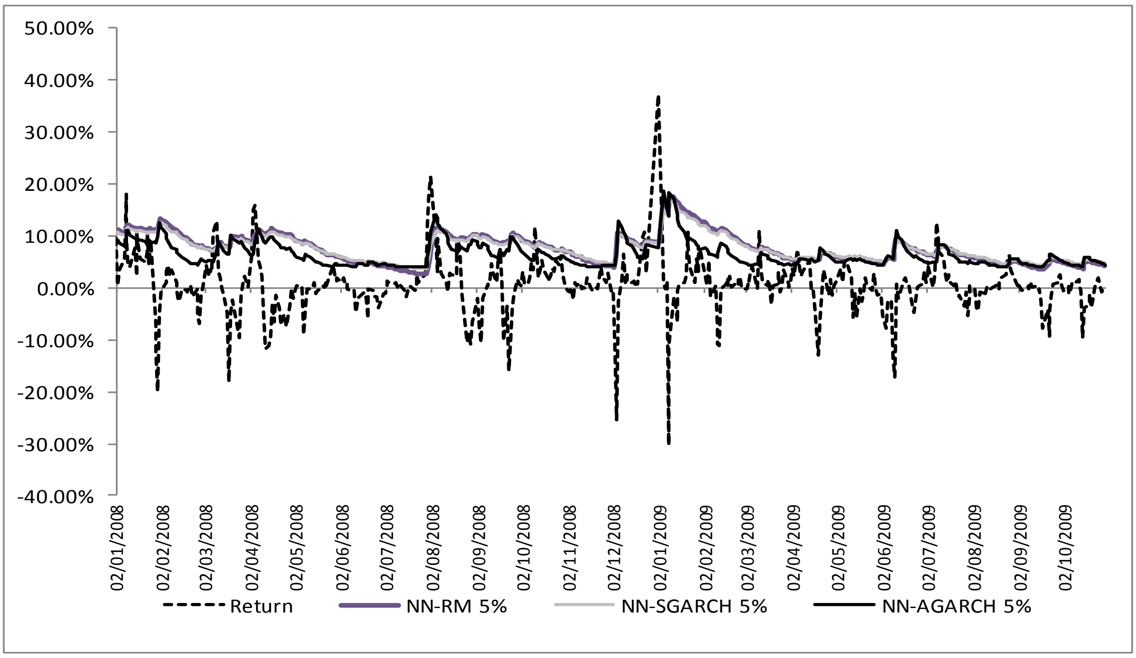
Non-Normal one-day 1% value-at-risk for the tanker route TD3



Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d), and AGARCH-t(d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 5% value-at-risk for the tanker route TD3



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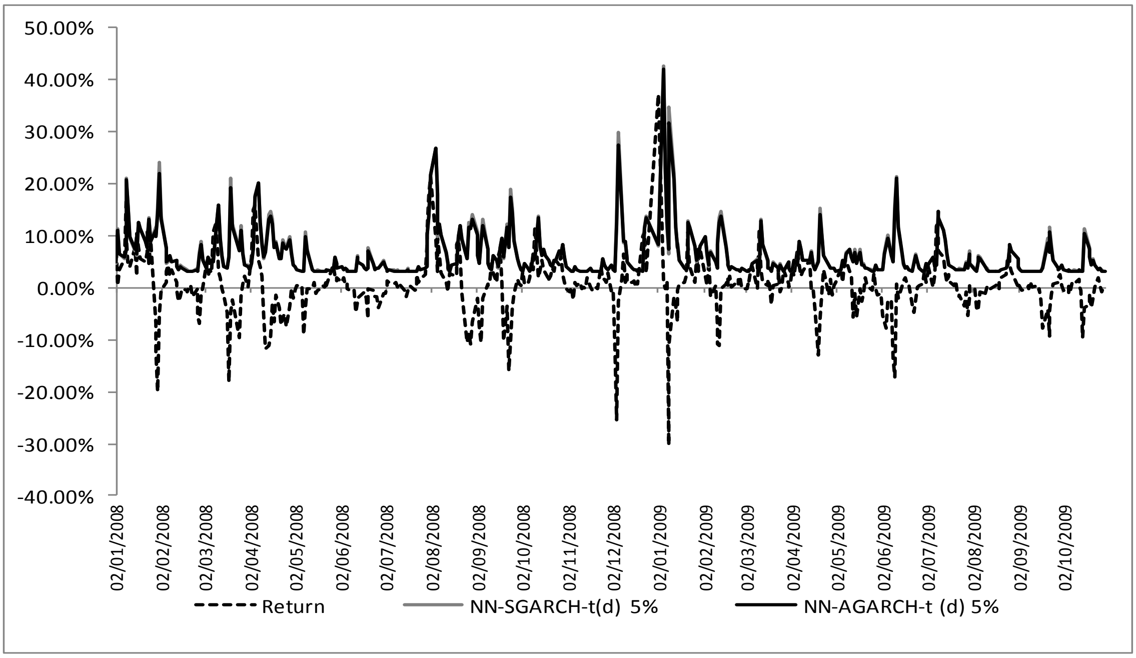
Non-Normal one-day 5% value-at-risk for the tanker route TD3



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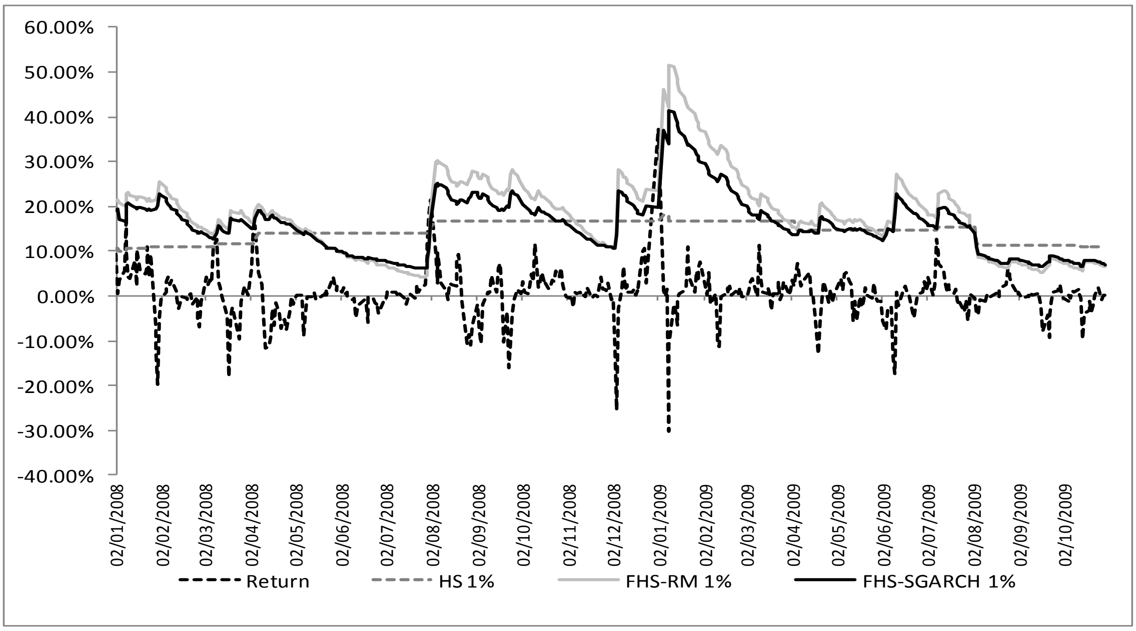
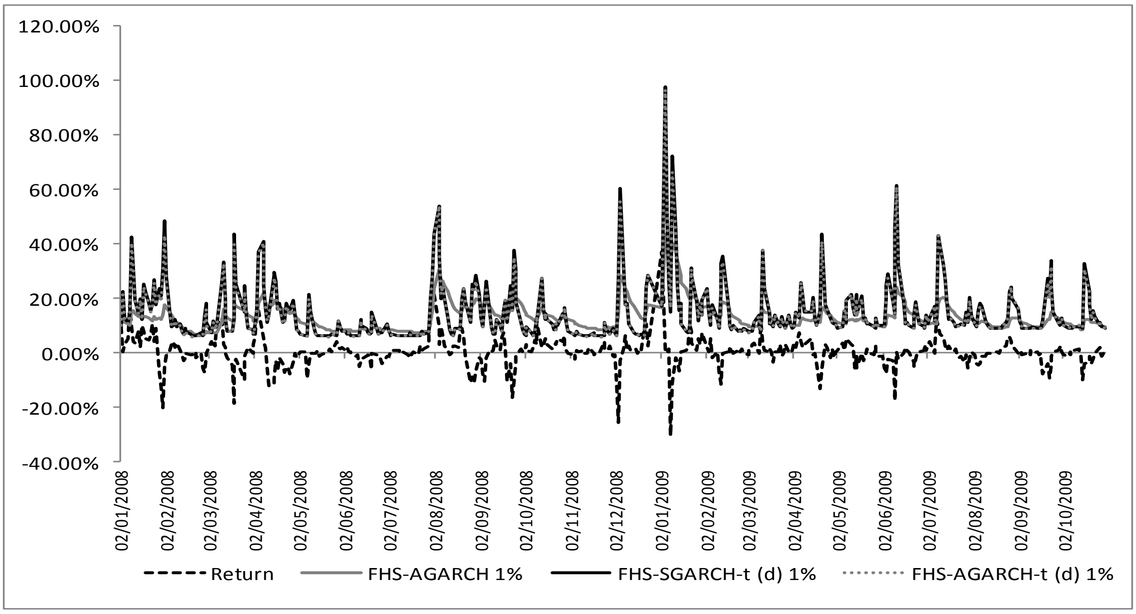
HS and FHS one-day 1% value-at-risk for the tanker route TD3



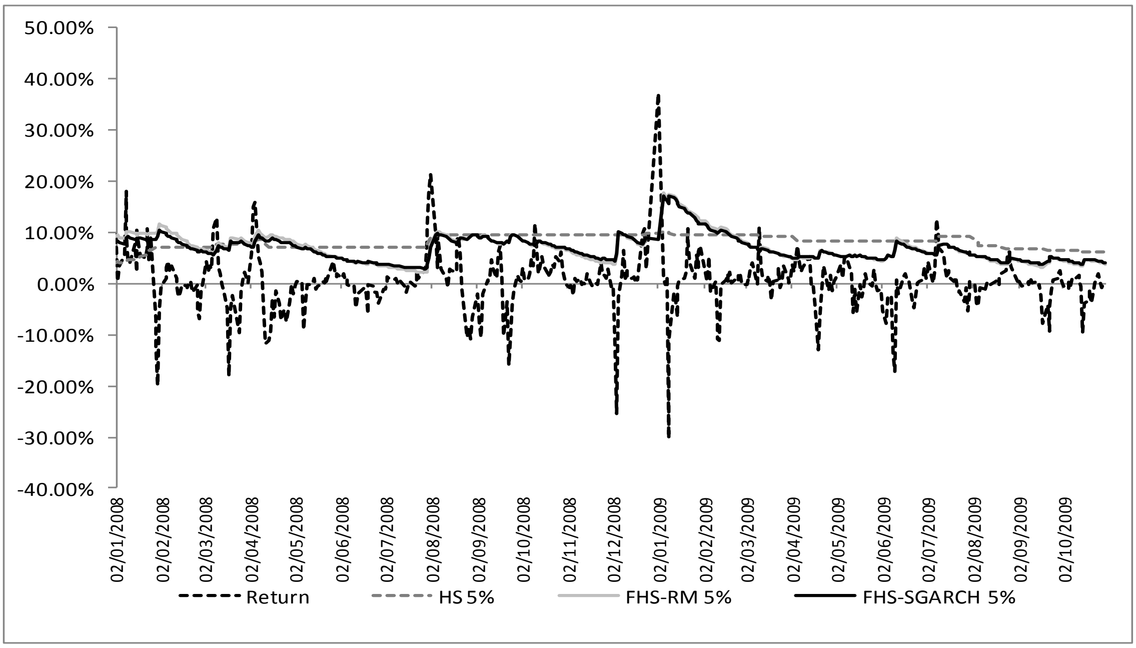
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, and SGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 1% value-at-risk for the tanker route TD3



Note: Illustrations of one-day ahead value-at-risk measure based on non a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are AGARCH, SGARCH-t(d) and AGARCH-t (d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 5% value-at-risk for the tanker route TD3



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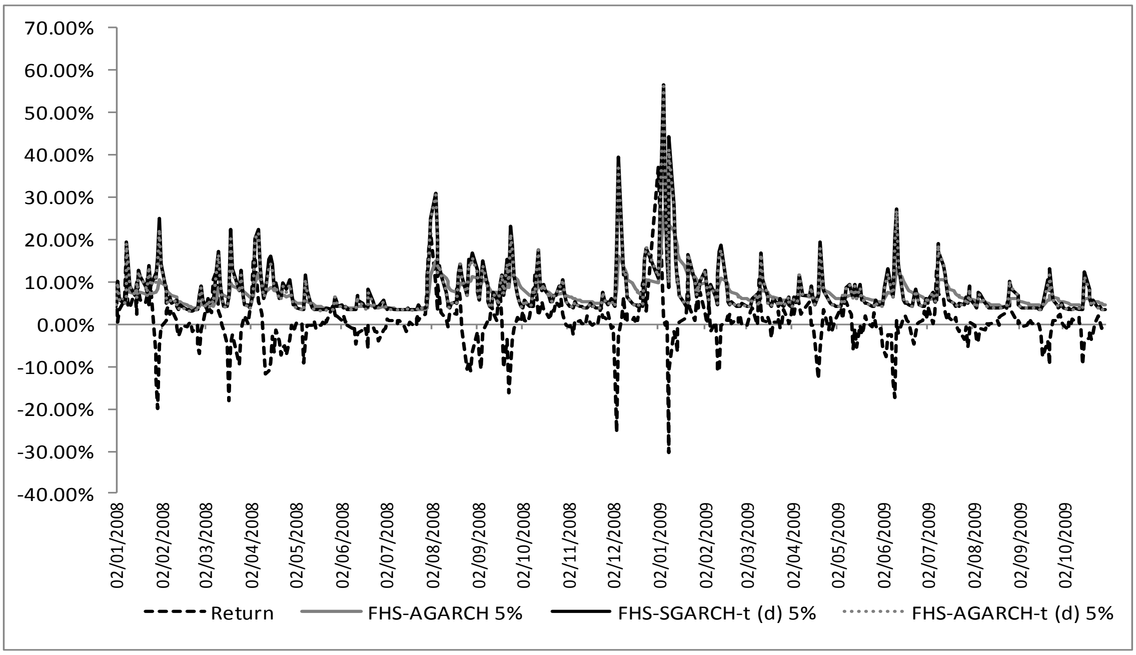
HS and FHS one-day 5% value-at-risk for the tanker route TD3



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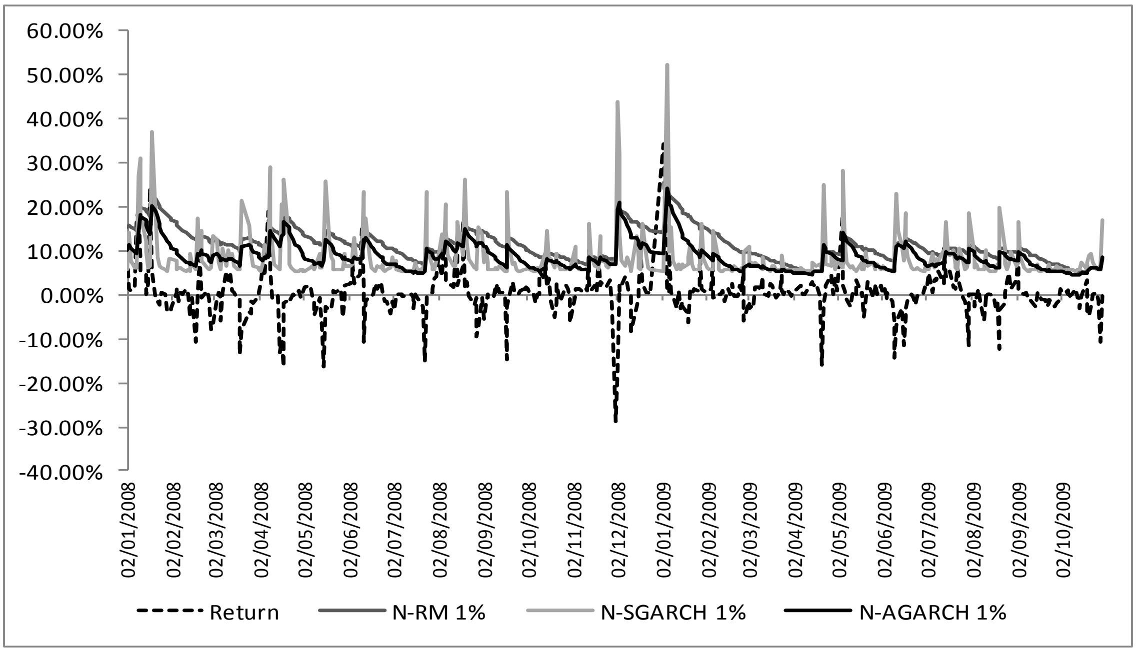
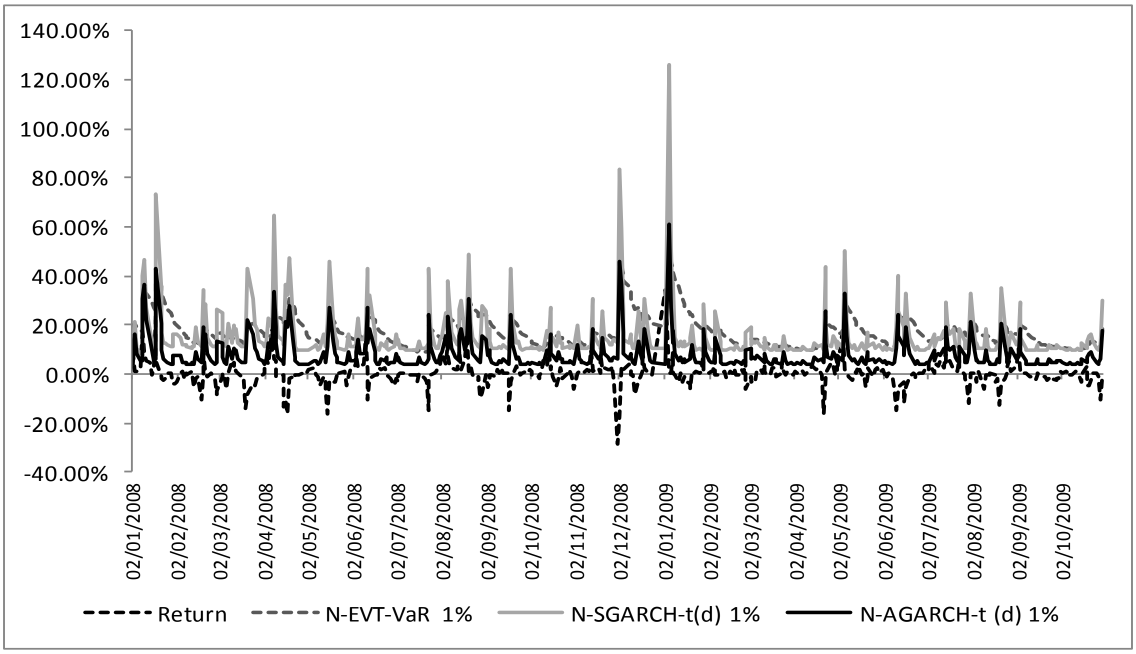
Normal one-day 1% value-at-risk for the tanker route TD4



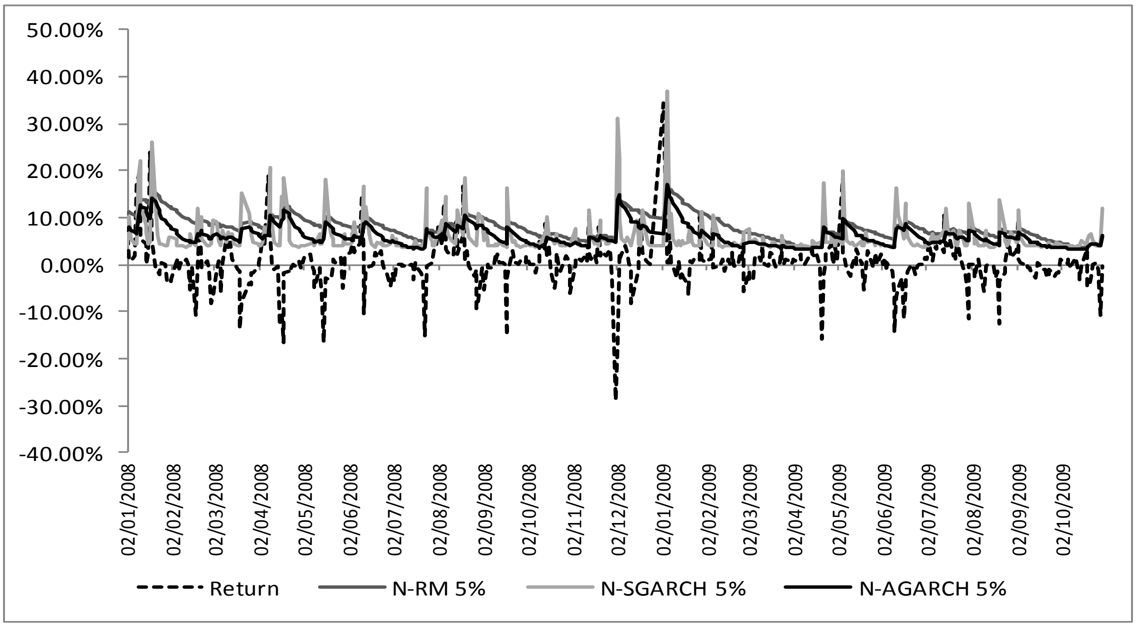
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author’s estimations.

Normal one-day 1% value-at-risk for the tanker route TD4



Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d), AGARCH-t(d) and EVT. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author’s estimations.

Normal one-day 5% value-at-risk for the tanker route TD4



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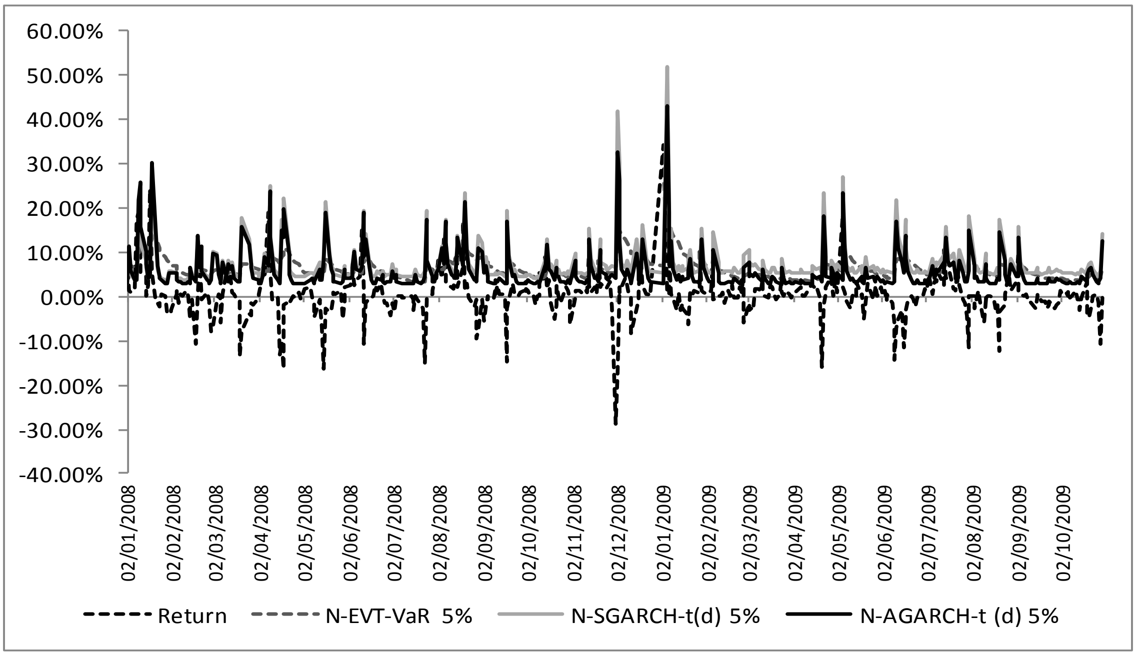
Normal one-day 5% value-at-risk for the tanker route TD4



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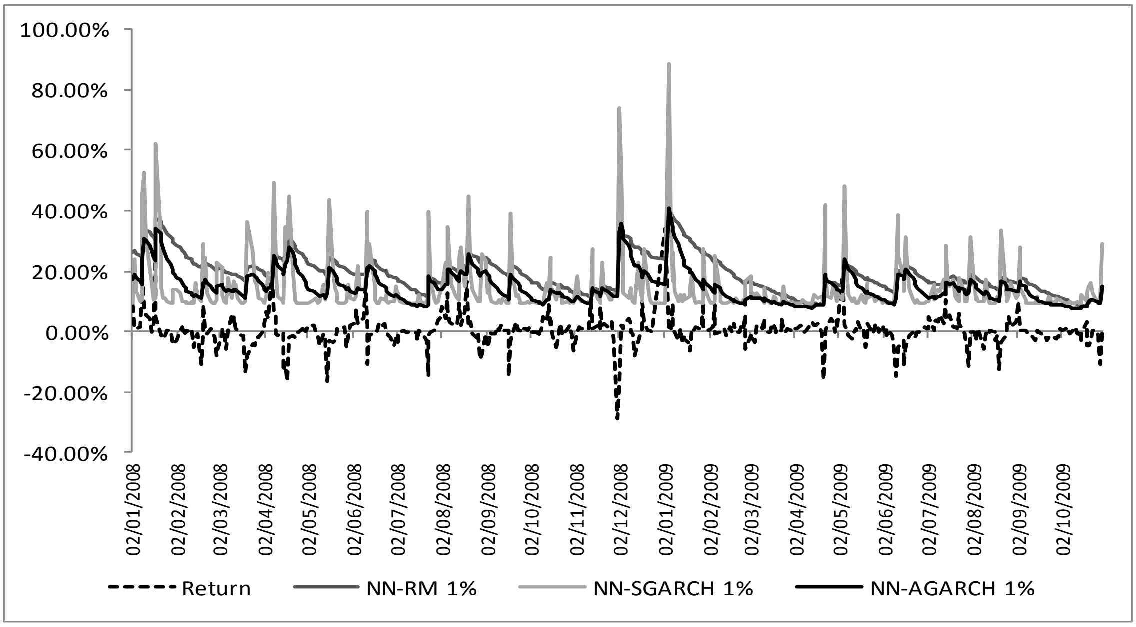
Non-Normal one-day 1% value-at-risk for the tanker route TD4



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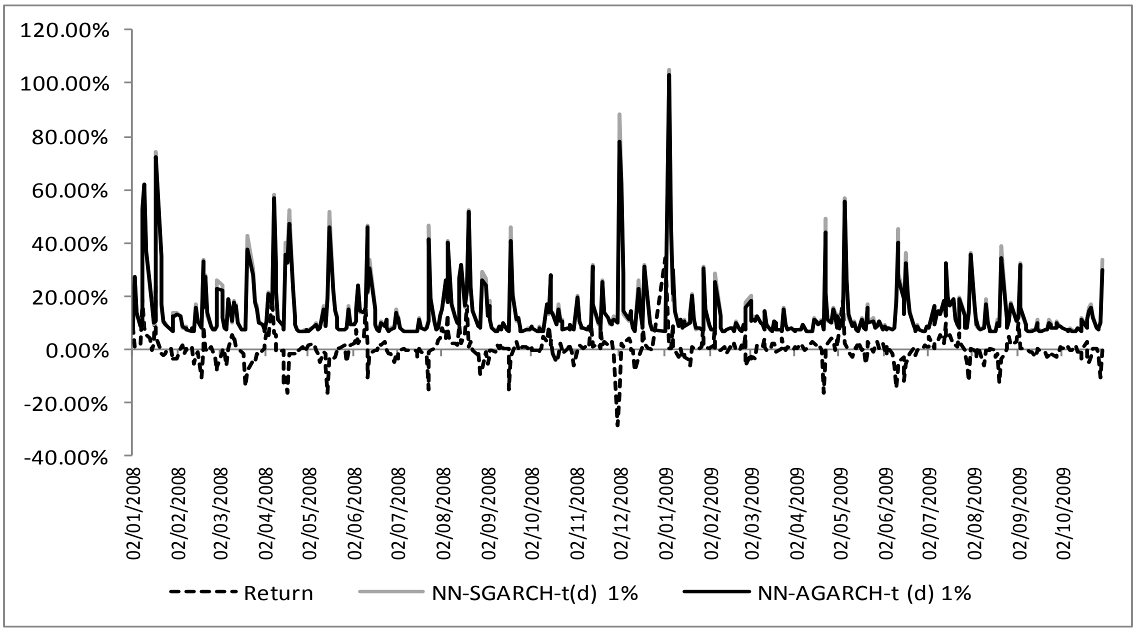
Non-Normal one-day 1% value-at-risk for the tanker route TD4



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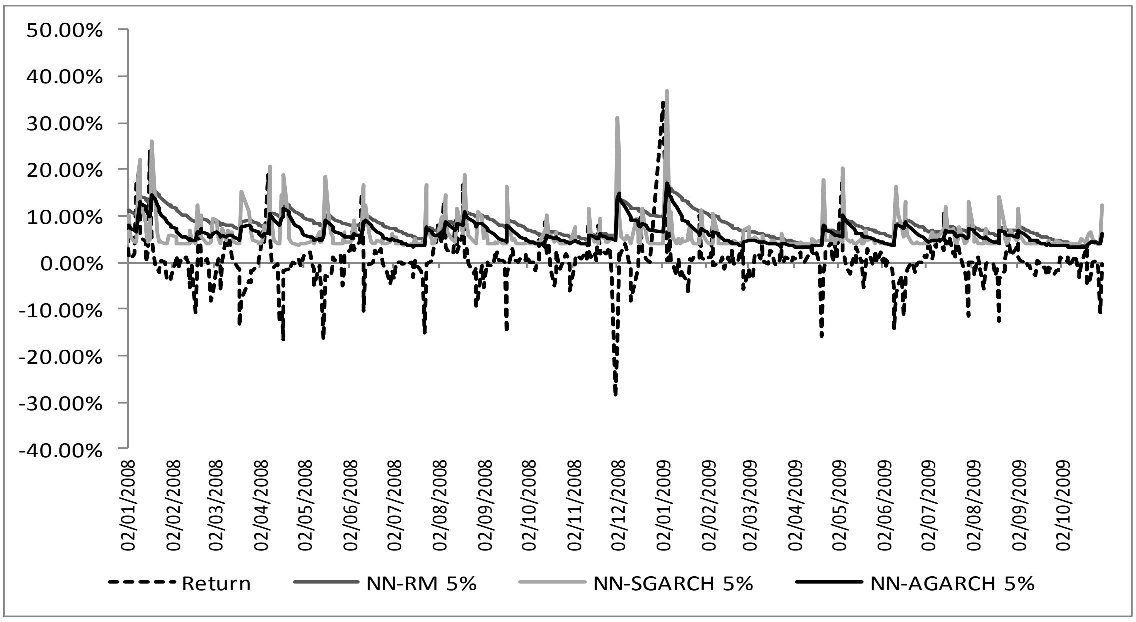
Non-Normal one-day 5% value-at-risk for the tanker route TD4



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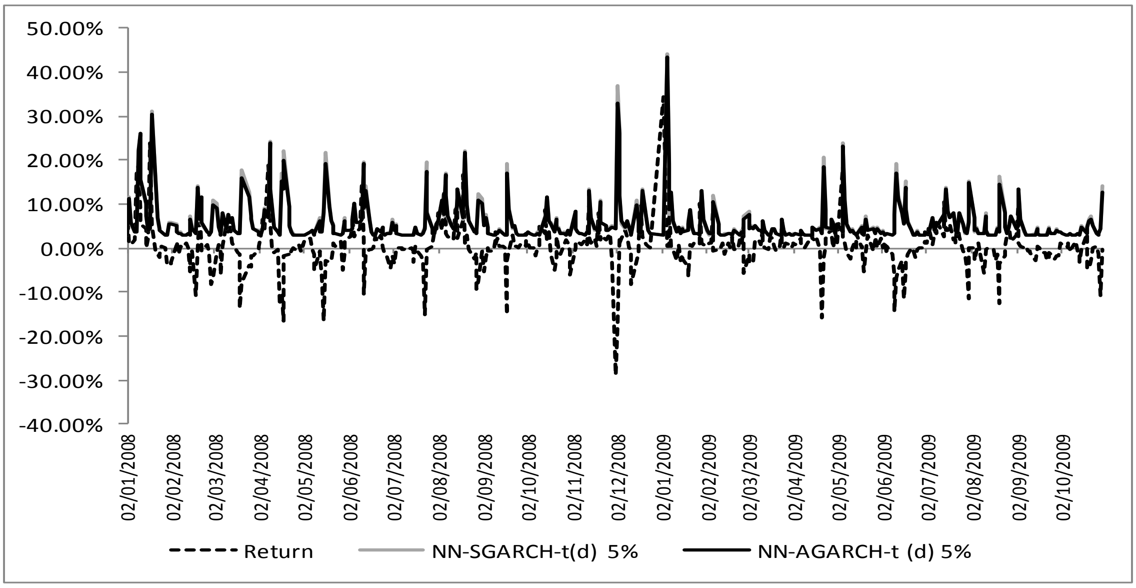
Non-Normal one-day 5% value-at-risk for the tanker route TD4



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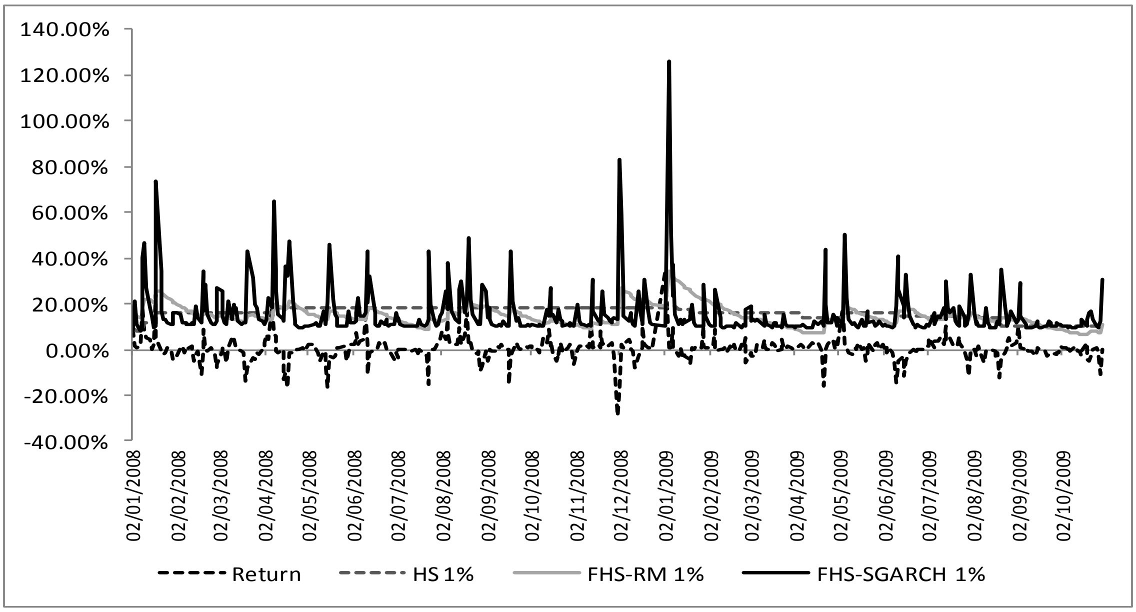
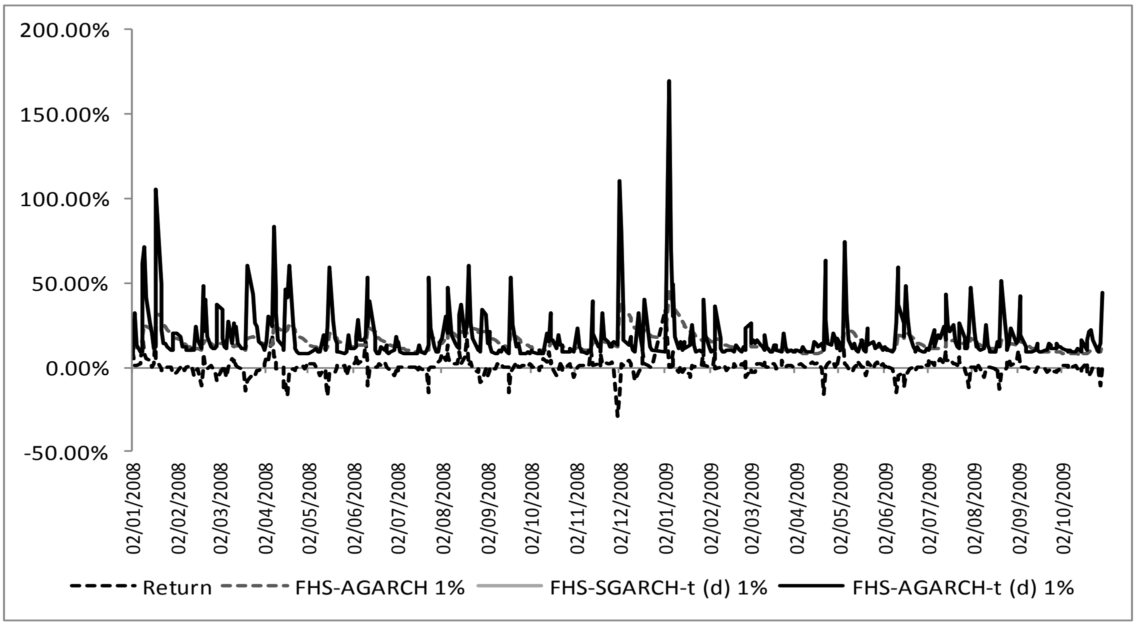
HS and FHS one-day 1% value-at-risk for the tanker route TD4



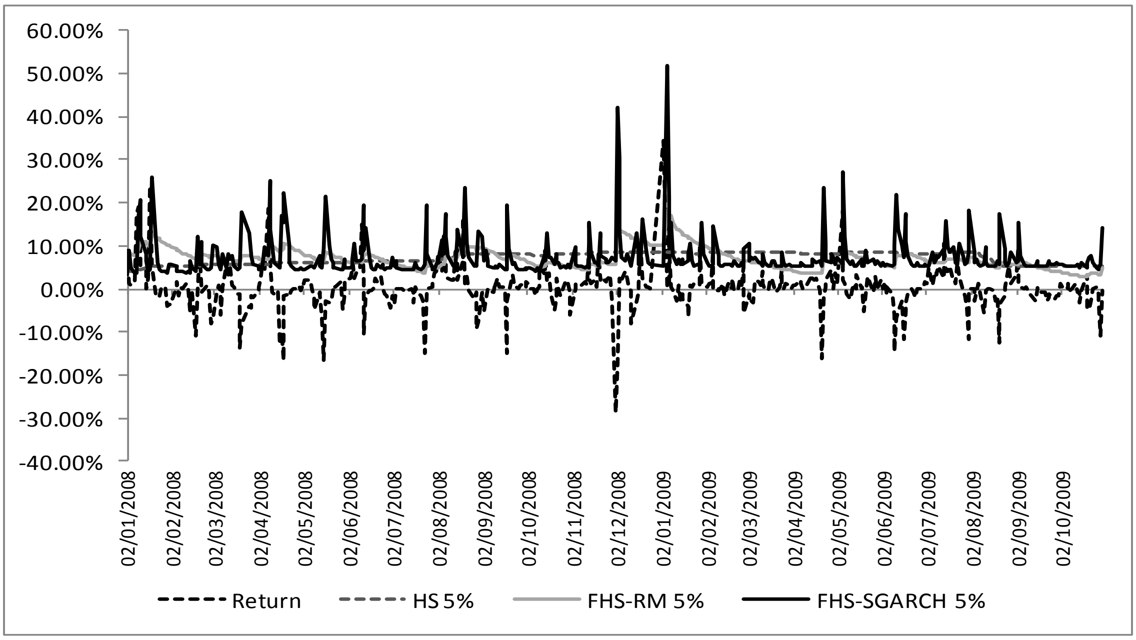
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, and SGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 1% value-at-risk for the tanker route TD4



Note: Illustrations of one-day ahead value-at-risk measure based on non a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are AGARCH, SGARCH-t(d) and AGARCH-t (d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 5% value-at-risk for the tanker route TD4



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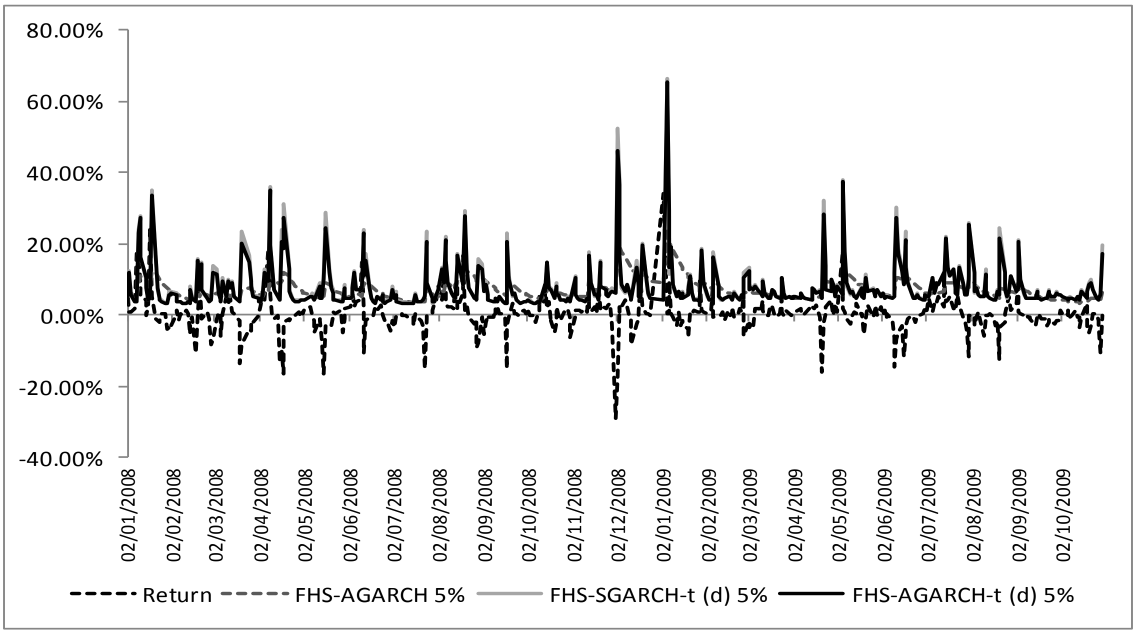
HS and FHS one-day 5% value-at-risk for the tanker route TD4



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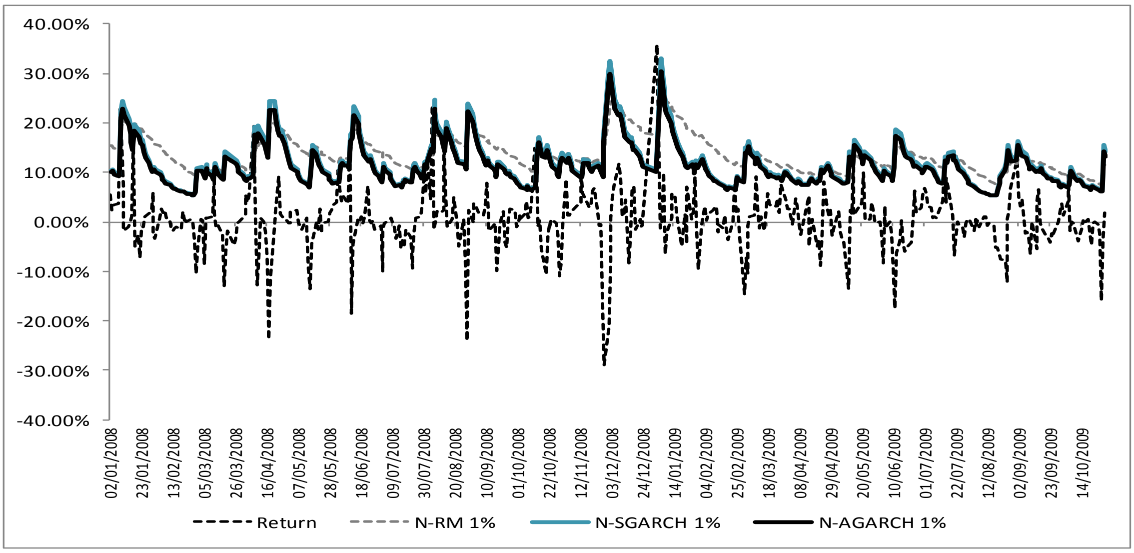
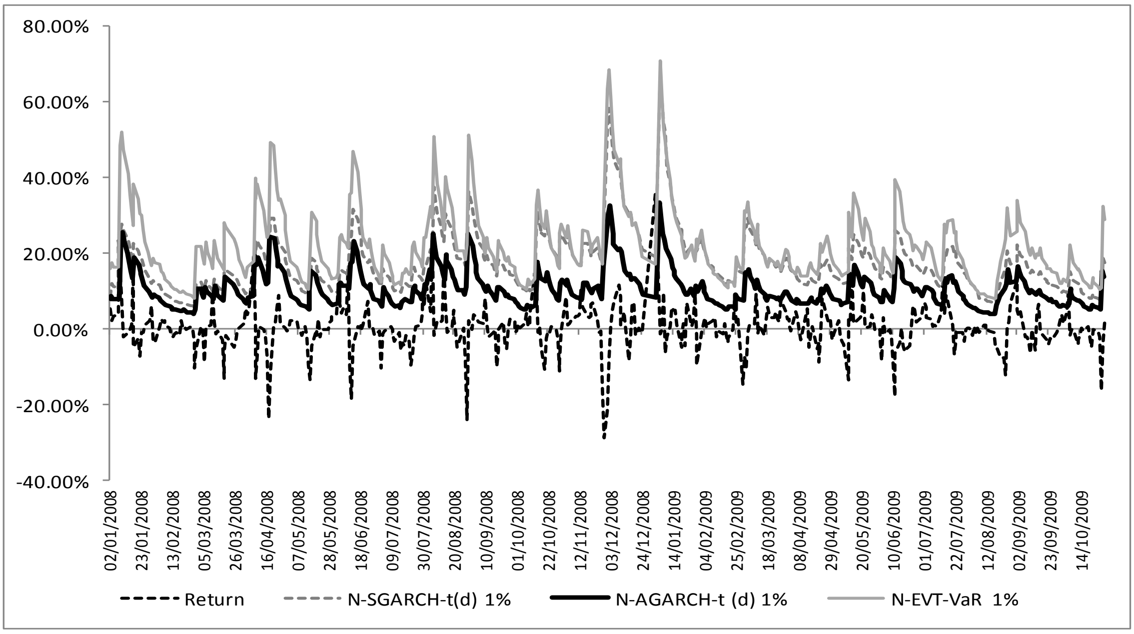
Normal one-day 1% value-at-risk for the tanker route TD5



Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 1% value-at-risk for the tanker route TD5



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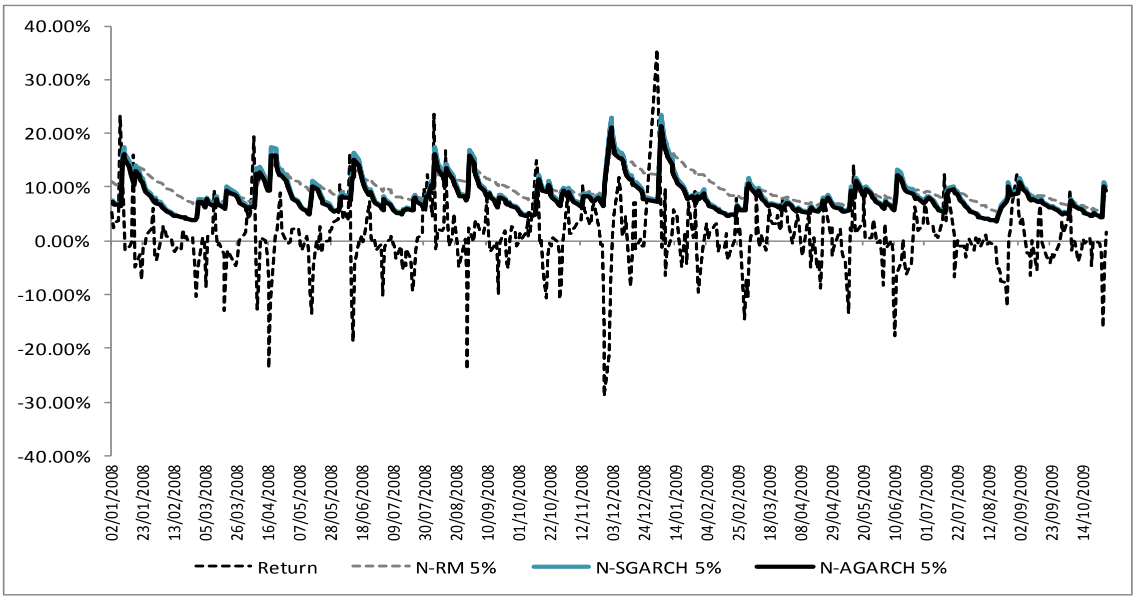
Normal one-day 5% value-at-risk for the tanker route TD5



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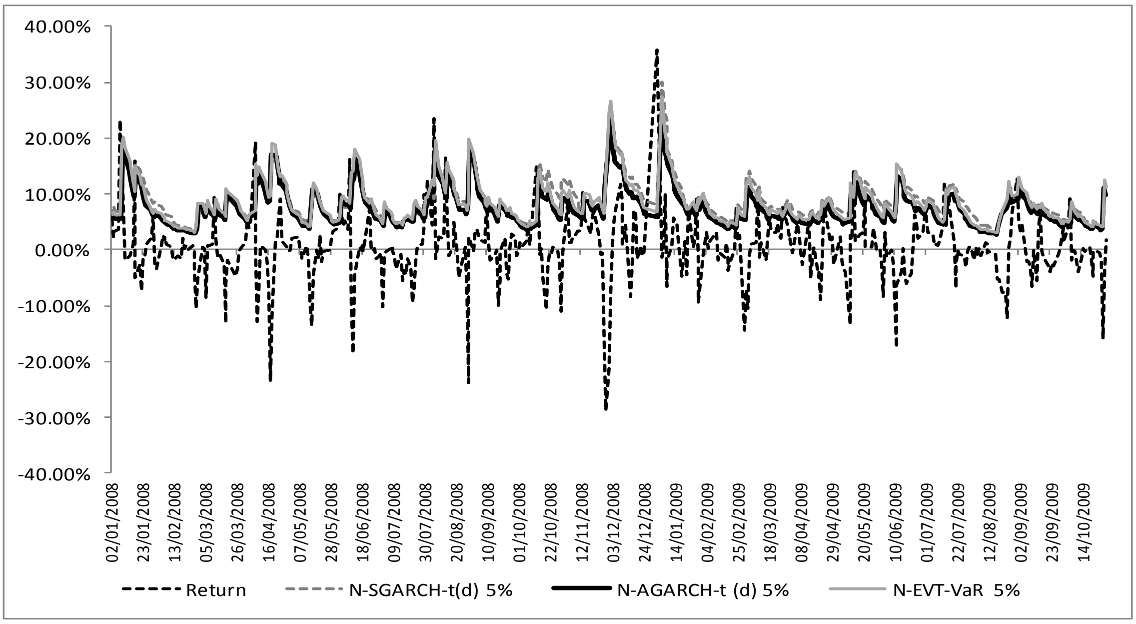
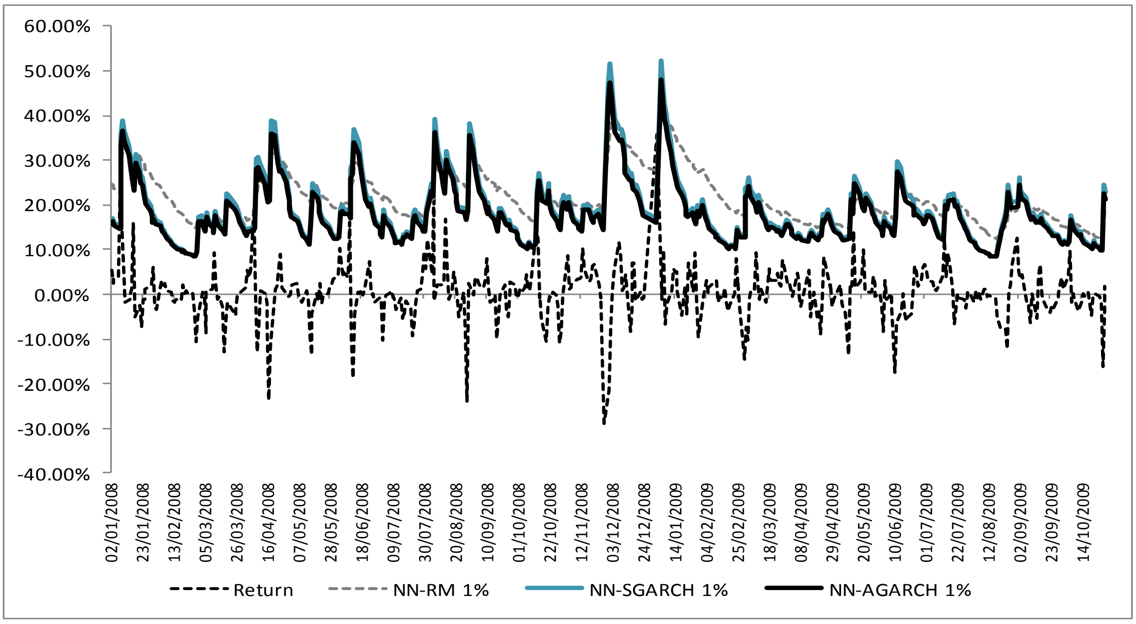
Normal one-day 5% value-at-risk for the tanker route TD5



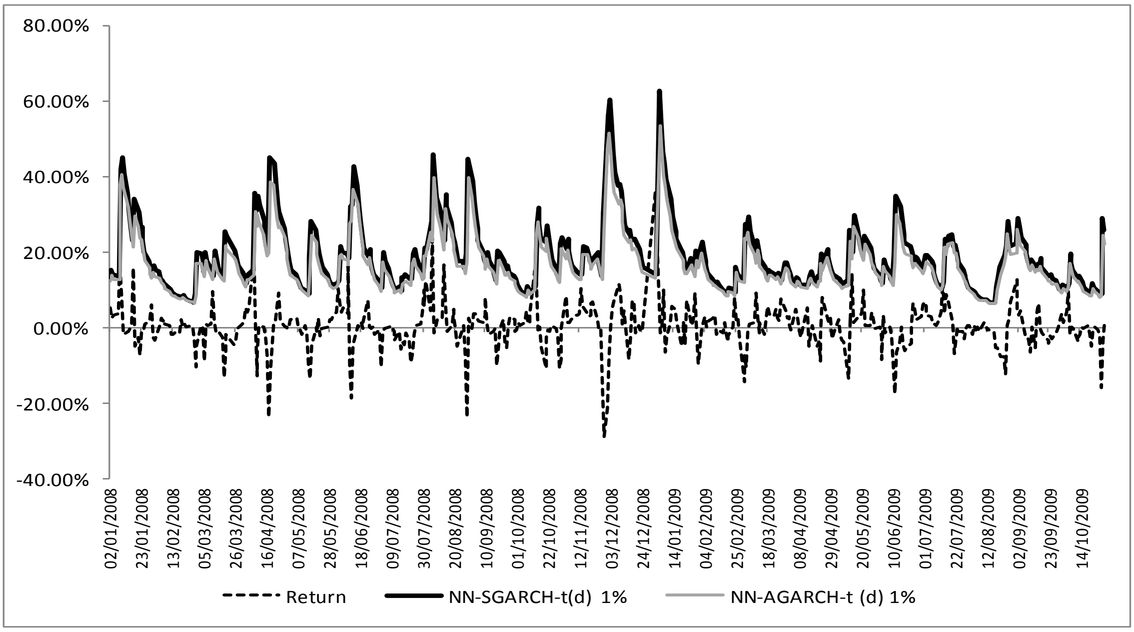
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d), AGARCH-t(d) and EVT. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author’s estimations.

Non-Normal one-day 1% value-at-risk for the tanker route TD5



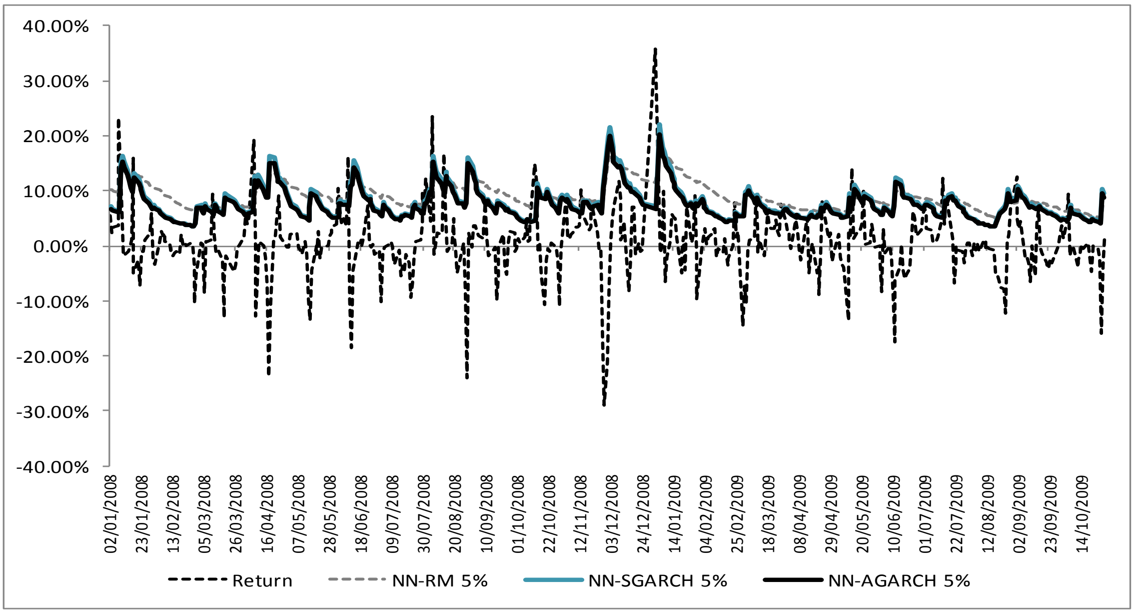
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 1% value-at-risk for the tanker route TD5



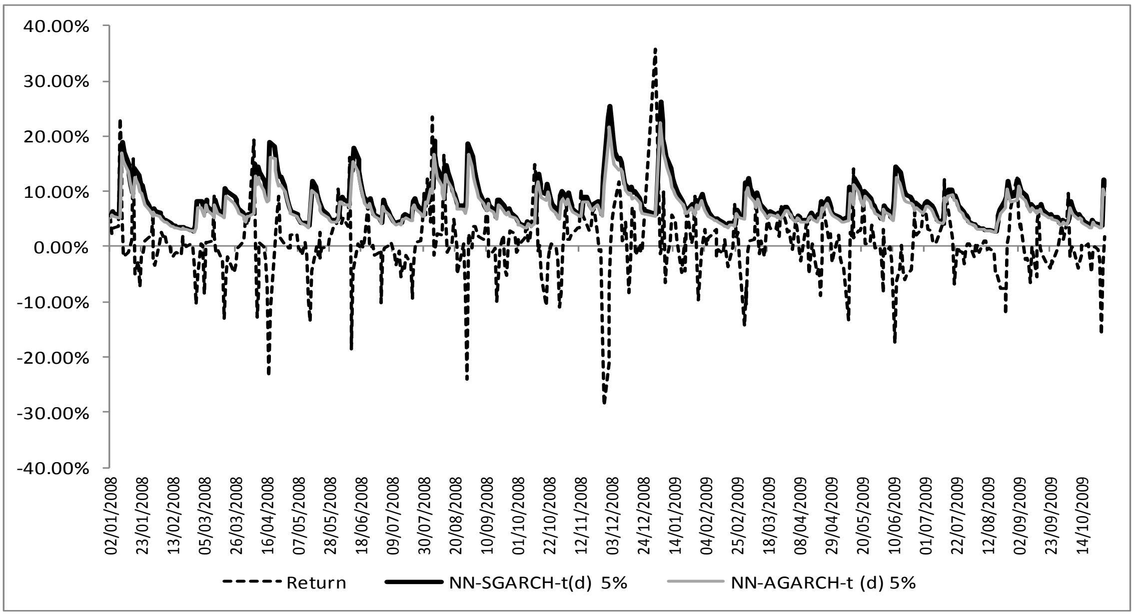
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 5% value-at-risk for the tanker route TD5



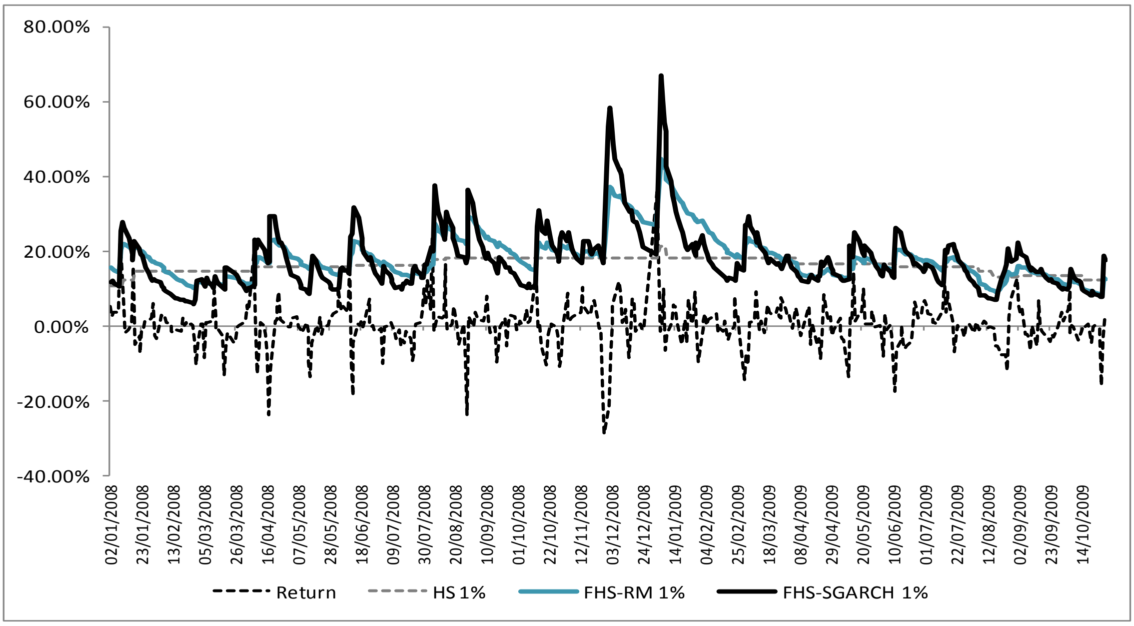
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 5% value-at-risk for the tanker route TD5



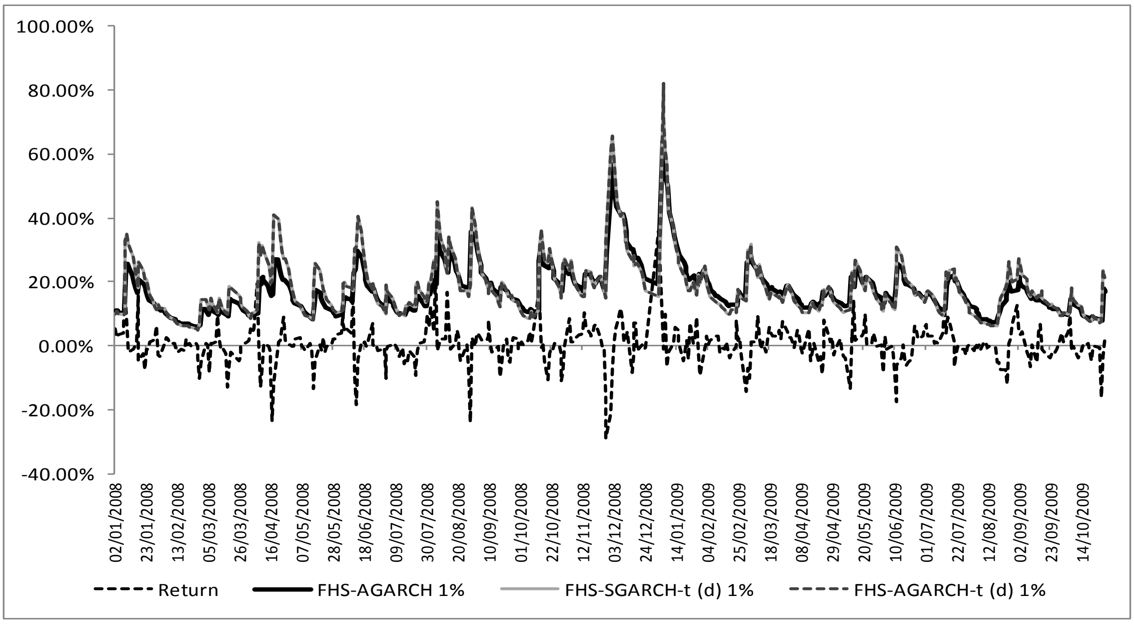
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 1% value-at-risk for the tanker route TD5



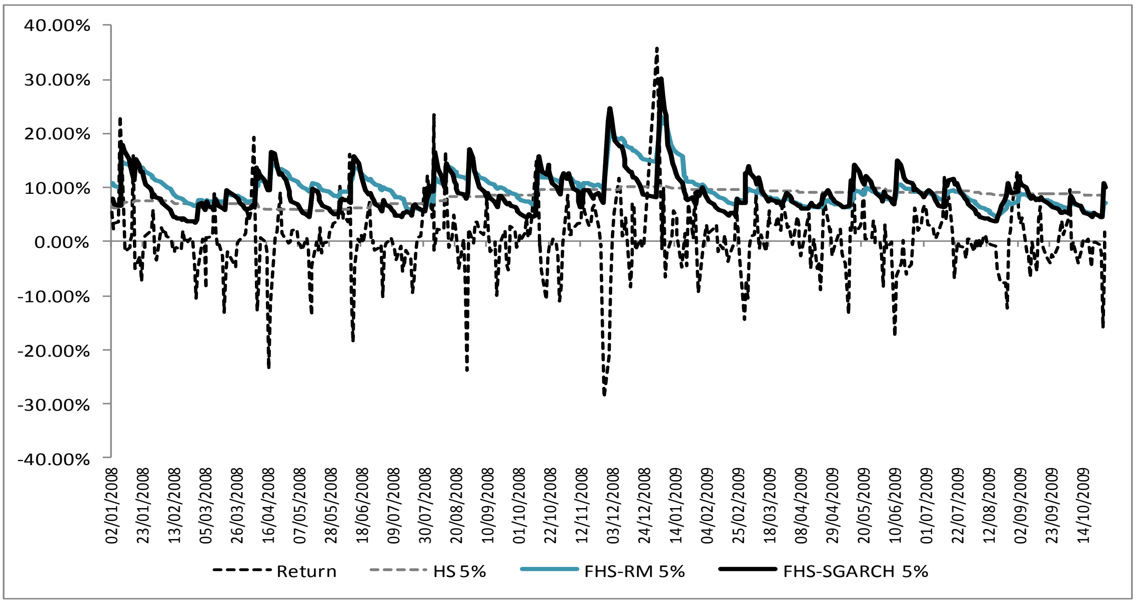
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, and SGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 1% value-at-risk for the tanker route TD5



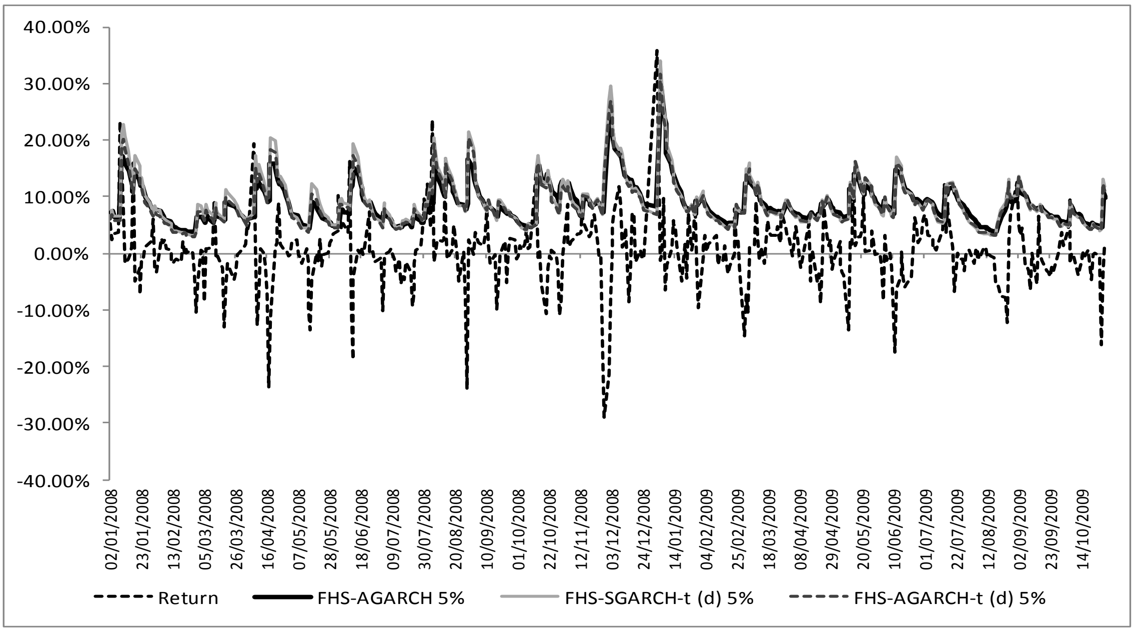
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are AGARCH, SGARCH-t(d) and AGARCH-t (d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 5% value-at-risk for the tanker route TD5



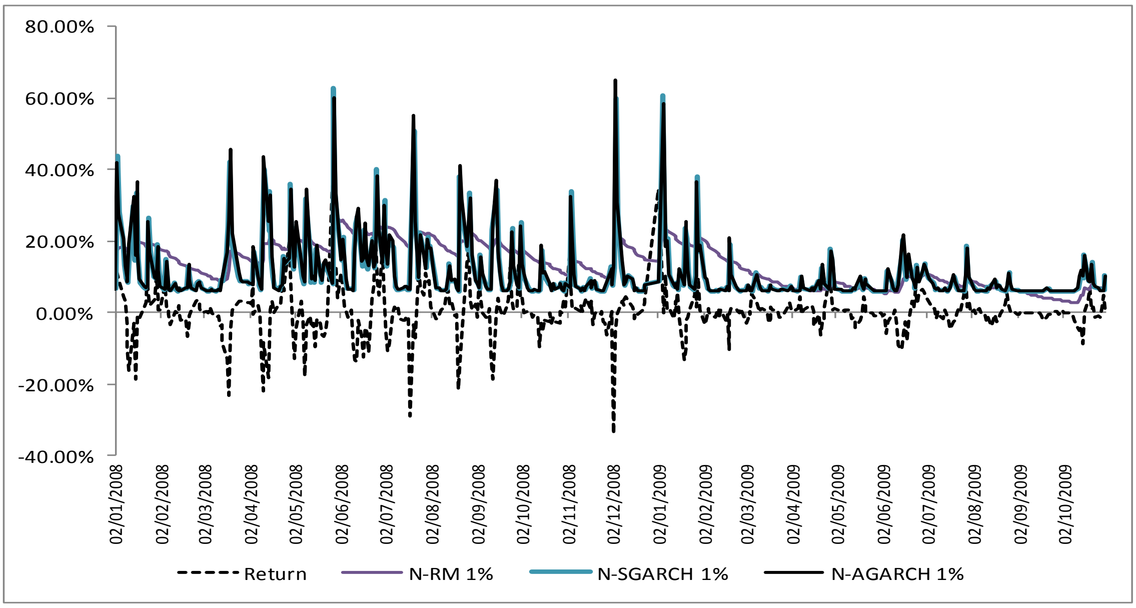
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, and SGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 5% value-at-risk for the tanker route TD5



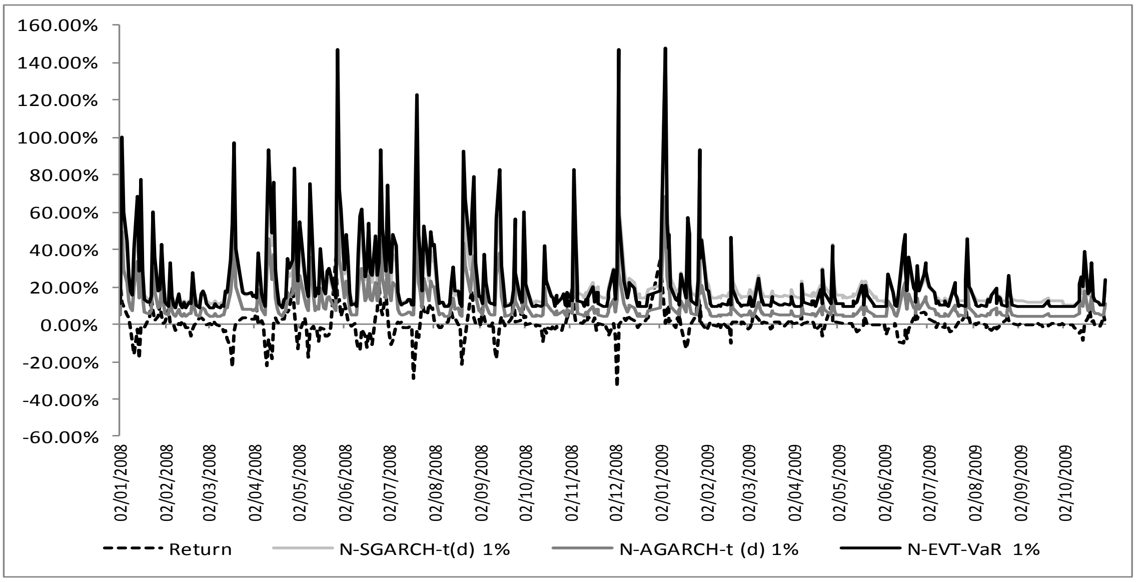
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are AGARCH, SGARCH-t(d) and AGARCH-t (d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 1% value-at-risk for the tanker route TD7



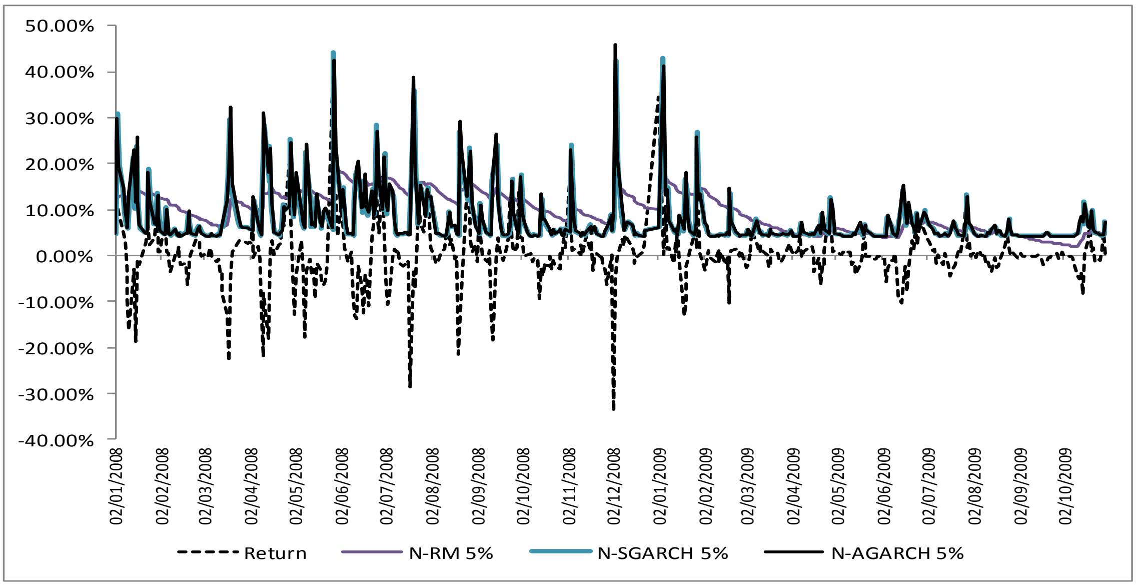
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 1% value-at-risk for the tanker route TD7



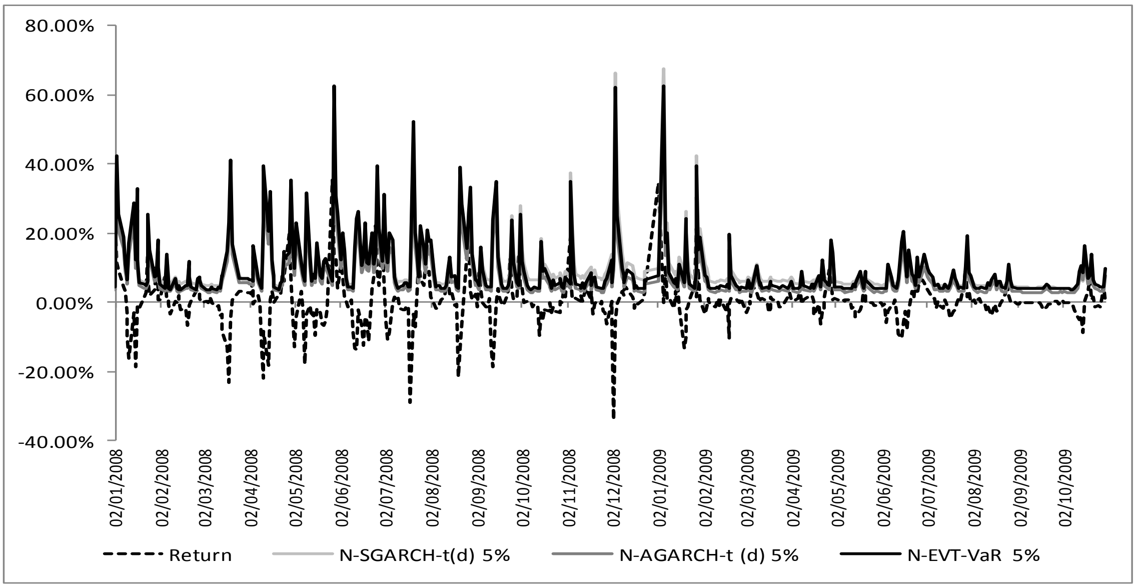
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d), AGARCH-t(d) and EVT. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 5% value-at-risk for the tanker route TD7



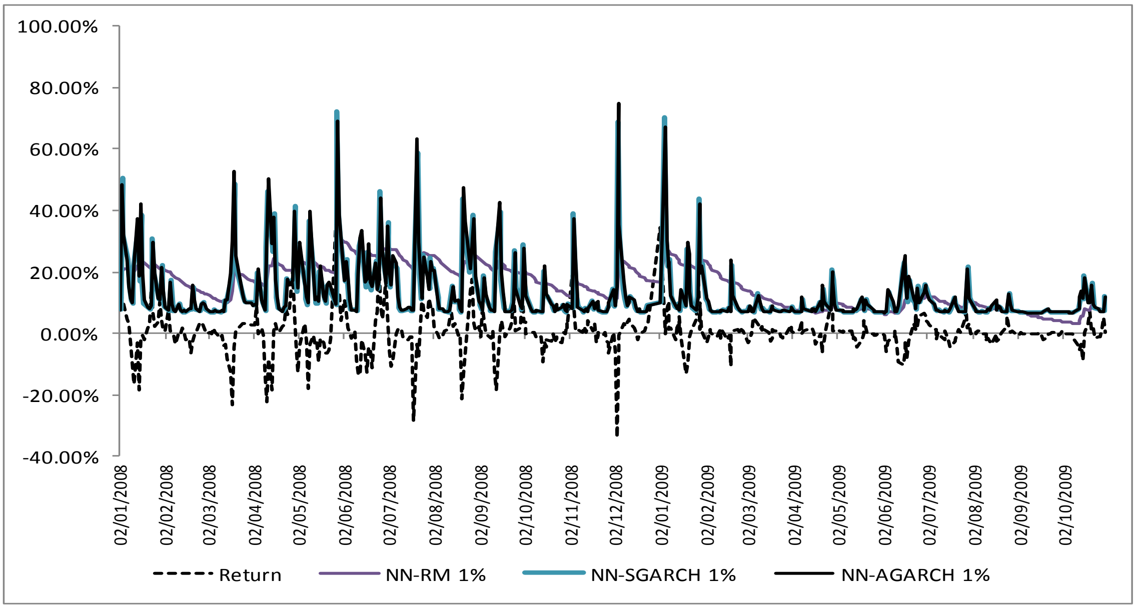
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 5% value-at-risk for the tanker route TD7



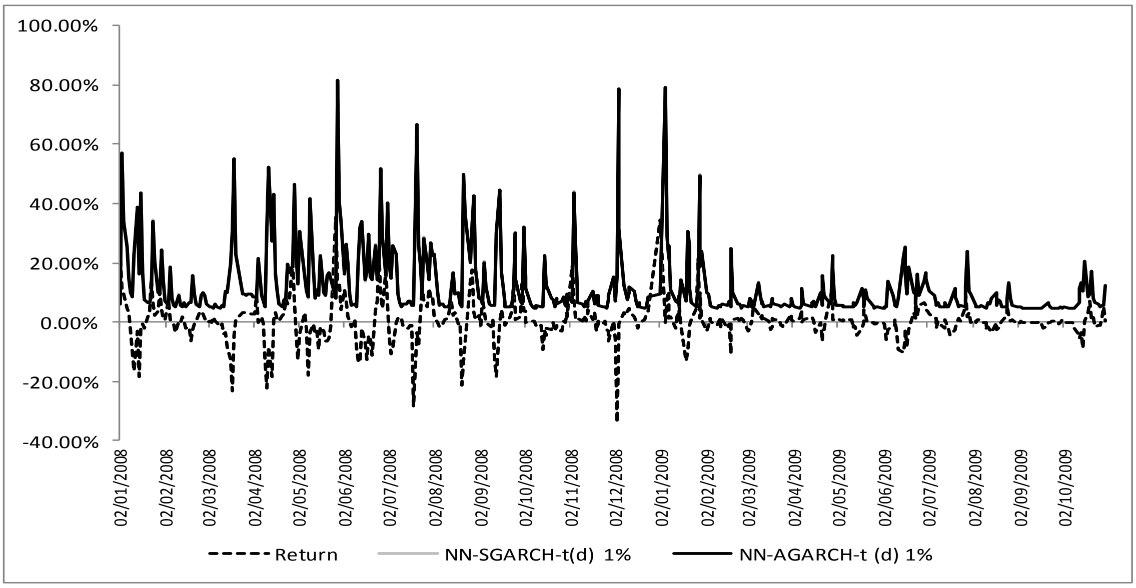
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d), AGARCH-t(d) and EVT. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 1% value-at-risk for the tanker route TD7



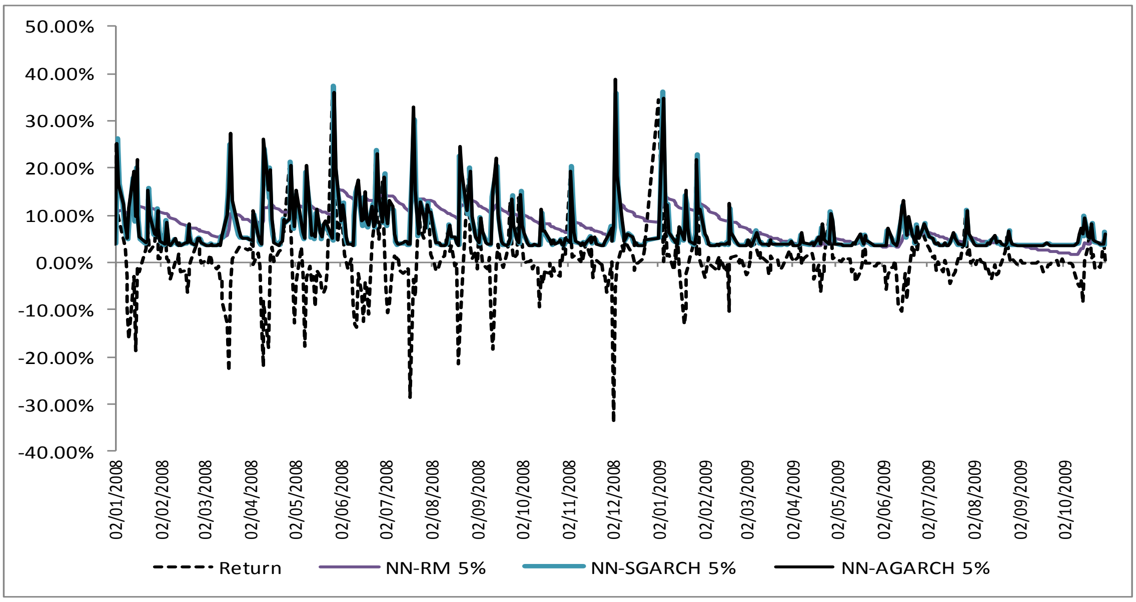
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 1% value-at-risk for the tanker route TD7



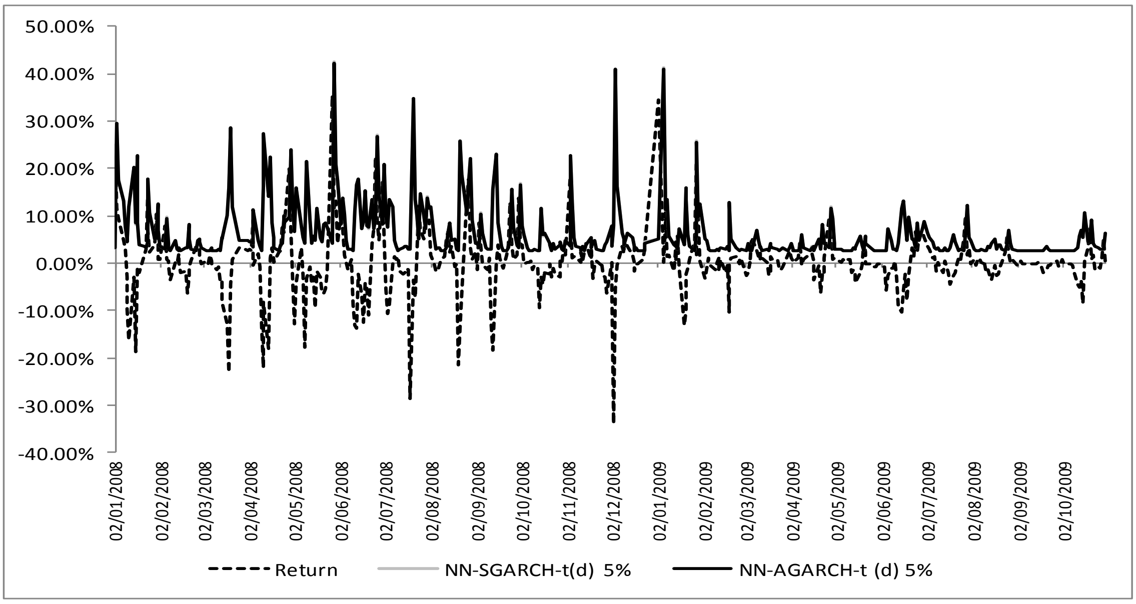
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 5% value-at-risk for the tanker route TD7



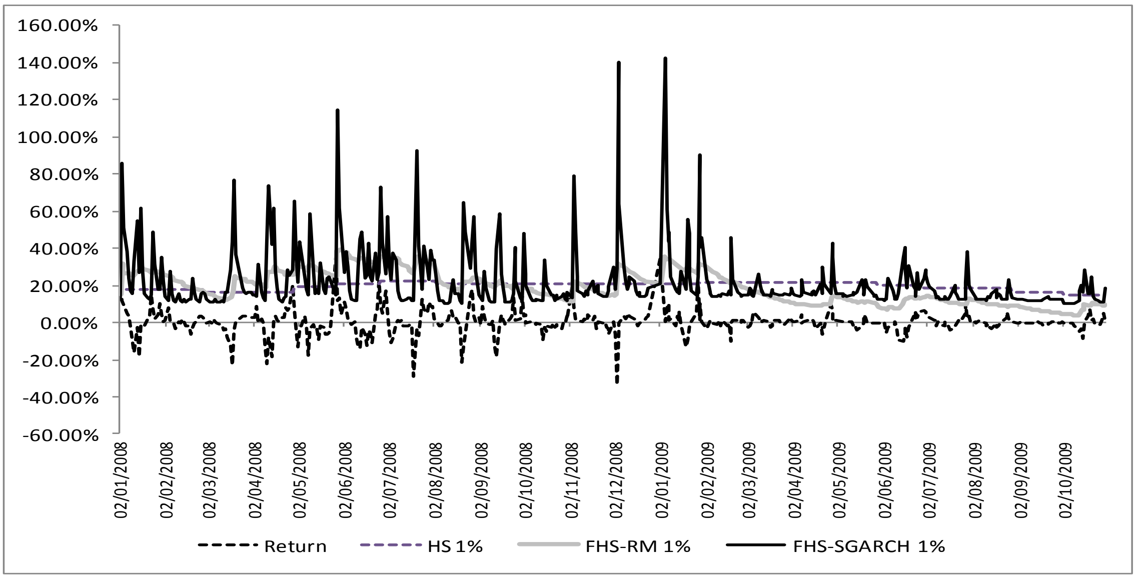
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 5% value-at-risk for the tanker route TD7



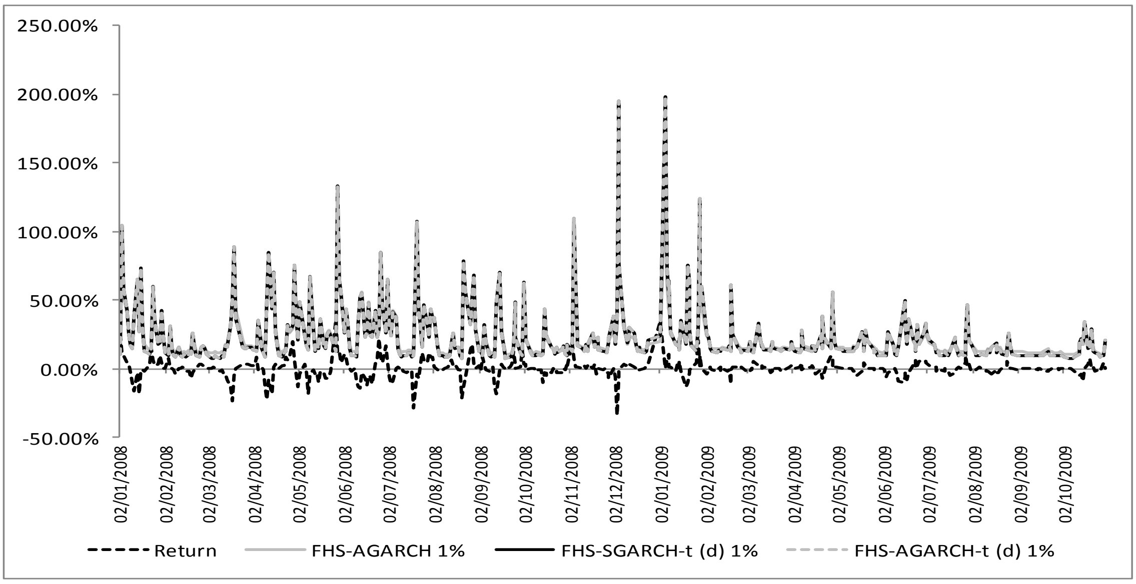
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 1% value-at-risk for the tanker route TD7



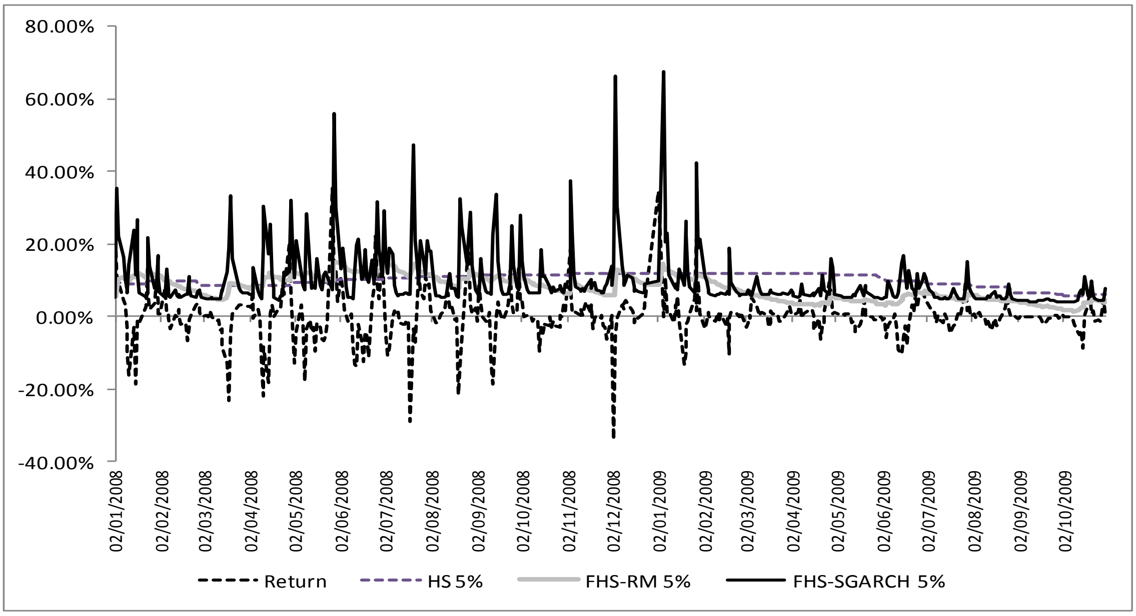
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, and SGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 1% value-at-risk for the tanker route TD7



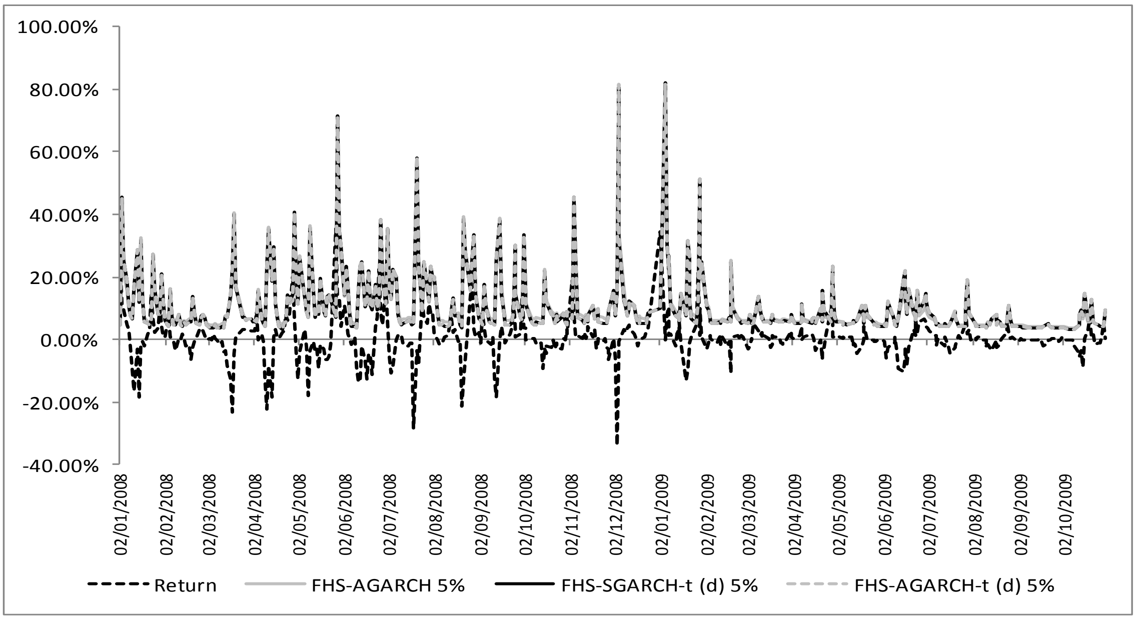
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are AGARCH, SGARCH-t(d) and AGARCH-t (d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 5% value-at-risk for the tanker route TD7



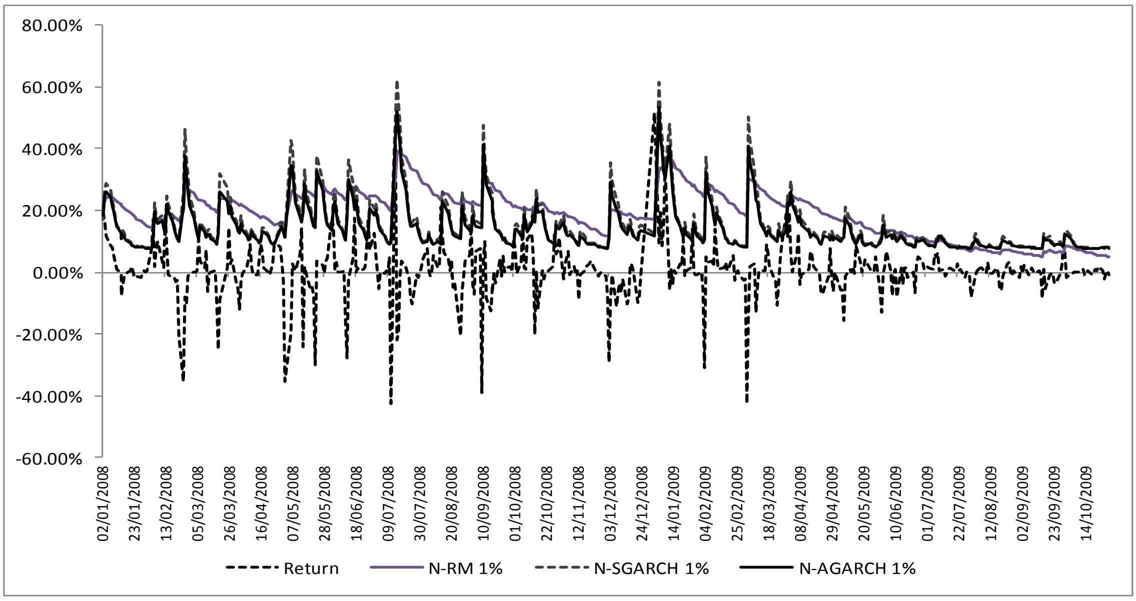
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, and SGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 5% value-at-risk for the tanker route TD7



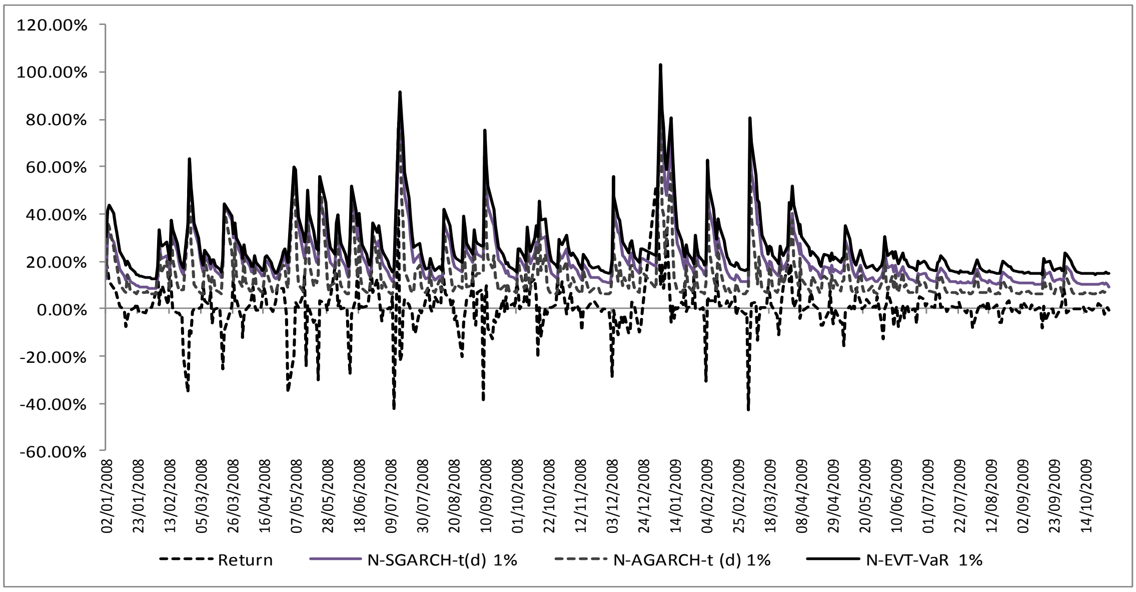
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are AGARCH, SGARCH-t(d) and AGARCH-t (d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 1% value-at-risk for the tanker route TD9



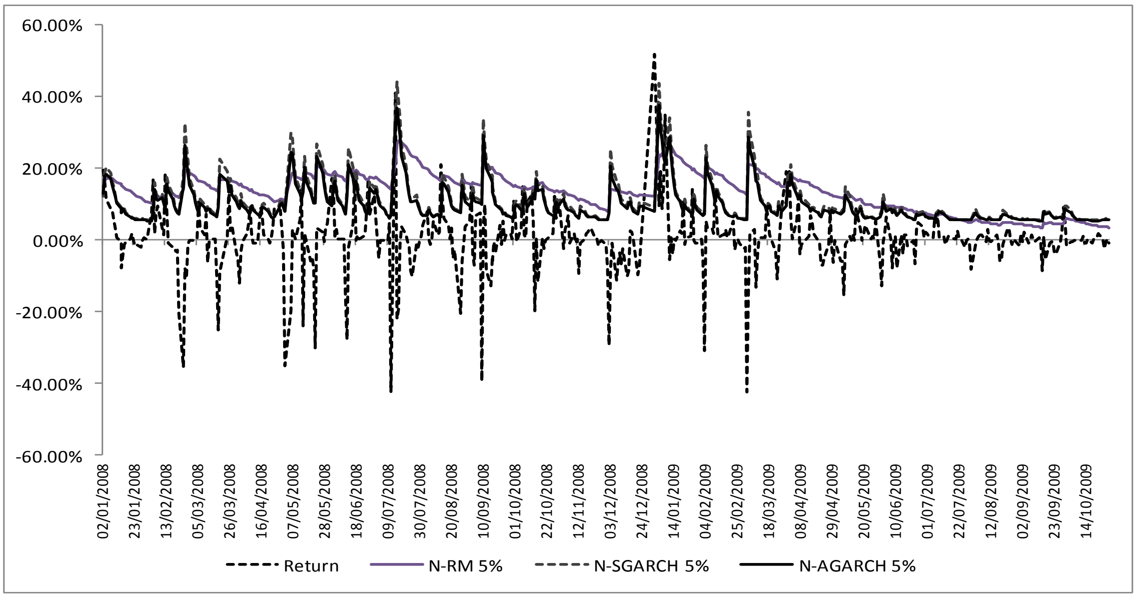
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 1% value-at-risk for the tanker route TD9



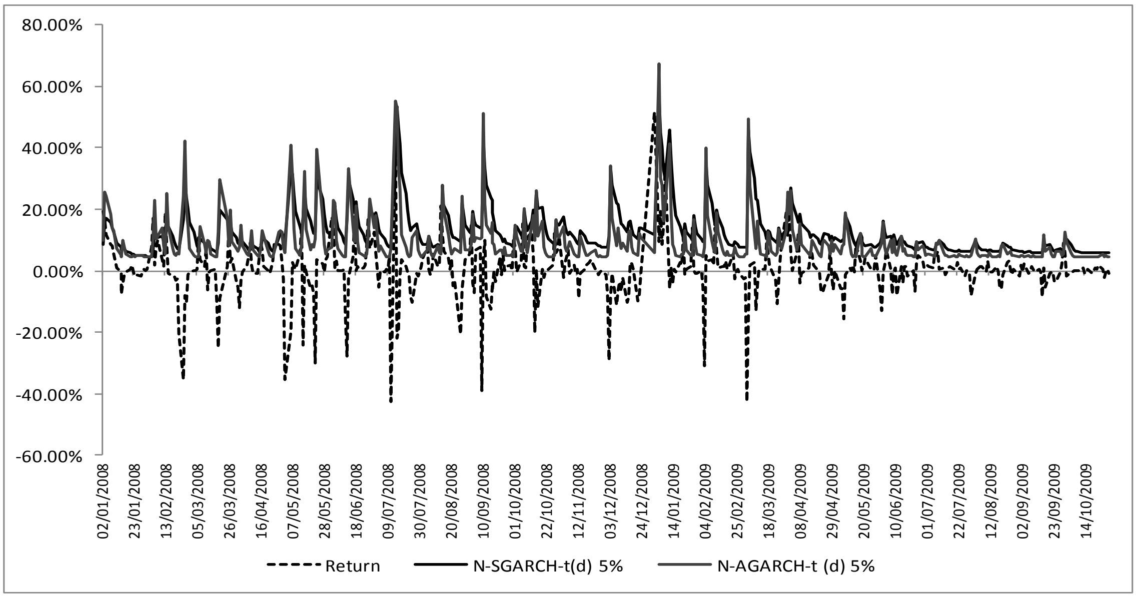
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d), AGARCH-t(d) and EVT. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 5% value-at-risk for the tanker route TD9



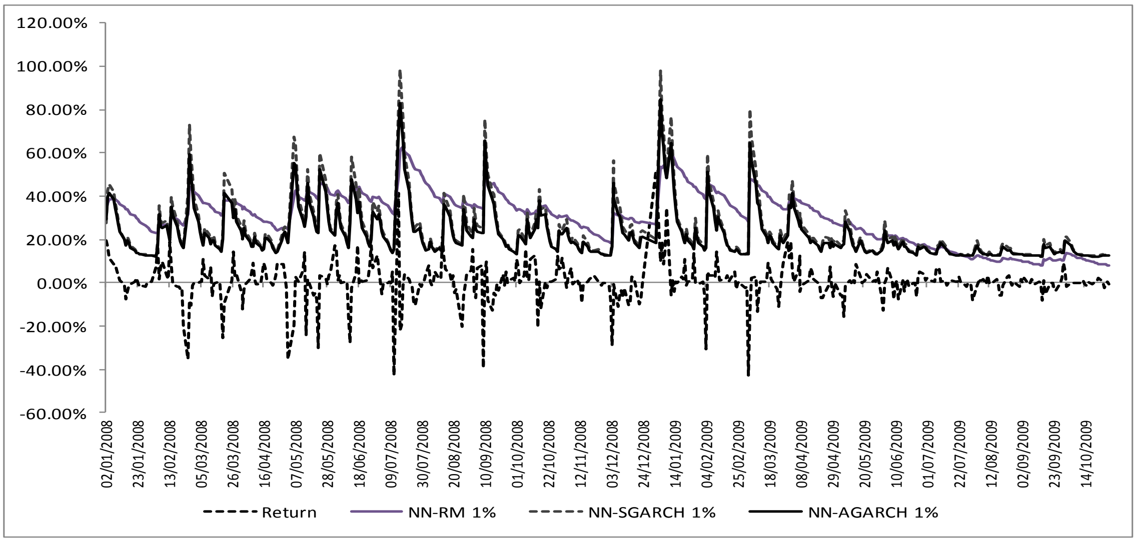
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Normal one-day 5% value-at-risk for the tanker route TD9



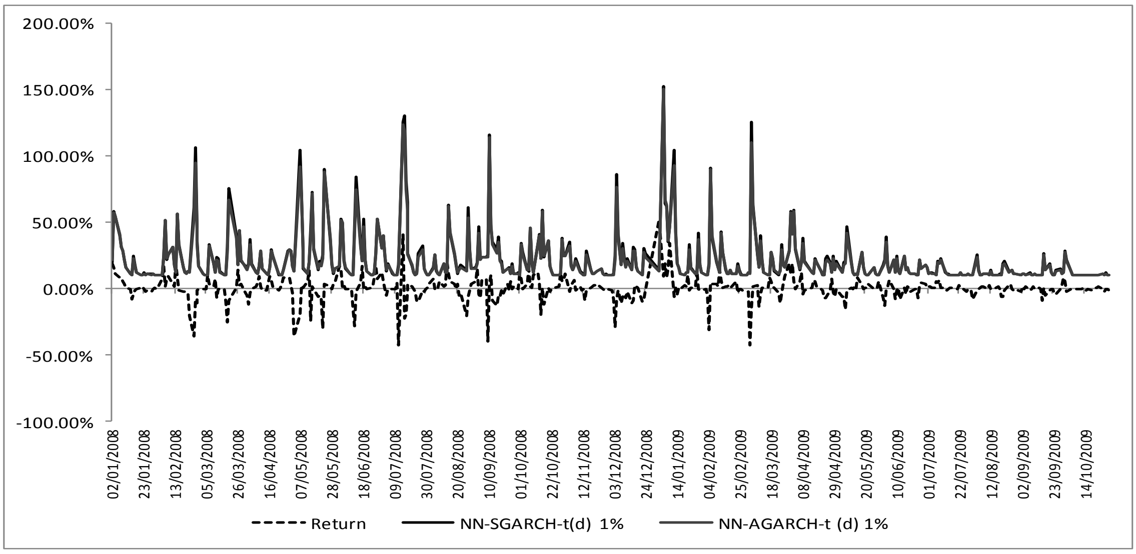
Note: Illustrations of one-day ahead value-at-risk measure based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d), AGARCH-t(d) and EVT. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 1% value-at-risk for the tanker route TD9



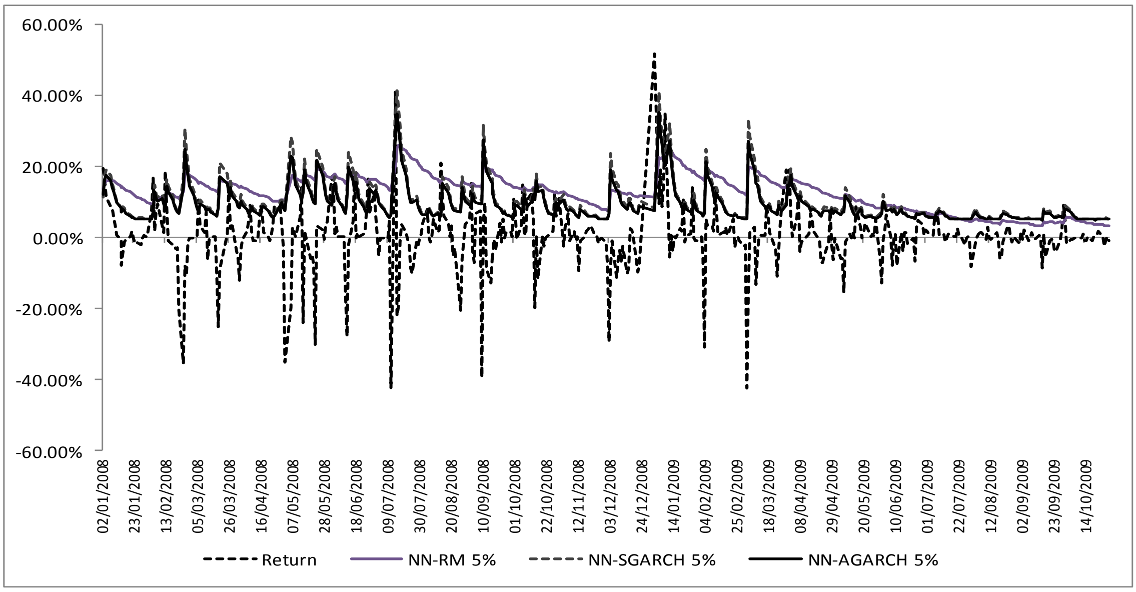
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 1% value-at-risk for the tanker route TD9



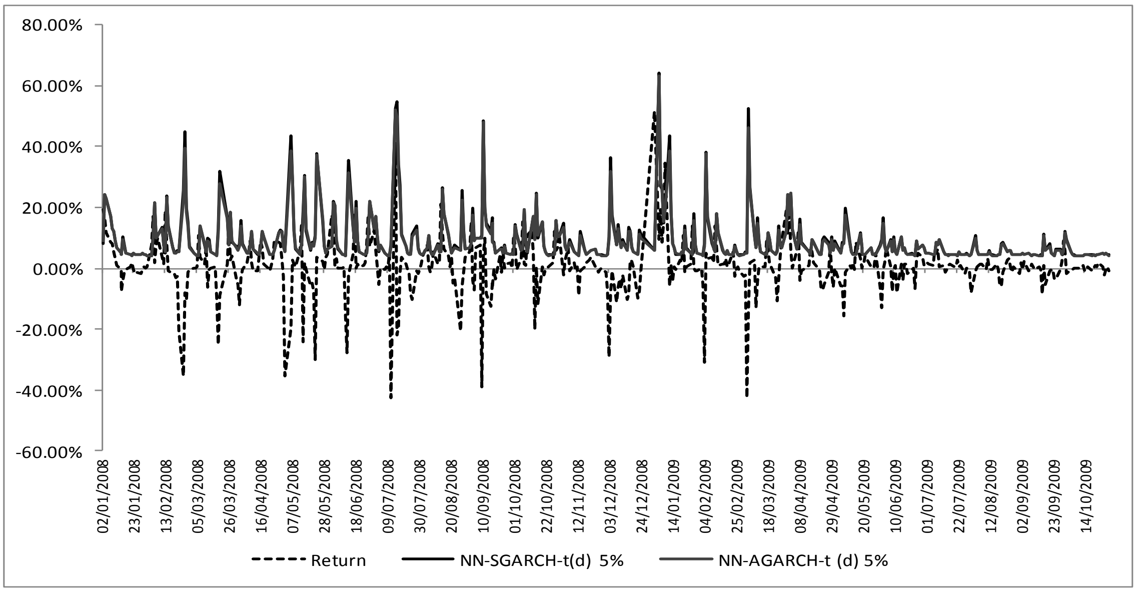
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 5% value-at-risk for the tanker route TD9



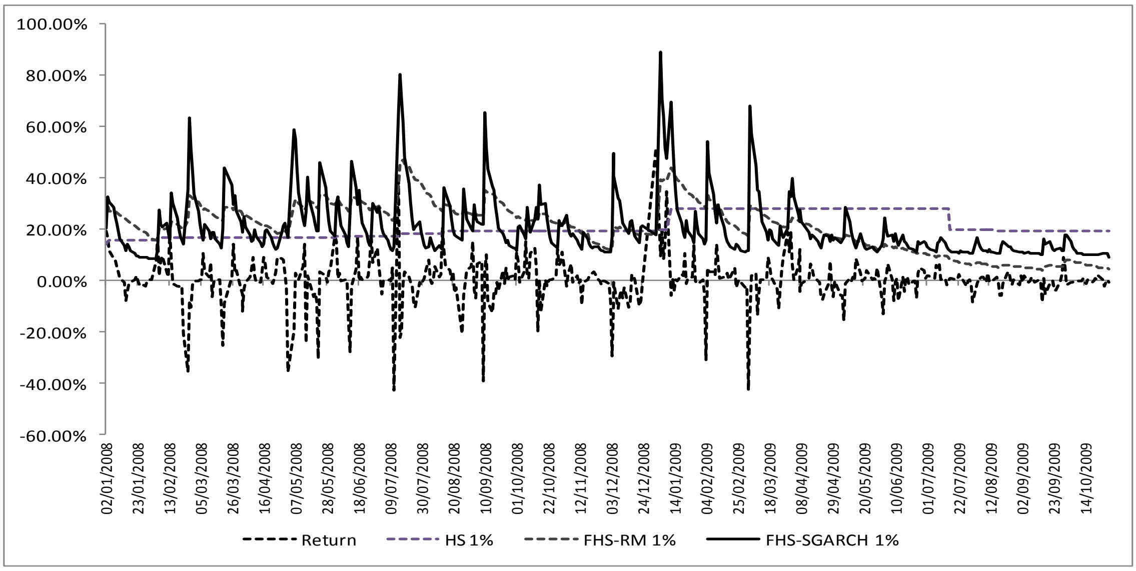
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH and AGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

Non-Normal one-day 5% value-at-risk for the tanker route TD9



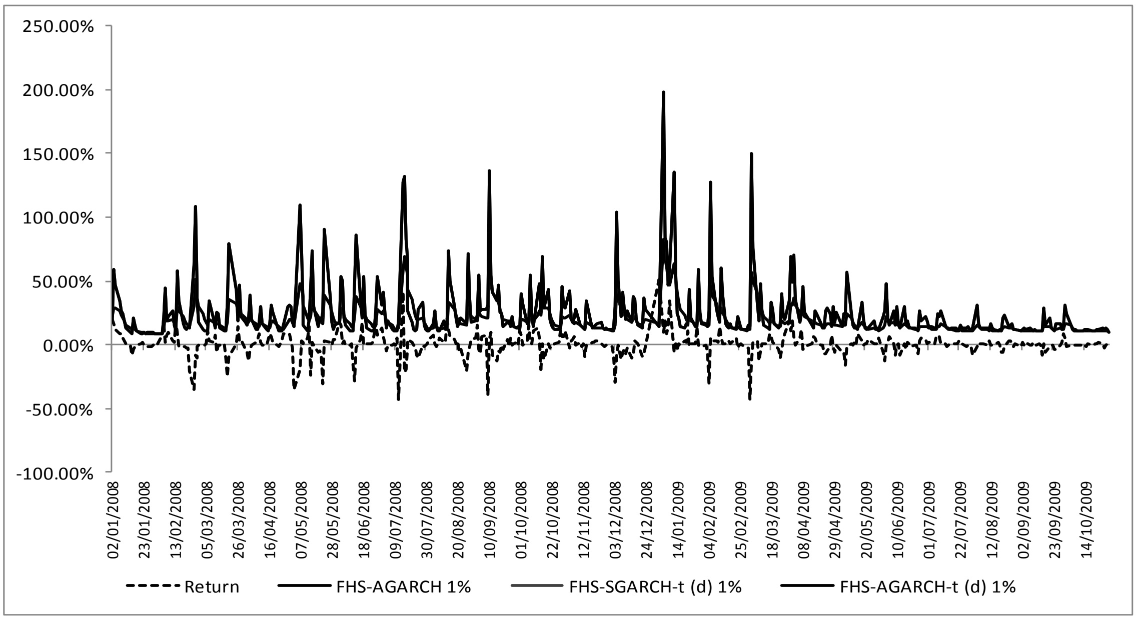
Note: Illustrations of one-day ahead value-at-risk measure based on non-normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 1% value-at-risk for the tanker route TD9



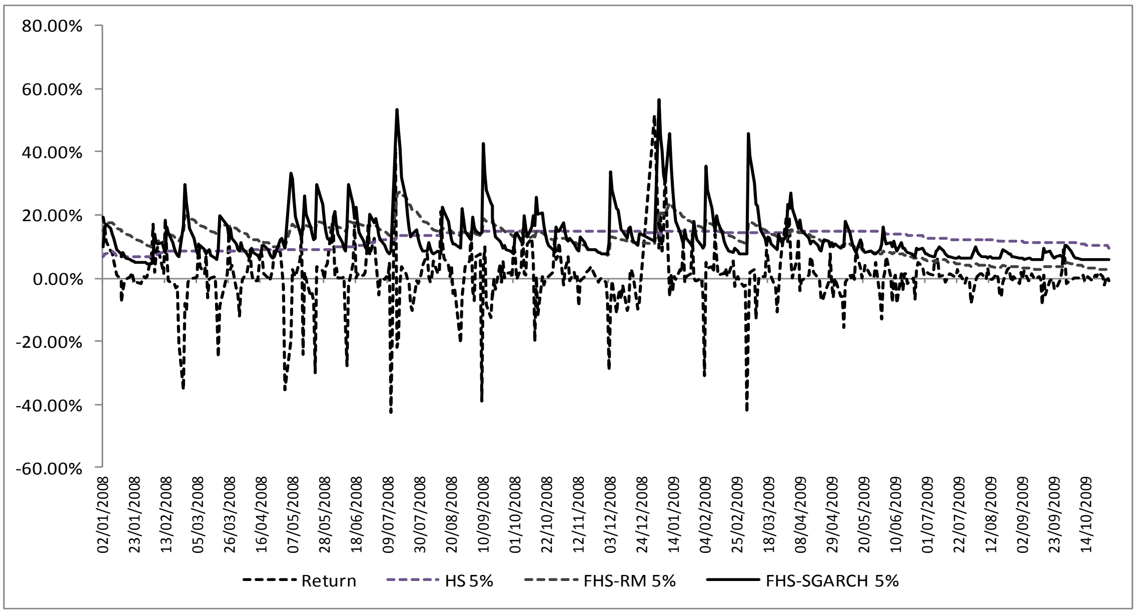
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, and SGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 1% value-at-risk for the tanker route TD9



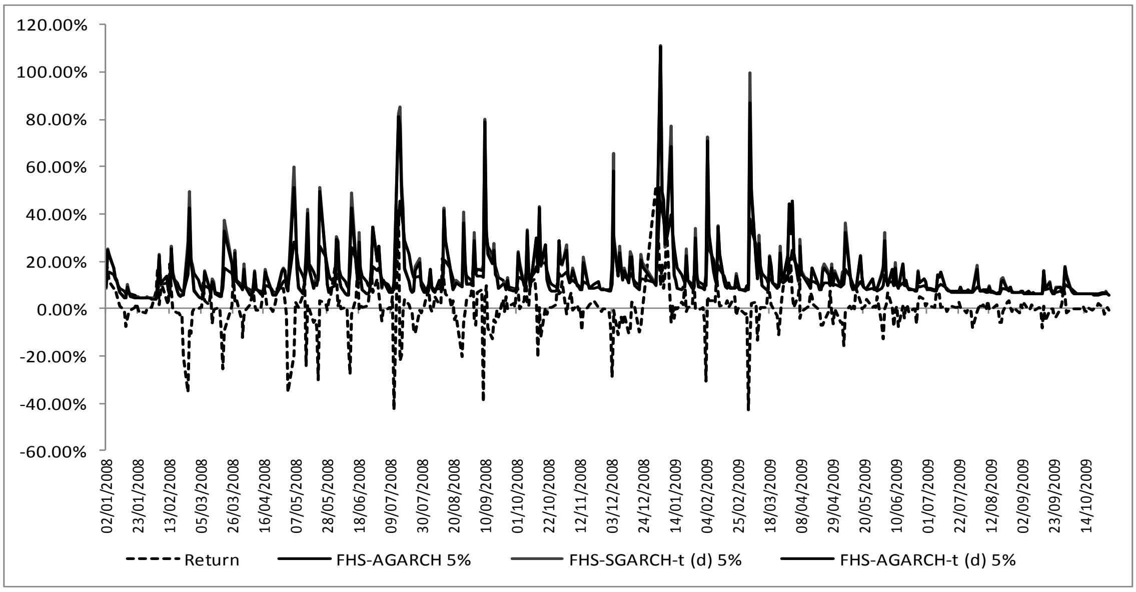
Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are AGARCH, SGARCH-t(d) and AGARCH-t (d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

HS and FHS one-day 5% value-at-risk for the tanker route TD9



Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, and SGARCH. The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

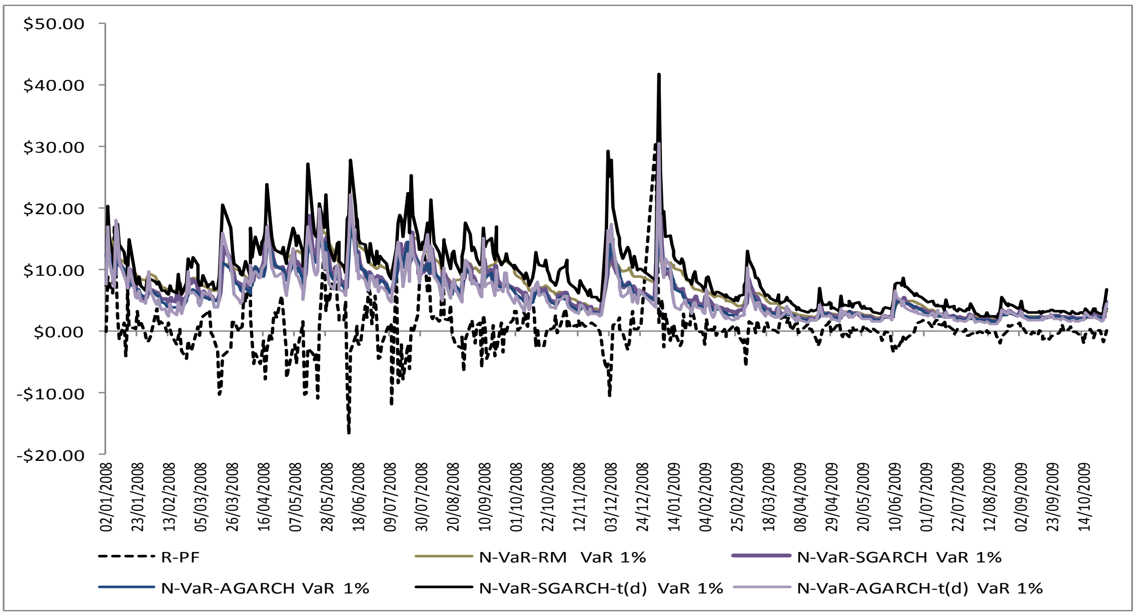
HS and FHS one-day 5% value-at-risk for the tanker route TD9



Note: Illustrations of one-day ahead value-at-risk measure based on a free method for distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are AGARCH, SGARCH-t(d) and AGARCH-t (d). The vertical axis is freight rates in WorldScale points that refer to the spot price of one transported tonne of cargo in dollars. **Source:** Author's estimations.

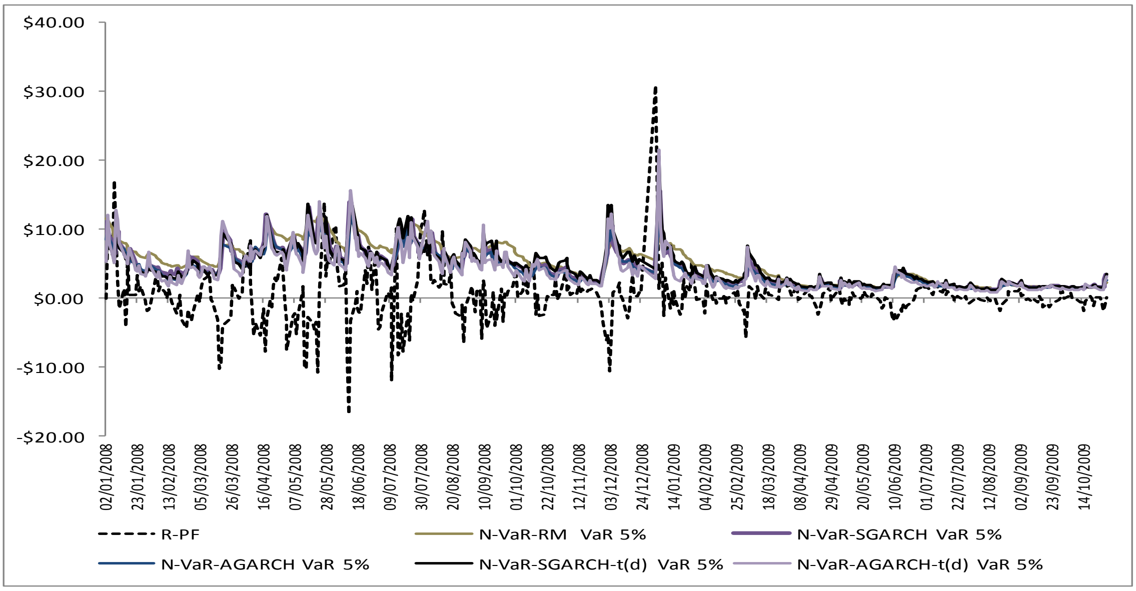
Appendix II

A one-day normal 1% value-at-risk for a portfolio of freight returns



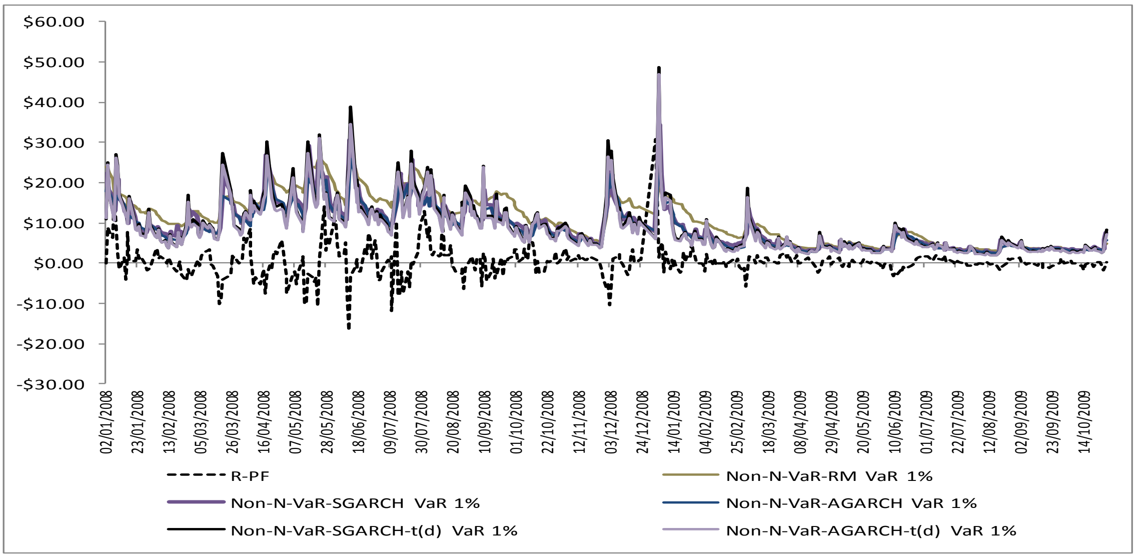
Note: Illustrations of one-day ahead value-at-risk measure for a portfolio of freight returns based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH, AGARCH, SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in dollars per tonne. **Source:** Author's estimations.

A one-day normal value-at-risk 5% for a portfolio of freight returns



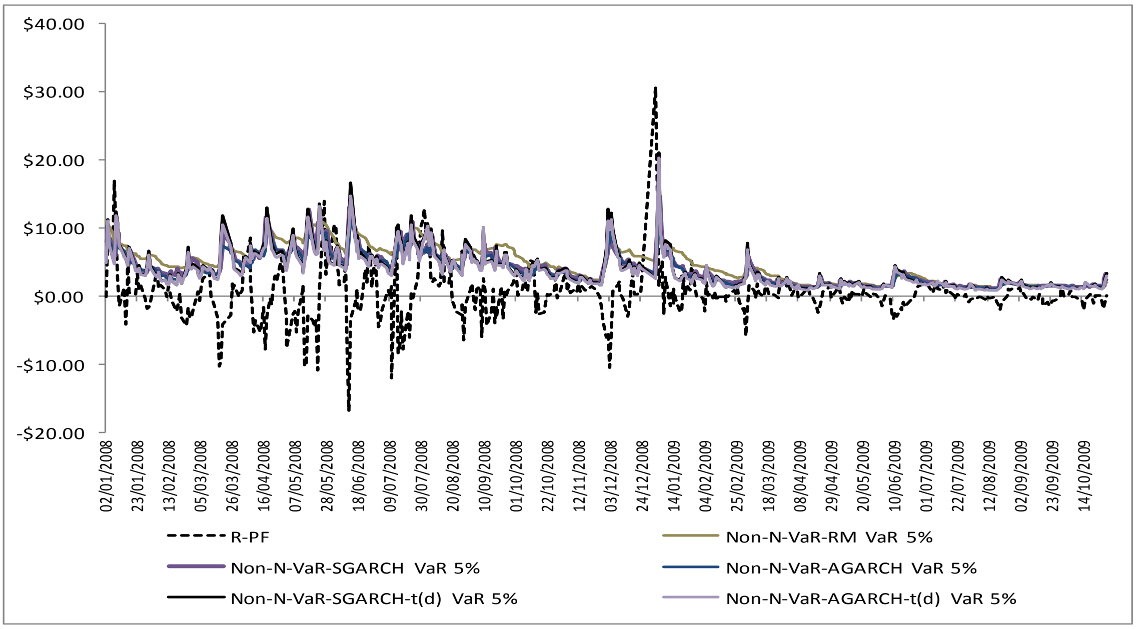
Note: Illustrations of one-day ahead value-at-risk measure for a portfolio of freight returns based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH, AGARCH, SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in dollars per tonne. **Source:** Author's estimations.

A one-day non-normal 1% value-at-risk for a portfolio of freight returns



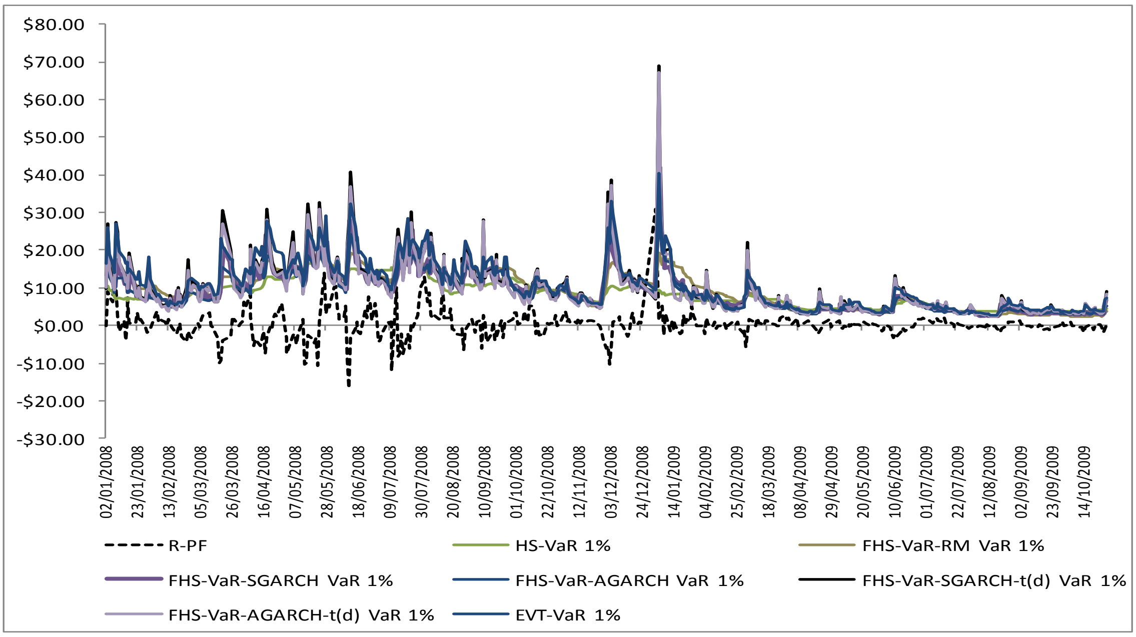
Note: Illustrations of one-day ahead value-at-risk measure for a portfolio of freight returns based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH, AGARCH, SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in dollars per tonne. **Source:** Author's estimations.

A one-day non-normal 5% value-at-risk for a portfolio of freight returns



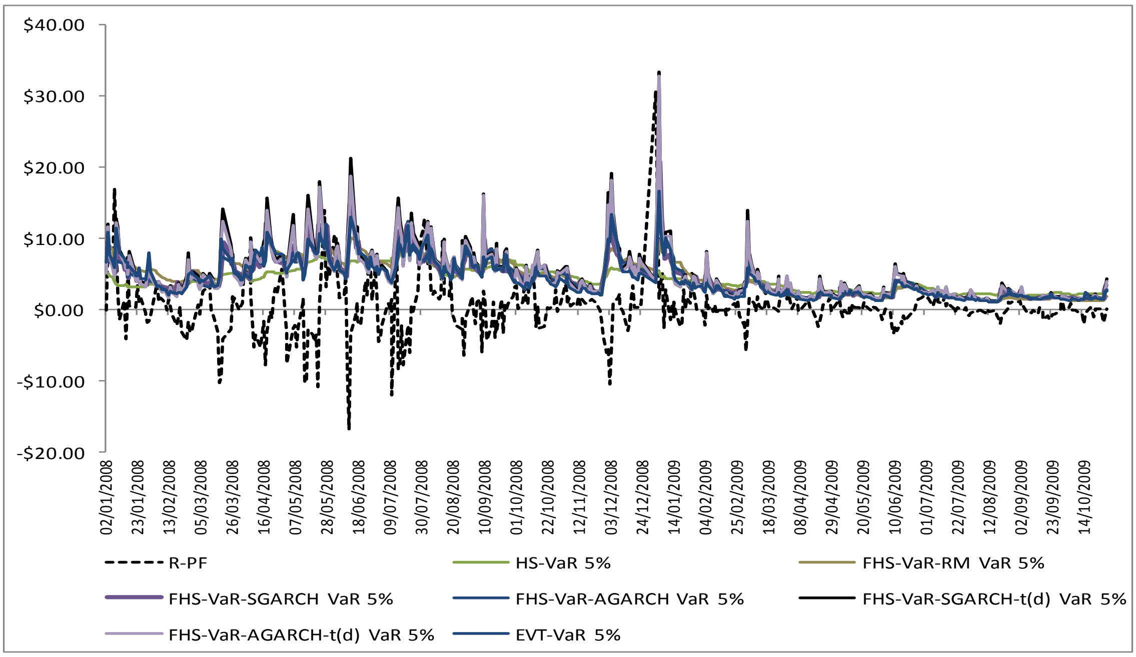
Note: Illustrations of one-day ahead value-at-risk measure for a portfolio of freight returns based on normal distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are RM, SGARCH, AGARCH, SGARCH-t(d) and AGARCH-t(d). The vertical axis is freight rates in dollars per tonne. **Source:** Author's estimations.

A one-day 1% FHS-value-at-risk for a portfolio of freight returns



Note: Illustrations of one-day ahead value-at-risk measure for a portfolio of freight returns based on free method of distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, SGARCH, AGARCH, SGARCH-t(d), AGARCH-t(d) and EVT. The vertical axis is freight rates in dollars per tonne. **Source:** Author's estimations.

A one-day 5% FHS-value-at-risk for a portfolio of freight returns



Note: Illustrations of one-day ahead value-at-risk measure for a portfolio of freight returns based on free method of distributed risk factors of returns imposed on actual returns in the black dashed line. The estimated models are HS, RM, SGARCH, AGARCH, SGARCH-t(d), AGARCH-t(d) and EVT. The vertical axis is freight rates in dollars per tonne. **Source:** Author's estimations.